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Data-Driven Production Planning and Control using Work Density for On-Site Building Construction

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By

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By

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Abstract

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The construction industry faces challenges due to escalating project complexity, demands for accelerated project delivery, and dwindling contractor margins. Traditional planning and control methods, characterized by deterministic and transformation-focused approaches, struggle to manage the dynamic interactions within production systems, including workflows and variabilities. Despite the potential of takt production and other location-based methods to streamline workflows and enhance project outcomes, their practical adoption remains limited due to several inherent challenges.

This dissertation addresses the challenges in adopting location-based production planning and control methods by identifying key obstacles such as the non-repetitive nature of work, dynamic production rates, and the lack of objective and data-driven systems necessary for effective production planning and control. To mitigate these issues, I propose a comprehensive Data-Driven Production Framework (DDPF), which integrates planning and control components using work density to measure, store, and utilize actual production data. While this framework is developed using takt production principles, its final objectives are left to the users, making it relevant for other location-based methods.

Employing a qualitative case study approach based on Design Science Research (DSR) principles, this research develops and validates artifacts including a comprehensive suite of tools and methods under the DDPF. I validated the application of these artifacts in real-world settings on two case studies, highlighting their practical applications and the benefits of using work density for planning and control.

The first case study involves the application of the Work Density Method (WDM) through the ViWoLZo tool (Visual Workload Leveling and Zoning), demonstrating the utility of work density in enhancing decision-making during production planning by enabling an objective way to reduce variability and improve process flow, among several other production metrics proposed to support planning. Furthermore, the role of cost modeling is explored, reimagining cost from a production perspective and integrating cost considerations directly into the planning process to ensure cost-effective production decisions.

In ViWoLZo, I utilize work density maps for each process step with non-uniformly spaced grid lines to calculate work density per cell and aggregate the cells into zones to calculate the workload per step per zone. However, its application highlighted challenges with manual and

subjective data collection and analysis required to create the work density maps, leading to the development of the DDPF with a novel data model and data schema, leveraging real-time data collection and advanced data-driven methods. This data model moves away from the original definition of work density that is cell-based and is calculated using estimates, to a new definition that is location-based, where a location is a room or zone, and is measured empirically. Comparing it to the original definition, this work density can be considered cumulative work density for the cells in a room or a zone, hence referred to as measured workload.

The second case study focuses on the DDPF's application in production control, utilizing advanced data collection and analysis methods, including a 360° camera-based tracking, and a production performance dashboard for supporting production control. Algorithms for work detection, such as the computer vision-based algorithm used in this research, are constantly improving. Current implementations are limited as they only work with objects in line-of-sight and with a certain range and accuracy, limited by the nature of the work to be detected, the resolution of the sensor, and the types of detection models used. I used the actual performance data to measure the duration of steps by location, representing the step's measured workload. A combined dataset with the workload for a location along with the contextual data describing what work was done, by whom, where, and how, are stored as historical work density. I used this dataset to fit machine learning (ML) models that can predict work density for future planning efforts.

In this research, unsupervised learning methods were employed to understand the data and enhance the supervised learning-based prediction of work density. The investigation of the model's prediction performance demonstrated the DDPF's potential utility in production planning, achieving an expected error of 3.7 days compared to the historical data. The model's performance was constrained due to the limited amount of data collected and higher variability in the higher range of values of measured workloads. The distribution of measured workloads in the dataset has a mean of 20.44 days with a standard deviation of 19.03. To use the model on takt plans requiring smaller workloads, the ML model will have to be exposed to empirical data from processes with similar workloads. Although on separate occasions, the ML models have been trained and tested on real-world data and work density has been used for planning with ViWoLZo, and they are connected using the DDPF, the prediction model and ViWoLZo have not yet been integrated for use in real-world scenarios to plan future projects using predicted work density.

The use of work density enabled ViWoLZo and the production performance dashboard to translate production system dynamics into a data-driven model. Interviews with field personnel confirmed the DDPF's effectiveness in implementing takt-like production to reduce process duration through increased concurrency, enhance stakeholder communication through transparency and visual management, and improve overall project performance through reduced variability and increased predictability of the production performance. The ML models and data analyses demonstrate that contextual data contain valuable insights that can streamline the implementation of location-based production planning and control methods. However, due to the small size of data collected from a single case study, the complex relationships within the data, and many features left to be collected and tested, these results are just the building blocks for further research.

The dissertation concludes with recommendations for broadening the adoption of the DDPF, emphasizing the need for advancements in data collection technologies and analysis methods, and the need to standardize historical work density libraries. Improved performance combined with simpler implementation can potentially increase the adoption of these methods in the industry, and in turn, lead to further advancements.

To my mother, Priya Singh, for her boundless sacrifices,

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Definitions

The following definitions are used in this dissertation.

Term	Definition
Batch	“The number of units that are being worked on simultaneously before a process produces output (production batch) or the number of units that together are being handed off from one production unit to the next (transfer batch).” (P2SL 2022)
Big Room	“A designated place for a team to co-locate, engage in collaborative problem solving, and maintain a visual workplace.” (P2SL 2022)
Buffer	“A mechanism for deadening the force of a concussion.” (P2SL 2022) Some types of buffers include capacity buffers, time buffers, monetary buffers (contingency), and spatial buffers (tolerances or allowable dimensional variation). See Capacity Buffer.
Capacity	“An upper limit on the throughput of a production process is its capacity. In most cases, releasing work into the system at or above the capacity causes the system to become unstable (i.e., build up WIP without bound).” (Hopp and Spearman 2008)
Capacity Buffer	“A capacity buffer is created by scheduling less than all the time available (aka. underloading the production unit or other resource). If production falls behind schedule, there is capacity available for catching up. Capacity buffers may be preferred over inventory buffers.” (P2SL 2022) See Buffer.
Choosing By Advantages (CBA)	“CBA is a decision-making system, developed by Jim Suhr (1999), that provides a rational and objective approach to compare the advantages (beneficial differences) of each option.” (Defined in Section 2.4.2.5)
Cost Modeling	Cost modeling involves “formulating a cost model to estimate cost at some level of abstraction of a component or a system under design.” (Nguyen 2010)

Critical Path Method (CPM)	"A project management tool that identifies critical and non-critical tasks with the goal to prevent time-frame problems and process bottlenecks." (Kelley and Walker 1959)
Customer Takt (aka. Demand Takt) (T_c)	"The upper bound for the takt of a plan, i.e., every step's worth of work must be completed within this amount of time. Whether or not that customer takt can be met depends on how steps and zones are defined, and how much concurrency is feasible. By assuming the maximum allowable duration D of a process (e.g., defined by schedule milestones) and knowing the number of steps S and the number of zones Z, one can calculate the time for customer takt T_c." (Defined in Section 3.1.1), See Operable Takt and Takt.
Cycle Time (CT)	"Of a given routing is the average time from the release of a job at the beginning of the routing until it reaches an inventory point at the end of the routing (i.e., the time the part spends as WIP)." From a lean perspective, cycle time is the sum of value-added time and non-value-added time. Thus, reducing non-value-added time decreases the cycle time and improves efficiency. (Hopp and Spearman 2008, p. 230)
Data-Driven Production Framework (DDPF)	A framework for the collection, transformation, and application of production data in on-site production planning and control of building construction projects. (Defined in Section 4.3.1)
Evenness of Flow	"Production achieved based on load leveling (Heijunka)." (P2SL 2022)
Feature (aka. variable, attribute)	Feature is an individual measurable property or characteristic of the observations. These are the inputs used by the machine learning model to make predictions or uncover patterns. See Observations.
Inventory Turns or Turnover Ratio	"A measure of how efficiently inventory is utilized, expressed as the ratio of throughput to average inventory." (Hopp and Spearman 2008, p. 230)
Last Planner® System (LPS)	"Improves plan reliability through the subdivision of planning into finer levels, commonly used with activity-based methods like CPM at higher planning levels." (Ballard 2000; Ballard and Tommelein 2021)

Lead Time	"Of a given routing or line is the time allotted for production of a part on that routing or line." (Hopp and Spearman 2008, p. 230)
Lean Construction	"Application of lean thinking to the designing and making (or delivery at large) of capital projects (or projects in general)." (P2SL 2022)
Lean Project Delivery System (LPDS)	A "production management-based approach to designing and building capital facilities in which the project is structured and managed as a value generating process." (Ballard 2000)
Load Leveling (Heijunka)	See Workload Leveling.
Machine Learning (ML)	Machine Learning is the intersection of computer science and statistics and is described as a collection of algorithms that apply computational and statistical techniques to identify patterns in data. (Jordan and Mitchell 2015)
Muda (waste)	"The Japanese word for waste referring to anything that fails to add value to the product or service delivered to the customer, i.e., anything unnecessary." (P2SL 2022)
Mura (unevenness)	"The Japanese word for waste stemming from unevenness or inconsistency of workload imposed on people or machines (resources). It may be alleviated through application of heijunka and kanban systems." (P2SL 2022)
Muri (overburdening)	"The Japanese word for waste stemming from overburdening people or machines (resources). It may be alleviated, for example, through application of 5S." (P2SL 2022)
Observation (aka. data point, sample, row)	An observation is a single instance or record in a dataset that contains values for each feature. It represents one unit of data that a machine learning model will learn from or make predictions on. See Feature.
Operable Takt (*T(Z)*)	For a specific process and work space, Operable takt *T(Z)* is "defined as the maximum time needed to complete any step in any zone, a key parameter in workload leveling using takt time approaches. *T(Z)* gives the minimum process duration possible for a takt plan with the given workloads. *T(Z)* defines the lower bound for the takt of a plan, i.e., all step's workloads in all zones are

	estimated to be less than or equal to this amount of time." (Defined in Section 3.1.1), See Customer Takt and Takt.
Operation	"An operation describes a sequence of steps a single trade performs to complete work or to deliver a service as per their scope of work (e.g., installing a sink is one step for the plumber, one of several trades involved in the process of building a bathroom)." (Defined in Section 2.1.4.)
Phase	"A phase refers to inter-dependent scopes of work of trades who will work on site more-or-less concurrently. A phase's start and end are delimited by milestones in the master schedule. A phase comprises one or several processes." (Defined in Section 2.1.4.)
Process	"A phase comprises one or several processes. Each process comprises steps, each one pertaining to a certain scope of work performed by a single trade (or possibly a crew composed of multiple trades)." (Defined in Section 2.1.4.)
Process Capacity	"The upper limit on a production process throughput, typically beyond which the system becomes unstable due to excessive WIP." (Hopp and Spearman 2008, p. 229)
Process Duration (*D*)	"Total time taken from the commencement to the end of a process sequence, inclusive of all steps and zones involved." (Adapted from Singh and Tommelein's (2023a) usage)
Production Control	Monitoring and adjusting production in real-time to maintain desired production targets. (Discussed in Chapter 5)
Production Metrics	"Metrics to measure the performance or success of a production system can be based on the anticipated performance for a plan or based on the actual performance for work completed." (Defined in Section 3.3.2.)
Production Parameters	"Production parameters are configurable variables that detail aspects of the production system." (Defined in Section 3.3.1.)
Production Planning Component	"Part of the DDPF that uses predicted work density to establish a production plan to achieve desired takt times." (Introduced and explained in Chapter 4)

Production Unit (PU)	An "individual or a group performing some production tasks. PUs commits to assignments. PUs includes design squads and construction crews." (Ballard 1999)
Step (short for Process Step) (*S*)	"Each process comprises steps, each one pertaining to a certain scope of work performed by a single trade (or possibly a crew composed of multiple trades). Each step in a process lies at the intersection of a process and an operation." (Defined in Section 2.1.4.)
Takt (aka. Takt Time) (*T*)	"The time interval between the start of production of one unit and start of the next unit, when these start times are set to match the rate of customer demand." (Tompkins et al. 2010). In this dissertation, as defined in Section 3.1.1, "The final process design selected in the plan should have a takt T, that is equal or greater than the operable takt $T(Z)$ to reliably complete all steps within the takt, and equal or smaller than the customer takt T_c to be able to meet the maximum allowable process duration D." (Defined in Section 3.1.1), See Customer Takt and Operable Takt.
Takt planning	Takt planning is a "work structuring method that aligns the production rates of trades by pacing work through a set of zones in a set sequence to create continuous workflow, reliable handoffs, and an opportunity to continuously improve the production system." (Frandson 2019)
Takt Production	Takt production involves a combination of takt planning and control of a production system. See Takt Planning.
Throughput (TH)	"The average output of a production process (machine, workstation, line, plant) per unit time (e.g., parts per hour) is defined as the system's throughput (TH), or sometimes throughput rate." (Hopp and Spearman 2008, p. 229)
Trade (aka. subcontractor, specialty contractor)	A trade, also known as a subcontractor or specialty contractor, is a specialized construction professional (organization) employed by a general contractor (GC). Generally, a trade provides skilled workers who specialize in a particular craft.
Transformation-Flow-Value (TFV) Model	The TFV model of production, made up of the transformation, Flow, and Value concepts, extends the attention to modeling, designing, controlling and improving production from all these three points of view (Koskela 2000).

Utilization	"The utilization of a workstation is the fraction of time it is not idle for lack of parts. This includes the fraction of time the workstation is working on parts or has parts waiting and is unable to work on them because of a machine failure, setup, or other detractor." (Hopp and Spearman 2008, p. 231)
Variability	Hopp and Spearman (2008, p. 264) define variability as the quality of nonuniformity of attributes. They use attributes of manufacturing systems for which variability is of interest and are prone to nonuniformity, such as physical dimensions, process times, machine failure, repair times, setup times, and so on. Variability is quantified using standard measures from statistics including variance, a measure of absolute variability, and standard deviation, defined as the square root of the variance.
ViWoLZo	"A visualization and computing support tool that computes work density for workload leveling and zoning in construction project production planning." (Introduced and explained in Chapter 3)
Waste	"Anything with a cost of any kind, the elimination of which does not reduce value delivered." (P2SL 2022). See Muda, Mura, and Muri.
Work Density (WD)	"Given a certain work area, work density describes how much time a given trade will require to do their work in that area, based on the product design and the scope of work done by that trade for a given task in the schedule (thus depending on work already in place and work that will follow), the means and methods the trade will use to do their work while accounting for their crews' capabilities and crew size." (Tommelein 2017)
Work Density Method (WDM)	A process planning method based on units of work density as the means to time the use of work space, involving linear sequences of trade steps and zoning of work space. (Tommelein 2017; Tommelein 2022)
Work In Process (WIP)	"The inventory between the start and end points of a product routing is called work in process. Since routings begin and end at stock points, WIP is all the product between, but not including, the ending stock points." (Hopp and Spearman 2008, p. 230)
Work Structuring	"The development of operation and process design in alignment with product design, the structure of supply chains, the allocation of resources, and design-for-assembly efforts with the goal of

	making workflow more reliable and quicker while delivering value to the customer" (Ballard 2000)
Workable Backlog	"Workable backlog is work that needs to be done, but is not on the critical path of the Master Schedule, and can be used to increase utilization of crews when planned work is not ready to start." (Frandson 2019)
Workload Leveling	Workload leveling is used to manage and distribute workloads evenly across different steps in a process and various zones in a work space. It aims to reduce or eliminate variability in workloads, which is generally considered undesirable. By implementing workload leveling, planners seek to achieve a smoother workflow. (Introduced and explained in Section 2.2.5)
Zone (*Z*)	In takt production, a zone is "a delimited space where one production unit gets scheduled to complete their work within the Takt time." (Frandson 2019)

Acronyms

The following acronyms are used in this dissertation:

Acronym	Abbreviation for
2D	Two-Dimensional
3D	Three-Dimensional
4P	Philosophy, Process, People and Partners, And Problem-Solving
ADAS	Advanced Driver Assistance Systems
AEC	Architecture, Engineering, and Construction
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ASCE	American Society of Civil Engineers
BIM	Building Information Model
BLE	Bluetooth Low Energy
CBA	Choosing By Advantages
CDE	Common Data Environment
CFI	Construction Flow Index
CNN	Convolutional Neural Network
COV	Coefficient of Variation
CPM	Critical Path Method
CSI	Construction Specifications Institute
CT	Cycle Time
CV	Computer Vision
DBSCAN	Density-Based Spatial Clustering of Applications with Noise

DDPF	Data-Driven Production Framework
DNN	Deep Neural Network
DSR	Design Science Research
ERD	Entity Relationship Diagram
ETL	Extract, Transform, and Load
FN	False Negatives
FP	False Positives
FSAE	Fire Service Access Elevator
GBR	Gradient Boosting Regressor
GC	General Contractor
GPS	Global Positioning System
GRU	Gated Recurrent Unit
ICMS	International Cost Management Standard
IFoA	Integrated Form of Agreement
IGLC	International Group for Lean Construction
IMU	Inertial Measurement Unit
IoT	Internet of Things
IPD	Integrated Project Delivery
IPS	Indoor Positioning Systems
JIT	Just In Time
KPI	Key Performance Indicator
LBMS	Location-Based Management System
LBS	Location Breakdown Structure

LDA	Linear Discriminant Analysis
LoB	Line-of-Balance
LoRa	Long Range
LPDS	Lean Project Delivery System
LPS	Last Planner® System
LSTM	Long Short-Term Memory
ML	Machine Learning
MSE	Mean Square Error
NN	Neural Network
OAC	Owner-Architect-Contractor
OCCS	OmniClass Construction Classification System
OSHPD	Office of Statewide Health Planning and Development
P2SL	Project Production Systems Laboratory
PBCM	Process-Based Cost Modeling
PC	Principal Component
PCA	Principal Component Analysis
PCC	Pearson Correlation Coefficient
PCS	Predictability, Computability, and Stability
PPC	Plan Percent Complete
PSD	Production System Design
PU	Production Unit
QTO	Quantity Take-Off
R^2	Coefficient of determination

RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
RSM	Repetitive Scheduling Method
RSSI	Received Signal Strength Indicator
SINDy	Sparse Identification of Nonlinear Dynamics
SIPS	Short-Interval Planning System
SPI	Schedule Performance Index
SVM	Support Vector Machine
TCO	Total Cost of Ownership
TFV	Transformation-Flow-Value
TH	Throughput
TMR	Tasks Made Ready
TN	True Negatives
TP	True Positives
TPS	Toyota Production System
TQM	Total Quality Management
t-SNE	t-Distributed Stochastic Neighbor Embedding
TVD	Target Value Design or Target Value Delivery
UAV	Unmanned Aerial Vehicle
UCSF	University of California, San Francisco
UWB	Ultra-Wideband
ViWoLZo	Visual Workload Leveling and Zoning

VM	Visual Management
VSLAM	Visual Simultaneous Localization and Mapping
VUT	Variability, Utilization, and Time
WBS	Work Breakdown Structure
WD	Work Density
WDM	Work Density Method
WIP	Work In Process
WLAN	Wireless Local Area Network
WoLZo	Workload Leveling and Zoning
XGBoost	eXtreme Gradient Boosting

Chapter 1
Introduction

1.1 Background

The construction industry faces challenges of increased project complexity, heightened demands for faster delivery, rising quality standards, and shrinking profit margins (Luo et al. 2017). The industry also deals with stringent regulations, imbalances in risk and rewards, outdated management methods, fragmentation, and inefficiencies, hindering innovation and performance. Such challenges affect project performance in many ways including deficient scheduling and coordination, late supply of resources, skilled labor shortages, cost and schedule overruns, and material wastage. Cumulatively, these challenges impact labor performance (Ibbs and McEniry 2008, Ibbs and Vaughan 2015), which, in turn, affects the overall performance of the industry. The industry's labor productivity, often measured as value-added per employee, ranks among the lowest across industries (Barbosa et al. 2017). Although productivity can be defined in different ways (Crawford and Vogl 2006), a consensus exists that the construction industry lags behind others in process and technology innovation.

Addressing these challenges and driving significant change in construction project management requires a comprehensive approach, integrating people, processes, and technology. At the forefront of applying this approach is lean construction. Lean construction applies lean production principles to the construction context.

At the core of lean construction is the transformation-flow-value (TFV) model introduced by Koskela (1992, 2000). Historically, construction planning and control have depended on activity-based methods. Construction managers have extensively used the Critical Path Method (CPM), a key example, since the late 1950s (Kelley and Walker 1959). Despite having merits, the focus on discrete activities in these methods presents challenges. It particularly affects workflow continuity when viewed through the lens of the TFV model (Kenley 2004).

In addressing these challenges, researchers have proposed a variety of production-focused methods. The Last Planner® System (LPS) (Ballard 2000, Ballard and Tommelein 2021) stands out for scholars and industry practitioners both. LPS improves plan reliability through the subdivision of planning into finer levels. Planners usually use it in combination with activity-based methods such as CPM, which are extensively used at higher and coarser levels of planning—phase-, master-, and project execution planning. LPS breaks down the plan to lower and finer levels of planning—look-ahead and weekly planning processes. Figure 1.1 shows levels of planning in construction using LPS.

In their recent benchmark study of the LPS, Ballard and Tommelein (2021) highlight several methods that achieve LPS functions. They advocate for location-based work structuring and planning methods, especially when work is spatially divisible. Ballard and Tommelein discuss various location-based planning methods in the benchmark, including the Line-of-Balance (LoB) method, the Short-Interval Planning System (SIPS), the Repetitive Scheduling Method (RSM), block scheduling, even flow production, and takt planning. Among these, takt planning has gained prominence as an effective approach for project production planning and control, particularly at the phase- and look-ahead planning level. For the purpose of consistency, this dissertation refers to takt planning as takt production, as the method encompasses both production planning and control.

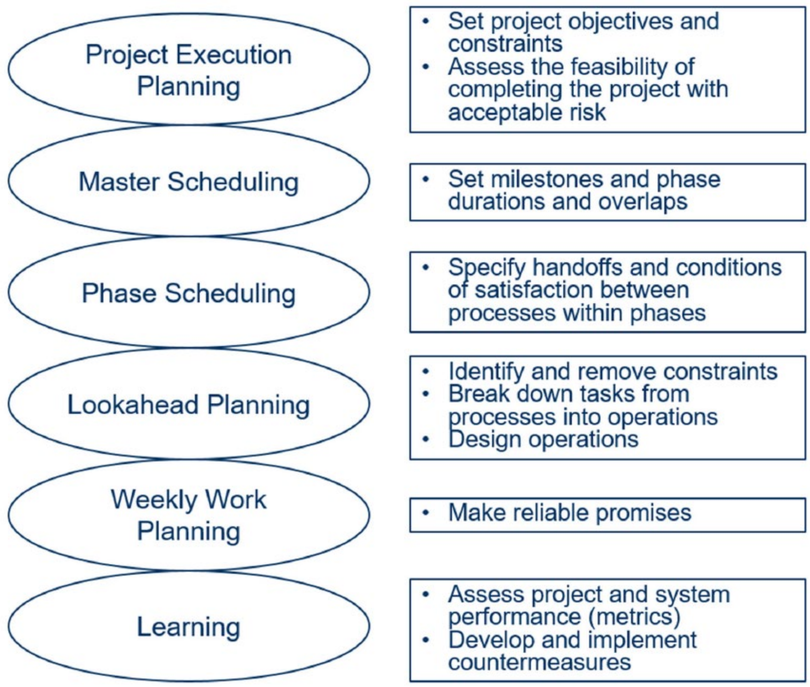


Figure 1.1: Levels of planning and control in Last Planner® System (Figure 2 in Ballard and Tommelein 2021, used with permission).

Takt production aims to optimize construction work space and time allocation, while eliminating trade stacking. It involves a combination of takt-based planning and control of a production system, sometimes used in conjunction with LPS. Research case studies in the last decade (Frandson et al. 2013, Linnik et al. 2013, Frandson and Tommelein 2014b, Binninger et al. 2018, Lehtovaara et al. 2021b) highlight the benefits of takt production. These include shorter production durations, better stakeholder communication, improved workflow, reduced variability, and enhanced quality and productivity.

Implementation challenges unique to the on-site building construction industry limit adoption of takt production. The non-repetitive nature of work and dynamic production rates present distinct obstacles. Successful implementation of a takt production system requires moving away from conventional planning methods. In these conventional methods, practitioners often rely on personal experience, deterministic scheduling, and cost estimation. They are characterized by top-down and push-based planning, informal status updates for control, and a general absence of data-driven decision-making.

Effective application of takt production to improve workflow and reduce duration requires addressing process variability. Within takt planning, workload leveling is essential for achieving consistent workflow. Recent development of the Work Density Method (WDM) (Tommelein 2017, Tommelein 2022) offers a practical solution to the workload leveling problem. It provides a unit of quantity that allows planners to shape project production systems with leveled workflows, clear trade handoffs, and controlled variability. This method aims for predictable on-time project completion. The WDM has shown success in supporting takt planning across various studies (Bardaweel 2018, Diab 2020, Dunnebier et al. 2014, Jabbari et al. 2020a, Luktuke 2019, Singh et al. 2020, Singh and Tommelein 2023a). Its flexibility makes it suitable for any location-based production planning method, even when the objective is not necessarily to level the workload across all process steps and locations.

1.2 Relevance

Implementing methods such as the WDM presents challenges related to data acquisition necessary for calculating work density. General Contractors (GCs) often do not possess sufficiently detailed production data, and trades may be reluctant to share precise data, fearing the implications of over-commitment. Additionally, the lack of a standardized framework for the collection, storage, and management of production data exacerbates these challenges, particularly in unique, non-repetitive construction projects. These challenges underscore the need for a comprehensive framework for production management that integrates the complete data lifecycle—from collection and processing to storage and application.

Concurrently, technological advancements facilitating data collection, processing, and consumption are becoming increasingly accessible and reliable. These advancements are marked by improvements in frequency, autonomy, accuracy, and efficiency, which concurrently reduce effort, time, and costs. The construction industry has witnessed a substantial financial influx aimed at its technological evolution. The shift towards industry digitization, which began to gain momentum two decades ago and has accelerated significantly over the past three years, aligns with global trends observed in the construction industry during this period (Luis Blanco et al. 2023). The trends include increase in demand for long-duration construction projects, a shortage of skilled labor, and stringent government regulations, suggesting a sustained shift towards digital solutions to increase productivity.

This shift has facilitated the transformation of construction projects from traditional, paper-based, and manual documentation to modern, digital, and automated data capture systems, thereby generating substantial amounts of data. Simultaneously, the computational capabilities required to analyze the “big data” and tackle various industry challenges have become economically feasible and scalable (Jordan and Mitchell 2015). Developments in the field of artificial intelligence (AI), which aims for computers to possess human-like capabilities, is driving innovation in utilizing data-driven methods such as machine learning (ML), natural language processing, knowledge representation, and automated reasoning (Russell and Norvig 2010, p. 2). Among these, ML algorithms have proven to be helpful in processing vast amounts of data to detect and extrapolate patterns, much more quickly and accurately than humans. These developments make it an appropriate time to focus research on improving construction production planning and control using data-driven methods.

1.3 Motivation

From the identified challenges and existing capacity of data-driven methods to meet them, stems a two-fold motivation for this research: (1) filling the theoretical knowledge gap that hinders data-driven production planning and control in building construction, and (2) developing a data-driven approach to support the production planning and control.

With lean production philosophy at the core and takt production as a method for production planning and control, the pain points driving the first part of my research motivation include:

- Limitations of planning construction as a project versus a production system

- No existing standard measurement of flow and variability in the system, for planning and control
- Minimal transparency in project planning methods to inform who will be working where and at what time
- Ignoring space and capacity (people with tools and equipment) as a resource explicitly in planning
- Sequential work with large inventories and work in progress
- No clear handoffs between trades (on a daily to weekly basis) and trade stacking negatively impact labor productivity, safety, and quality
- Intuition and experience-based decision-making for the division of work areas and leveling workload
- Changing crew size or hampering the flow of work in efforts to achieve high worker utilization

The second motivation is seeking to address the challenges in achieving the first motivation in a data-driven approach. The pain points driving the second part of my research motivation include:

- Manual and demanding process of collecting and organizing production and quantity data to generate work densities
- Incomplete understanding of factors affecting production rates
- Non-existent historical data for the WDM or takt production
- Fragmented ways of collecting and storing production data across trades
- Incomplete understanding of objectives to optimize when zoning and workload leveling
- Inability to use historical production data for ML and other predictive applications

In this research I combined these two motivations to develop a framework for data-driven production planning and control in building construction, unifying the theoretical and technical knowledge. The goal is to enhance construction production management practices and the construction industry's performance and productivity.

1.4 Research Objectives

The objective of this research is to develop a framework for the collection, transformation, and application of production data for on-site production planning and control of building construction projects. The framework uses the work density construct for handling the production data. This framework, referred to as Data-Driven Production Framework (DDPF), includes theoretical foundations, principles, assumptions, methods, and tools to support production planning and control with a data-driven approach. The framework comprises interconnected components working together to help its user(s) achieve a common objective of improving production performance as per their needs.

Sub-objectives required to develop and validate DDPF include:

1. To enhance comprehension of production planning and control specific to on-site building construction. This involves delineating the principles and theoretical constructs foundational to the DDPF. (covered in Chapter 2)
2. To develop the DDPF by:
    a. Developing a method and proof-of-concept tool(s) for production planning using the work density construct. This also includes establishing workload leveling and zoning throttles, metrics, and visualizations that support production planning decisions. (covered in Chapters 3 and 6)
    b. Developing a method and proof-of-concept tool(s) for production control using the work density construct. This also includes establishing production metrics and visualizations to support production performance measurement and production control decisions. (covered in Chapter 5)
3. To use tracking technologies for capturing on-site production or progress data and support the production control component of the DDPF. This includes:
    a. Exploring and identifying tracking technologies suited for the real-time or near real-time monitoring of production progress by location. (covered in Chapter 2)
    b. Identifying the contextual data required to support production control. (covered in Chapter 5)
    c. Constructing a data model that interlinks hardware, software, processes, and personnel with the objectives of DDPF. (covered in Chapter 4)
    d. Creating a technology-neutral system that facilitates production control on a near real-time basis. Implementing the system on a case study project. (covered in Chapters 4 and 5)
4. To use captured production data to calculate work density and support the production planning component of the DDPF. This includes:
    a. Identifying the contextual data required to calculate and support ML-based prediction of work density. (covered in Chapter 5)
    b. Developing a data-driven algorithm to transform and store actual production progress- and contextual data from case study project(s) into historical production database. (covered in Chapter 6)
    c. Training ML models for work density predictions to support production planning. (covered in Chapter 6)
5. To develop a framework for cost modeling to facilitate location-based production planning and control. This includes:
    a. Examining the strengths and weaknesses of current cost models, cost estimation and management practices. (covered in Chapter 2)

b. Identifying elements of a cost model that translates production system design decisions, in a location-based methods such as takt production, to the project cost. (covered in Chapter 3)

c. Organizing the elements to create a descriptive framework that is compatible with DDPF. (covered in Chapter 3)

1.5 Research Questions

The main research questions, grouped by the five objectives identified in Section 1.4, are:

1. Principles and theoretical constructs foundational to the DDPF:
    a. What are the foundational principles and theoretical constructs of a data-driven production system in the context of on-site building construction?
    b. How do the principles and constructs influence production planning and control?
2. DDPF:
    a. Is it possible to develop a data-driven approach to production planning and control using the work density construct?
    b. What existing methods can be used, or new ones developed, for effective data-driven production planning in building construction?
    c. What tools can be developed for enhancing data-driven production control in building construction?
    d. What metrics and visualizations are effective in supporting production planning decisions?
    e. What metrics and visualizations are effective in supporting production performance measurement and control decisions?
3. Data collection and data-driven methods for production control:
    a. What tracking technologies are most suited for real-time or near real-time monitoring of production progress by location in building construction?
    b. What data-driven methods can be used with tracking technology and contextual data to support DDPF?
    c. What contextual data is essential for supporting production control and performance measurement?
    d. How can a data model interlink hardware, software, and processes to achieve the objectives of the DDPF?
4. Data processing and ML-based prediction for production planning:
    a. What contextual data is essential for supporting work density prediction?
    b. How can collected production progress data be transformed into work density and stored in a historical production database for construction projects?

    c. How can historical production database be used to train ML models for work density prediction and production planning?

5. Framework for cost modeling in the DDPF:
    a. What are the strengths and weaknesses of current cost models, estimation, and management practices in location-based production planning and control?
    b. How can the cost impacts of production system design decisions, in a location-based methods such as takt production, be identified and modeled?
    c. How can a cost modeling framework be used to effectively guide planning and control within the DDPF?

1.6 Research Scope

The scope of this research is to study construction project production planning and control during the construction phase. The case study projects are focused on on-site construction of buildings during their interior finishing phase.

Building construction projects are marked by challenges such as spatial constraints, limited crew and equipment mobility, various degrees of repetition of work, numerous and varying processes and trades, and the need for coordination between trades. These challenges occur in various types of building construction, including residential, commercial, institutional, and mixed-use structures.

Within building construction, the research narrows its scope to the interior finishing phase due to its unique characteristics. This phase involves complex processes, with multiple trades sharing work space, and potentially using smaller batches of work, making it a phase where knowledge contribution can be more impactful compared to other phases of building construction.

Use of technology for production or progress tracking is valuable not only for production planning and control applications, but also for other project management applications. Safety, logistics planning, construction hoist scheduling, etc. can benefit from the use of tracking technologies. This research is focused on using tracking technology to support a data-driven production management framework.

1.7 Research Methodology

The research methodology is designed to systematically develop a robust framework, starting with a foundation in existing literature and iteratively improving the framework through case studies and action-based research. This methodology is rooted in the principles of Design Science Research (DSR), which entails the creation, implementation, and evaluation of an artifact with the aim of generating generalized knowledge (March and Smith 1995). In this research, the proposed artifact is an overarching framework, comprising methods, and associated proof-of-concept tools, intended to facilitate data-driven production planning and control.

Figure 1.2 depicts the research methodology, divided into three stages: 1) preparation, 2) development, which includes development of the methods and proof-of-concept tools, and 3) reporting. The high-level process and outputs of the methodology are guided by the general principles of DSR.

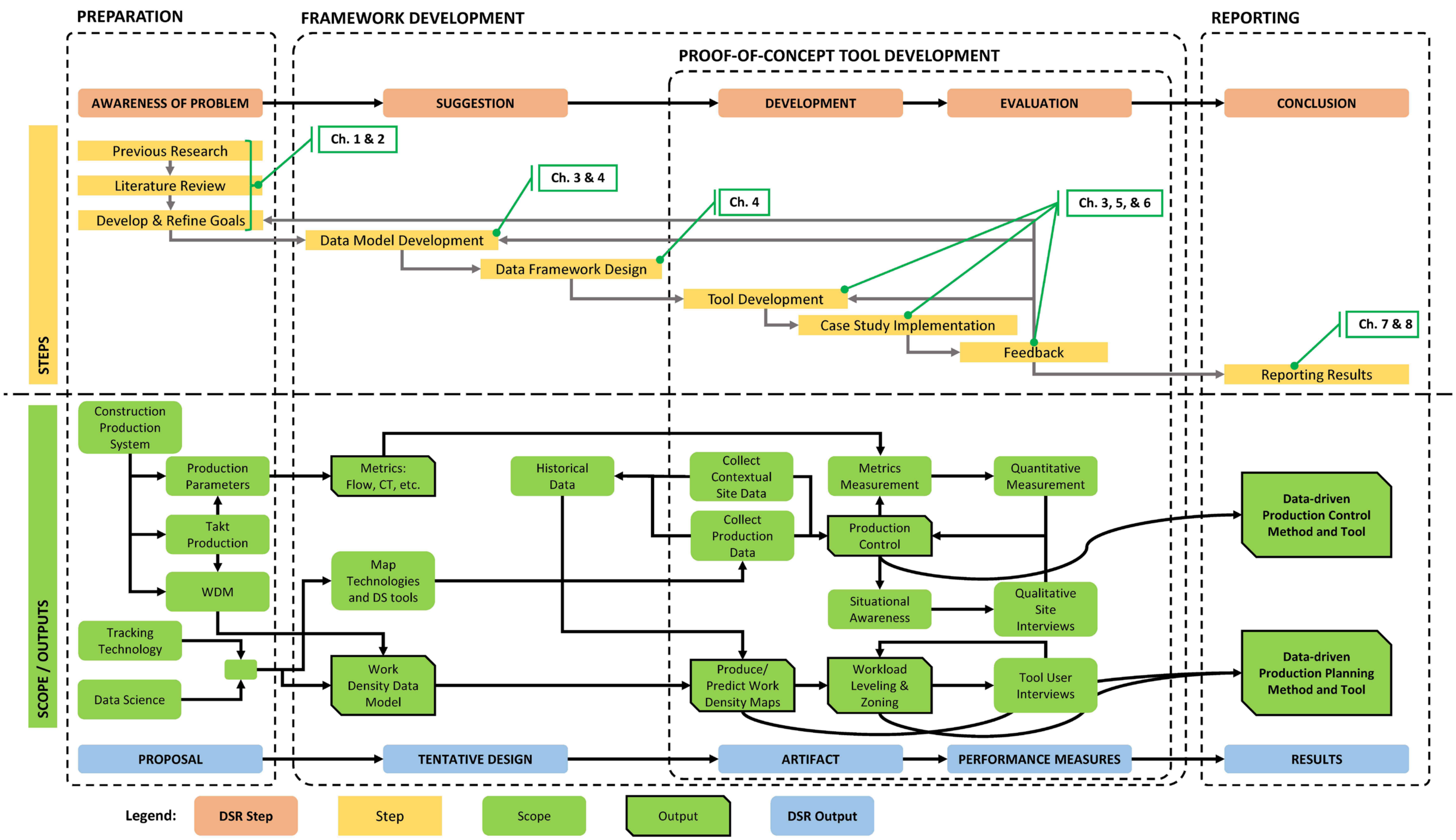


Figure 1.2: Research design.

Adapted from Vaishnavi and Kuechler (2004), Figure 1.2 presents the DSR process steps with orange boxes in the top section, and the corresponding output at each step in blue boxes in the bottom section. The research steps are shown in yellow boxes. Scopes and outputs for this research are shown in green boxes. The development process ends at the creation of DDPF which includes two components and their sub-components:

1. Data-driven Production Planning Method and Tool:
   a. Method to Produce or Predict Work Density: This method is developed to leverage historical production data and transform it into work density data to support production planning. This method encompasses work density that is an output of manual calculation as well as a ML-based prediction.
   b. Tool for Workload Leveling and Zoning: This tool is designed to utilize work density data to support production planning efforts. This includes a dashboard and metrics to achieve effective production design objectives.
2. Data-driven Production Control Method and Tool:
   a. Method to use Production Tracking Data: This method is developed to utilize real-time or near real-time production tracking data for effective production control.
   b. Tool for Production Tracking and Control: This tool is designed to harness real-life spatial production tracking data along with other project contextual data for effective production control.

In essence, the research methodology employs a systematic and iterative approach rooted in DSR principles to create a data-driven production planning and control system, incorporating spatial production tracking tools and the WDM.

1.8 Dissertation Structure

This dissertation structure is arranged in chapters as shown in Figure 1.3.

Chapter 1 Introduction outlines the research background, relevance, and motivation. It provides an understanding of the challenges in construction project management and the potential of production management and data-driven approaches to address these challenges. Based on the motivations, the following sections list the research objectives, questions, and scope, and then provide an overview of the research methodology.

Chapter 2 Theoretical Background provides the theoretical backdrop related to construction project production and the role of data-driven project production in construction management. The first three sections of the chapter cover the construction project production literature. It begins by covering topics under project planning & control, lean construction, production theory. Then it provides an in-depth review of location-based production systems, takt production, the WDM, workload leveling, and finally touches on the topic of cost modeling. The last section of the chapter covers the data-driven project production literature. It starts with presenting the need for data-driven methods and types of tracking technologies. Then it describes vision-based tracking, positioning-based tracking, their application in construction, and selecting suitable technology for the research. The section concludes with ML concepts to be considered in the DDPF.

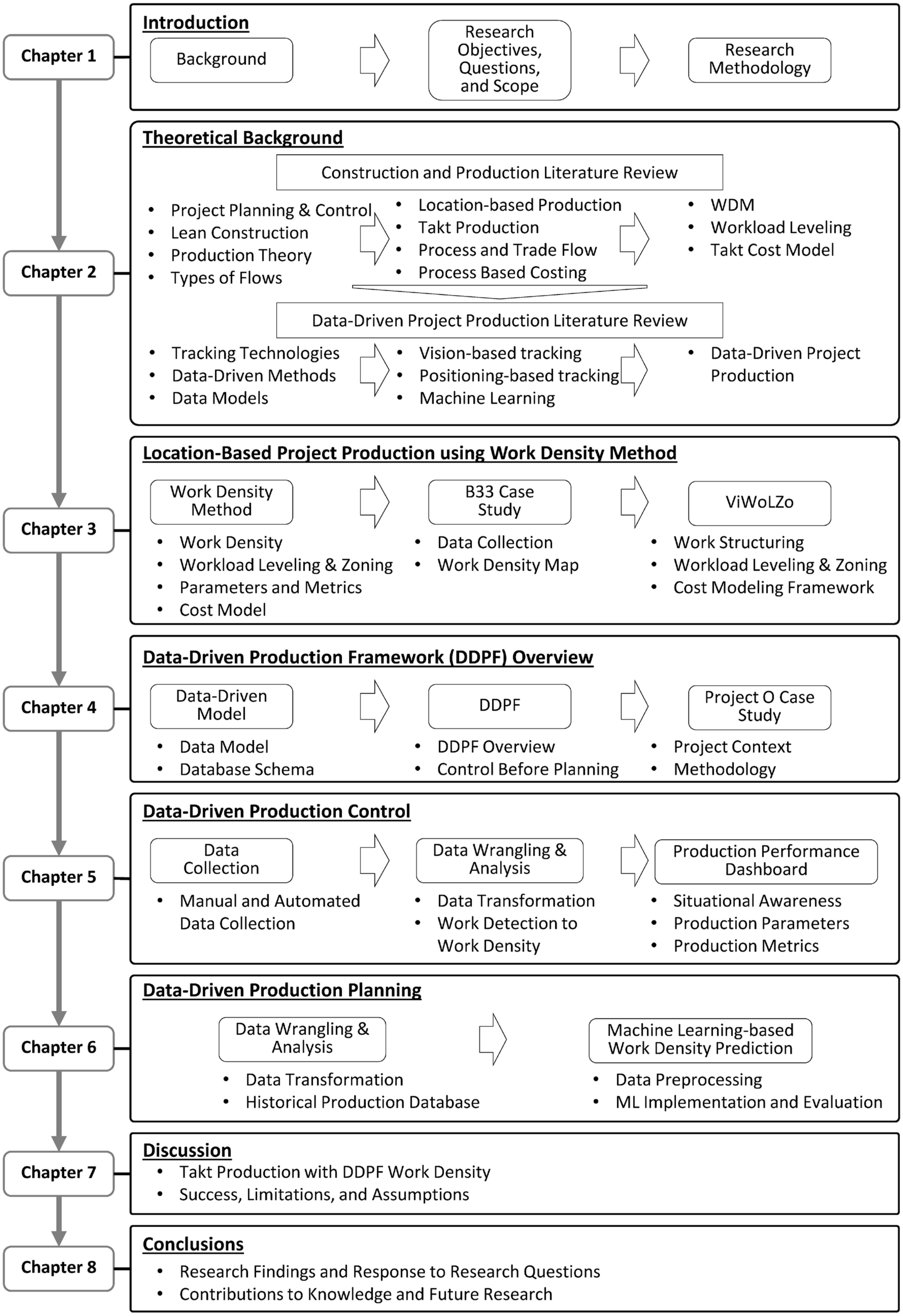


Figure 1.3: Dissertation structure.

Chapter 3 ViWoLZo for Location-Based Project Production introduces the WDM tailored for location-based project production planning, supported by a novel visualization and computing tool named ViWoLZo (Visual Workload Leveling and Zoning). This chapter details the development and application of ViWoLZo in the B33 case study, emphasizing its role in transforming traditional subjective planning approaches into objective, data-driven processes. Metrics and a cost modeling framework are also proposed to evaluate the quality of production plans. The chapter further explores the necessary data collection strategies, the practical application of ViWoLZo, and the metrics for assessing both planning quality and actual production performance.

Chapter 4 Data-Driven Project Production expands on the concepts introduced in Chapter 3 by presenting the DDPF, a novel framework designed to address the challenges of manual and subjective data collection and analysis in production planning and control. This chapter describes the transition from the labor-intensive ViWoLZo approach to a more automated and objective method within the DDPF. It details the framework's integration of ML and other data-driven methods to enhance work density prediction and streamline production processes. The chapter outlines the proposed data model, introduces a novel data schema designed to support the DDPF, and describes the operational aspects of the DDPF. It also described the methodology applied in the Project O case study, setting the stage for Chapters 5 and 6, which elaborate on the development of production control and planning components of the DDPF.

Chapter 5 Data-Driven Production Control focuses on advancing the production control component of the DDPF. This chapter explains the methodologies developed and the deployment of a proof-of-concept tool aimed at enhancing production control, highlighted through its practical application in Project O. The chapter details the data processing procedure covering the tracking of data, data analysis and storage, and production control performance dashboard. The chapter concludes with the results and insights gleaned from implementing the data processing steps and the application of the DDPF in the case study.

Chapter 6 Data-Driven Production Planning discusses the enhancement of the production planning component within the DDPF. This chapter provides a comprehensive overview of the methodology, and the application of a ML model designed to predict work density, which can later be used for production planning using tools such as ViWoLZo. The chapter details the data processing procedures used in Project O, which constitutes data wrangling, analysis, and storage and the work density prediction, including data preprocessing for ML and the deployment of ML models for predicting work density. The chapter concludes with the results and insights derived from implementing the ML model and the overall methodology.

Chapter 7 Discussion reflects on the findings from the case studies, discussing their implications for construction project production management, the applicability of theoretical principles, and the integration of data-driven approaches.

Chapter 8 Conclusions summarizes the research findings, itemized response to research the research questions, contributions to knowledge, and practical implications. It outlines the limitations of the study and suggests directions for future research.

The dissertation includes previously published and co-authored work. Chapters 2, 3, and 5 include materials from Singh et al. (2020), Singh and Tommelein (2023a, b), Tommelein and Singh (2019), and Tommelein et al. (2022). See Section 8.4 for a full list of published material.

Chapter 2
Theoretical Background

This chapter lays the foundational framework that informs the research described in this dissertation. Section 2.1 focuses on key concepts related to construction project production, including planning and control practices, the principles of lean construction, and the broader theoretical views on production systems within the construction industry. Section 2.2 focuses on location-based production planning and control methods, with a spotlight on takt production. It compares various location-based methods, discussing their goals, theoretical foundations, and challenges. This section underscores the importance of the Work Density Method (WDM) and workload leveling to support takt production. Section 2.3 describes the complexities of cost modeling for takt production in construction projects, addressing current practices, challenges in production-based cost modeling, and the shift towards stochastic cost modeling. Section 2.4 explores the transition to data-driven project production in construction, emphasizing the necessity and benefits of integrating data-driven methods for production planning and control. It covers the need for such approaches, reviews technologies supporting data-driven methods, and outlines basic concepts of machine learning (ML) to be used in these methods.

This chapter includes text from previously published and co-authored work in Singh et al. (2020), Singh and Tommelein (2023a, b), Tommelein and Singh (2019), and Tommelein et al. (2022).

2.1 Project Production

2.1.1 Planning and Control Practices

In construction project planning and control, planners start by identifying the sequence of activities required to complete a project and selecting the means and methods to accomplish them. However, due to the unavailability of information during the initial planning stages, planners defer detailed planning. The initial plans serve as the foundation for the development of construction schedules, adopting a finish-to-start representation to connect the identified activities. The Critical Path Method (CPM), introduced by Kelley and Walker in 1959, remains the prevailing method for such schedules. The CPM represents a project as a network of discrete activities with precedence relationships, and linear programming is used for schedule optimization. The initial plans are scheduled, often referred to as the master schedule, are part of a top-down approach—starting with a high-level master schedule and increasing detail with bottom levels of schedules such as phase schedule (see Figure 1.1 for level of planning).

At the master schedule level, project teams are supposed to use schedule activities to assess overall project feasibility, to subcontract work, and to identify significant milestones and long-lead items for procurement. However, market dynamics have shifted project teams' core responsibilities from predominantly focusing on the planning and control of the project to the intricate management of contracts and contractual obligations among stakeholders (Olivieri et al. 2019). This shift in the market has bolstered a widespread adoption of activity-based methods for management of contractual and financial obligations.

Although teams can use these methods effectively, they often tend to concentrate on managing individual activities in isolation, possibly overlooking the interdependencies that inherently exist among these activities. This creates a series of activities, which are connected but do not synchronize and sometimes even create bottlenecks. Koskela (2000) argues that though the CPM effectively supports the transformational aspect of production, it tends to overlook the flow and value perspectives. This can hinder the achievement of a balance among various scheduling objectives, including workflow reliability and flow evenness.

The answer to the first research question (Section 1.5) is sought by reviewing the history of production-thinking both from the scientific and the industrial points of view. Historical analysis reveals that three different conceptualizations of production have been used in practice and conceptually advanced in the 20th century. In the first conceptualization, production is viewed as a transformation of inputs to outputs. Here, production management equates to decomposing the total transformation into elementary transformations, tasks, and carrying out the tasks as efficiently as possible. The second conceptualization views production as a flow, where, in addition to transformation, there are waiting, inspection and moving stages. Here, production management equates to minimizing the share of non-transformation stages of the production flow, especially by reducing variability. The third conceptualization views production as a means for the fulfillment of the customer needs. Production management equates to translating these needs accurately into a design solution and then producing products that conform to the specified design.

In response to the misalignment of project teams' responsibilities and the recognition of the limitations of conventional approaches, construction project planners have progressively adopted lean principles and methods, exemplified by the Last Planner® System (LPS) and takt production (Ballard and Tommelein 2021). Despite the adoption, the conventional CPM continues to dominate the practical landscape.

As the project unfolds, the level of detail in the plan and schedule increases incrementally. Milestones established in the master schedule subsequently guide more detailed phase scheduling. The phase schedule transforms into a production schedule at the look-ahead and weekly work planning levels.

A shift toward a production schedule adopts a bottom-up approach that is closely aligned with the construction schedule, and vice versa. Among lean construction practitioners, LPS and takt production are prominent alternatives, either used in isolation or in tandem, for production planning and control. Traditional construction scheduling relies on estimates, historical data, and experience. A production schedule, however, is an output of production system design, which is a more collaborative process. This process entails understanding the intricacies of work execution and accommodating the diverse preferences of the various parties involved. The realization of this collaborative effort necessitates the use of pull-planning and iterative discussions, ultimately leading to a consensus plan that aligns with the unique requirements of the project. The LPS effectively facilitates this through the application of lookahead planning, weekly work planning, and a continuous learning process driven by breakdown analysis (Ballard and Tommelein 2016; Ballard and Tommelein 2021).

2.1.2 Lean Construction and Lean Principles

Originating from concepts of production efficiency such as Ford's mass production, Just in Time (JIT), and Total Quality Management (TQM), Toyota began to develop the Toyota Production System (TPS) in the 1950s. John Krafcik, a member of the MIT-Harvard team in the 1980s that researched the TPS, introduced the term "Lean Production" in (Krafcik 1988). This term encapsulated the TPS's efficient approach and set it apart from traditional mass and craft production methods. During the 1980s, Toyota's implementation of the TPS was widely recognized for its superior performance and rapid ascent as the leading global car manufacturer (Womack et al. 1990). Toyota's "Lean" methodology reduced the need for human labor, space, capital, and time, enabling the production of higher quality products that more closely aligned with customer preferences, in stark contrast to the conventional mass production system (Ohno 1988). Lean principles and methods have since found widespread application in various industries, leading to the proposal of lean construction by Koskela in 1992.

Lean principles, integral to lean construction, provide the pivot for viewing and managing construction projects from project-based systems to temporary production systems (Koskela 1992, Ballard and Howell 1998, Howell 1999, Koskela 2000). The fourteen lean principles, as defined by Liker (2004) using a 4P model (Philosophy, Process, People and Partners, and Problem-solving), play a pivotal role in lean construction implementation (Ballard et al. 2007). Importantly, the essence of lean philosophy prioritizes people over technology. Hence, this research emphasizes socio-technical methodological advancements and tool development while upholding this priority.

This research focuses on using lean principles to enhance reliability, predictability, and workflow. Five of these fourteen principles (Liker 2004, Liker and Meier 2006) are relevant to the objectives of this research. These five principles include:

- **Principle 2 - Create Continuous Process Flow to Bring Problems to the Surface:** Continuous flow, also known as one-piece flow, is central to lean production (Womack and Jones 2003). It results from the steady elimination of waste at all levels of the production system. Waste (called muda) encompasses activities within the value stream that do not enhance the final product. This includes (1) overproduction, (2) wait, (3) transportation, (4) overprocessing, (5) excess inventory, (6) unnecessary movement, (7) defects, and (8) untapped employee creativity.
- **Principle 3 - Use "Pull" Systems to Avoid Overproduction:** Lean philosophy endorses pull over push production. In a pull system, signals dictate how and when operations are executed based on customer demand. Operations are initiated when customer orders trigger these signals, ensuring work moves in response to customer requirements. In contrast, push systems operate without these signals, relying solely on forecasts to release work. This principle is important for sequencing and process flow in production planning.
- **Principle 4 - Level Out the Workload:** Variation in customer orders disrupts production processes and hinders standardization. To counteract these disruptions, the TPS promotes heijunka, which focuses on workload leveling. Instead of reacting to variations through buffers, leveling the workload addresses known and unknown variabilities within the production system. This principle underpins workload leveling and zoning, integral to production planning.
- **Principle 6 - Standardized Tasks and Processes Are the Foundations for Continuous Improvement and Employee Empowerment:** Standardization ensures consistent performance and forms the basis for continuous improvement (called kaizen). It allows teams to identify deviations from the standard, serving as the starting point for kaizen and waste reduction. This principle is core to the idea of standardizing processes and collecting historical production data, enabling managers to take corrective actions and understand the impact of production design decisions.
- **Principle 7 - Use Visual Controls So No Problems Are Hidden:** Visual controls, such as well-designed workstations and visual devices, reveal deviations from standard work

and create transparency. Transparency enhances communication, reduces effort in understanding information, and brings visibility to production data at all stages of design, execution, and control. Visual control is critical for takt production and the tools supporting it.

These five out of fourteen lean principles serve as a guiding philosophy for this research, prioritizing people over technology and aiming to create reliability, predictability, and workflow in production planning and control.

2.1.3 Project Production View and Production Theory

Schmenner (1993) categorizes production systems into distinct types, including projects, job shops, batch flow, line flow, and continuous flow. With unique product variation and high unit cost, construction is a project-based system. However, in the project production view, construction projects are regarded as a form of production system. Construction projects are different from continuous production because of their one-of-a-kind nature, site-based activities, and temporary multi-organizational structure (Koskela 1992).

Production planning structures projects by answering questions such as, what needs to be done, when, and with which resources. Planning provides preliminary answers to these questions but may not account for real-time adjustments. For a project production system to succeed, it must integrate production control mechanisms capable of continuously sensing, analyzing, and responding to deviations.

Monitoring project execution and identifying performance deviations may be achieved through on-site progress tracking. Metrics such as Schedule Performance Index (SPI) and Plan Percent Complete (PPC) are commonly employed, but they have limitations in assessing the efficient utilization of resources and flow performance (Yang et al. 2015). The principles guiding lean production offer a more comprehensive perspective, including resources and flow management, which aligns with the core objectives of this research.

To quantify a production system's performance and evaluate the impact of design and control changes, defining and measuring production parameters is crucial. Hopp and Spearman (2008) introduced operations science, offering insights into parameters and their behavior. According to them, parameters in production planning and control include:

- **Throughput (TH):** "The average output of a production process (machine, workstation, line, plant) per unit time (e.g., parts per hour) is defined as the system's throughput (TH), or sometimes throughput rate." (Hopp and Spearman 2008, p. 229)
- **Work in process (WIP):** "The inventory between the start and end points of a product routing is called work in process (WIP). Since routings begin and end at stock points, WIP is all the product between, but not including, the ending stock points." (Hopp and Spearman 2008, p. 230)
- **Process Capacity:** The upper limit on a production process throughput, typically beyond which the system becomes unstable due to excessive WIP (Hopp and Spearman 2008, p. 229).
- **Inventory turns or turnover ratio:** A measure of how efficiently inventory is utilized, expressed as the ratio of throughput to average inventory (Hopp and Spearman 2008, p. 230).

- **Cycle time (CT):** “Of a given routing is the average time from the release of a job at the beginning of the routing until it reaches an inventory point at the end of the routing (i.e., the time the part spends as WIP).” From a lean perspective, cycle time is the sum of value-added time and non-value-added time. Thus, reducing non-value-added time decreases the cycle time and improves efficiency. (Hopp and Spearman 2008, p. 230)
- **Lead time:** The time allocated for producing a part on a given routing or line (Hopp and Spearman 2008, p. 230). “Unlike cycle time, which is generally random depending on utilization, variability and WIP levels, lead time is a constant and a management policy decision. Service Level, a measure of customer delivery performance, is the probability that cycle time is less than or equal to lead time.” (PPI. 2024).
- **Utilization:** “The utilization of a workstation is the fraction of time it is not idle for lack of parts. This includes the fraction of time the workstation is working on parts or has parts waiting and is unable to work on them because of a machine failure, setup, or other detractor.” (Hopp and Spearman 2008, p. 231)
- **Variability:** Hopp and Spearman (2008, p. 264) define variability as the quality of nonuniformity of attributes. They use attributes of manufacturing systems for which variability is of interest and are prone to nonuniformity, such as physical dimensions, process times, machine failure, repair times, setup times, and so on.

Additionally, several “laws” describe how production systems and parameters behave under different conditions. These include:

- **Little’s Law** relates WIP, TH, and CT represented by Equation 2.1. It is a fundamental equation, through its rough approximations, helps in understanding performance boundaries and provides insights into average waiting time and the number of items waiting within a system (Little and Graves 2008). This law can be applied to a single station, a line, or an entire plant, as the relationship remains true over the long term (Hopp and Spearman 2008, p. 239).

$$WIP = TH \times CT \tag{2.1}$$

- **The Law of Capacity** outlines that in a steady state, work released must be lower than the average capacity. Typically, introducing work to the system at or beyond its capacity results in instability, characterized by a buildup of WIP. Stability at full capacity is only possible in unique systems (Hopp and Spearman 2008, p. 317).
- **The Law of Utilization** highlights that increasing resource utilization without other changes leads to nonlinear increases in WIP and CT (Hopp and Spearman 2008, p. 317). This law is represented by Kingman’s equation known as the VUT (Variability, Utilization, and Time) equation, and represented by Equation 2.2. The VUT represents how manifestation of variability and utilization over time produces the CT.

$$CT_q = V \times U \times T \tag{2.2}$$

- **The Law of Variability** emphasizes that increased variability within a production system negatively impacts performance (Hopp and Spearman 2008, p. 309).

These laws, although valuable for understanding system dynamics, come with specific assumptions. In a system with variability (such as a construction production system), it is impractical if not impossible to achieve 100 percent utilization of a resource, as WIP and CT would increase exponentially. Hopp and Spearman (2008) suggest that the management deals with this variability using combinations of inventory, capacity, and time buffers, instead of reactionary solutions. However in lean philosophy, rather than adding buffers to deal with variability, the goal is to remove the variability.

As pointed out by Little (1992), these "laws" used in operations management and industrial engineering are not universal. The behavior modeled is only true under a given set of assumptions. The "laws" are only applicable to an abstraction of the real world. Project production systems, with their distinctive characteristics, require adaptable production planning and control. Integrating lean principles and understanding production parameters and related laws offers a robust framework for effective management, enabling projects to adapt to dynamic conditions and deliver successful outcomes.

2.1.4 Common Terminology for Project Production

To clarify the applicability of production thinking to construction process planning, the following text by Singh and Tommelein (2023a) provides definitions of key terms adopted from Frandson et al. (2013), Jabbari et al. (2020a), and Ballard and Tommelein (2021). "The master schedule of a construction project may comprise one or multiple phases. A phase refers to inter-dependent scopes of work of trades who will work on-site more-or-less concurrently. A phase's start and end are delimited by milestones in the master schedule. A phase comprises one or several processes. Each process comprises steps, each one pertaining to a certain scope of work performed by a single trade (or possibly a crew composed of multiple trades). Trades may be responsible for performing one or multiple steps in a process. Each step in a process lies at the intersection of a process and an operation. An operation describes a sequence of steps a single trade performs to complete work or to deliver a service as per their scope of work (e.g., installing a sink is one step for the plumber, one of several trades involved in the process of building a bathroom)."

2.1.5 Types of Flow in Construction Production

In construction production, the concept of workflow is central to the trades' ability to reliably complete work in certain locations and, as a result, reliably handoff work locations to the next trade. Within lean construction, Ballard and Howell (1994) first introduced the concept of workflow through the LPS, as a strategy to improve workflow reliability. The LPS defines workflow as a sequence of work packages that are scheduled, allocated to production teams, and executed according to plan (Ballard and Tommelein 2021).

Planning and control challenges arise when activities exhibit varying durations and involve non-uniform spatial distribution of work. In such cases, identifying a consistent workflow becomes difficult. However, maintaining spatial continuity of planned work is crucial during the medium-term planning stage, also known as look-ahead planning. Spatial continuity of planned work fulfills two main functions. First, it reduces workflow disruptions including interruptions, relocations, remobilizations, and trade stacking. Second, it brings concurrency of work across multiple locations. Ensuring continuity requires accurately defining the work scope, including specifying trades and locations. Clarity on questions such as who, where, and what related to the scope of work planned, reduces non-value-adding work and the degree of control complexity (Alves and Formoso 2000).

This concept of workflow extends from Shingo's (1986) division of production flows into two distinct categories: process flow and operations flow. Process flow pertains to the sequential transformation of raw materials into finished products, representing how long it will take to deliver a product to the customer. The time it takes is called process cycle time and relates to the system's speed (aka. throughput rate); it is akin to a project's schedule duration. Operations flow focuses on the steps executed by a single trade's production unit (comprising workers, tools, and equipment). Operation steps are performed, one after the other, possibly but not necessarily all in a single location.

Recognizing process- versus operation flows, Tommelein et al. (2022) further distinguished trade location flow (synonymous with trade flow) from process location flow (synonymous with process flow) to characterize the two-dimensional nature of flows in construction, relevant to location-based planning methods. They defined trade location flow as the flow created by trade specialists moving from one location to another while performing work in each location, and process location flow as comprising steps performed by different trades, with each step being part of a trade's operation(s). Accordingly, process flows and operations flows are interwoven. Figure 2.1 illustrates the direction of a trade flowing from Floor 1 Zone 1 to Floor 1 Zone 2, all the way to Floor 2 Zone 3, i.e., changing work locations over time. It also illustrates process flow by showing the different trades' work (using different colors to distinguish trades), with each instance of the process being performed in a certain location (e.g., the process' second instance shown by the horizontal arrow takes place on Floor 1 in Zone 2).

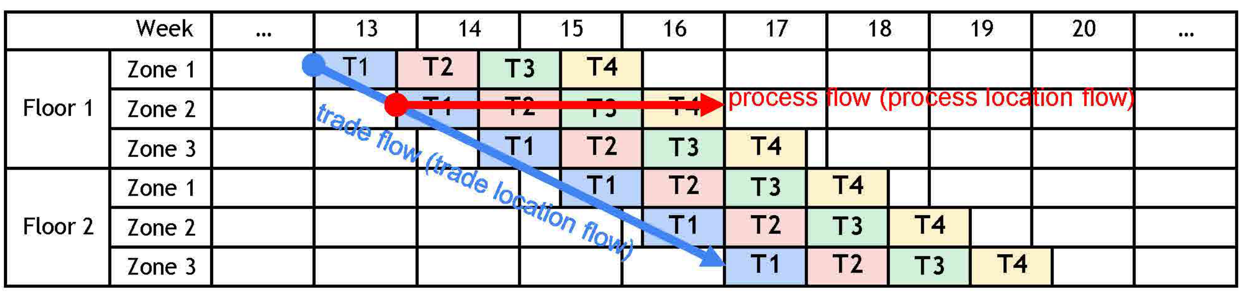


Figure 2.1: Plan with trade- and process location flow (after Figure 2 in Tommelein et al. 2022, used with permission).

Understanding such flows offers a new rationale for planning construction work. The rationale of CPM-based methods is to rely on an a-priori defined hierarchical WBS as the basis for planning and control. They focus on workflow along the critical path but tend to disregard all other flows. The rationale for location-based planning methods is to rely on an a-priori defined physical (or logical) hierarchical Location Breakdown Structure (LBS) (Harris and Ioannou 1998, Biotto et al. 2017, Kenley and Seppänen 2009). They tie workflow expressed in a measurable unit of production to time and (resource location) units, and aim to maintain resource continuity, i.e., many methods tend to focus on resource utilization. Of note is that, apart from such differences, CPM-based methods quite commonly refer to locations (e.g., in the naming of an activity) whereas location-based methods link activities using precedence logic and thereby allow for CPM calculations. E.g., in the LoB method, the target rate of delivery for the project is used to determine the rate of production of each activity (Lumsden 1968). When using the LoB, an objective is to ensure that each activity is continuously performed at the same rate in order to create "a smooth and efficient flow of resources" (Arditi and Albulak 1986, p. 411).

Many construction planning methods prioritize work to maintain a high utilization rate of resources (production units) and accordingly reduce the time 'workers wait on work' (trade flow) at the expense of 'work waiting on workers' (process flow). Such prioritization of trade flow over process flow is a consequence of shifting cost risk to trades (Linnik et al. 2013). It may lead to overall schedule sub-optimization. In contrast, prioritization of process flow can result in a more optimal schedule in terms of delivery speed and reliability, albeit possibly with lower utilization rates. To judiciously consider process flow as well as trade flow, planners can apply workload leveling and capacity buffering as is done in SIPS and takt planning.

The WDM provides an alternative to methods that rely on an a priori defined WBS or LBS, and helps planners balance their desire for process flow as well as trade flow, while explicitly considering trade-offs between them. The rationale of the WDM and its application with location-based production planning and control methods, including takt production, is described next.

2.2 Location-based Production and Work Density Method (WDM)

2.2.1 Location-based Production Planning and Control Methods

Incorporating spatial considerations into phase planning and look-ahead planning is crucial for ensuring trade location flow and process location flow. Location-based planning methods account for managing trades and locations. These methods explicitly address utilization of construction space (the product itself for on-site construction or workstation on a production line for offsite construction), enabling more efficient workflow organization by considering space availability and acknowledging the inherent competition for space (e.g., work areas, material storage, access routes, etc.) (Ballard and Tommelein 2021). Various location-based planning techniques, such as the LoB, SIPS, RSM, block scheduling, even-flow production, and takt production, are designed to create flow, each employing a unique approach.

Whereas this dissertation describes a range of location-based methods, the focus is on takt production due to its alignment with desired production outcomes mentioned in Section 2.1. However, the practical application of these methods often involves a combination of various approaches, tailored to the project team's objectives and the specific demands of planning and control. Consequently, I categorize location-based production planning and control methods into two primary groups: (1) Takt Production (Section 2.2.2), and (2) Non-Takt Location-Based Production (Section 2.2.3). Although the research is primarily oriented towards takt production, the framework is versatile enough to be applicable to non-takt based methods as well.

2.2.2 Takt Production

Lean practitioners and scholars have identified takt production as a mechanism for introducing and managing process and operation flows in construction production systems and to balance the trade-offs between them. "Takt" is a German word that means a 'beat', the regularity with which something is done, or the time between beats. It is used in lean production systems to pace the rate of a production system or the time between individual outputs of the system (Hopp and Spearman 2008). According to Baudin (2002, p. 43), assuming the production system completes "the product one unit at a time at a constant rate during the net available work time, the takt time is the amount of time that must elapse between two successive unit completions in order to meet the demand."

Takt for a system (supply rate) is defined by matching it with the downstream customer's need (demand rate). To state the obvious, the term "takt production" refers to both production planning and control. Haghsheno et al. (2016) provide a background on the historical development and implementation of takt production in construction.

According to Alves and Formoso (2000), takt planning helps to reduce the share of non-value-adding activities and reduce the degree of control complexity by introducing spatial continuity and limiting one crew in a location at a time. In construction, it is common to have more than one crew to work in a single location. In the industry it is known as "stacking of trades", and it usually reduces performance (Koskela 1999, Serag et al. 2010).

In other location-based planning methods such as the LBMS and LoB method, priority is given to labor utilization whereas takt production prioritizes the flow of work (Linnik et al. 2013). Due to the difference in priorities, durations of a task can vary in LBMS when quantities of work are not the same across locations, whereas takt production requires the duration to be the same.

Takt production requires planners to make certain trade-offs. One such trade-off involves improving overall workflow at the expense of capacity for a few trades, resulting in lower capacity utilization for trades with less work (faster trades) but making sure reliable completion of trades with higher amount of work (bottleneck trades) (Seppänen 2014). Consequently, the adoption of takt production is met with resistance, driven by the inherent challenges posed by this trade-off, which necessitates careful consideration of both workflow optimization and capacity utilization. Another trade-off is non-prioritization of operation flow to optimize the process flow (Lehtovaara et al. 2021a, Shingo and Dillon 1989). Adoption of takt production can (at times) be met with resistance because of this trade-off.

Lehtovaara et al. (2021b) conducted a holistic review of takt production in construction planning and control, finding a significant increase in studies in the last two decades, and even more so from 2017 onward. With increasing research and development, application of takt in certain types of projects has shown that the advantages of takt production can outweigh the disadvantages. Hence the adoption of takt continues to increase among construction management researchers and practitioners.

Takt planning is easier to implement in projects where easily identifiable repeatable chunks of work are found in large numbers, e.g., similar rooms in a hotel or a hospital. This allows the planning team to define a beat based on repeating physical space. The desire to plan work to a regular beat is challenged by the fact that construction work tends to be non-repetitive and production rates vary by crew size, the scope of work to be done in an area, means and methods used, etc. The WDM (Tommelein 2017) allows the planner to identify this repetition and gives a basis to level this workload. These repeatable workload chunks in terms of space are termed as "zones", whereas in time they are termed as the "takt". For an ideal situation, a planner would want an equal workload in terms of time for each trade in each zone, so that everyone can complete their work in the takt duration.

The research will use the WDM as the basis for collecting the data and developing workload distributions by trades and zones. Work density has been used along with construction takt planning till now (Dunnebier et al. 2014, Singh et al. 2020, Singh and Tommelein 2023a) and though the research will continue to use it as a basis to develop takt plans, the development of the methods and tools in this research will be generic such that they can be used in other location-based planning methods that also rely on work space zoning or workload leveling.

2.2.3 Non-Takt Location-Based Production

Non-takt location-based production planning and control methods are diverse, encompassing approaches such as the LoB, SIPS, RSM, block scheduling, and even-flow production. These methods primarily focus on maintaining continuous resource utilization and expediting project completion, but their approach and specific prioritizations differ.

The LoB method is particularly effective in projects with repetitive units, such as highways or tall buildings. It represents schedules by correlating activities with time and space—horizontal axes display space for horizontal projects and time for vertical projects, and vice versa. This method, as described by Kenley and Seppänen (2009), can be integrated into a Location-Based Management System (LBMS), which itself incorporates LPS concepts for managing workflow (Seppänen et al. 2015). Frandson et al. (2015) noted that LBMS differs from takt in its use of buffers—specifically time, space, and workable backlog—as opposed to capacity, space, and workable backlog in takt. Although both often use space buffers to mitigate variability in activity durations and to prevent schedule delays, LBMS prefers time buffers and takt prefers capacity buffers. Strategies around selection, sizing, and positioning of buffers in the schedule differentiates location-based methods.

RSM emphasizes continuous resource usage across multiple units in a project. Described by Harris and Ioannou (1998), it presents schedules as X-Y plots with production lines representing repetitive activities. It also introduces control points between lines to manage resource continuity, applicable to both vertical and horizontal projects with discrete or continuous activities.

Other methods, such as SIPS (e.g., Burkhart 1989, Horman et al. 2003), block scheduling, and even-flow production (Bashford et al. 2003), work top-down beginning at the master or phase schedule and moving downwards. They set the pace of progress to align with the start and end milestones of the project or phase, while simultaneously delineating work areas. Each specialty contractor involved identifies their scope by location and adjusts their production rate accordingly, a process that can lead to further schedule and work area adjustments.

Even-flow production, as suggested by Ballard (2001), benefits from enhanced workflow reliability and the development of multi-skilled, multi-craft teams. This allows for a reduction in the duration of activities, achieved through methods including first-run studies and operations analysis, and the overlapping of activities within their phase of the work. First-run studies involve examining a new process step or sequence of operations before full-scale production begins, identifying inefficiencies and potential improvements. This proactive approach allows teams to improve production and avoid recurring mistakes. Similarly, operations analysis provides a detailed examination of the current production operations, identifying bottlenecks and areas where time can be saved. These methods collectively contribute to more efficient use of resources and a reduction in the overall duration of steps.

SIPS typically features extended activity "trains" within its schedules. These trains incorporate significant time buffers, sometimes spanning entire weeks, to accommodate catch-up and rework, inspections, punch list work, and similar tasks (Horman et al. 2003). To maintain the predetermined weekly or other short-interval pace while facilitating rapid progress, these trains may comprise several trades in each "wagon" of the train. This necessitates careful coordination in the use of shared work spaces and resources, ensuring that all parties can work effectively without impeding one another.

In summary, although all of the non-takt location-based production methods aim to balance activity speed in a process sequence, their specific strategies and tools, such as the selection and positioning of buffers, vary. This variation caters to different project types and scenarios. Each method brings its unique approach to tackling the dual challenges of resource utilization and variation in construction projects.

2.2.4 Work Density and Work Density Method

This section includes text from previously published and co-authored work in Singh and Tommelein (2023a). Section 3.1.1 defines work density, the WDM, and other terms used here in detail.

Construction projects involve many trade specialists with crews working step by step, handing off work to those who follow them. When handoffs occur reliably, trades can follow their predecessors without delay and the process can have a smooth workflow. For projects with repeatable components, assemblies, or modules of some sort (e.g., hotel rooms with similar architectural features) planners can use such physical product characteristics to define handoffs, e.g., by takting the construction work (e.g., Binninger et al. 2017a refers to these handoff units as Standard Space Units or SSUs). Even without repetition in the product design, they can takt the work based on the workload of each trade, location by location, as is done in the WDM (Tommelein 2017, 2022, Jabbari et al. 2020a, 2020b).

The WDM is based on the work density construct, piloted on a project that tested concepts of construction takt planning (Dunnebier et al. 2014) and it has since been formalized (Tommelein 2022). "Given a certain work area, work density describes the time a given trade will require to do their work in that area, based on the product design and the scope of work done by that trade for a given task in the schedule (thus depending on work already in place and work that will follow), the means and methods the trade will use to do their work while accounting for their crews' capabilities and crew size" (Tommelein 2017). Work density compiles into a single number, expressed in time per area, specifics of several production-system throttles describing what work will be done, by whom, where, and how.

These throttles or adjustment mechanisms (Binninger et al. 2017b) are commonly used in planning. Planners use them to adjust work density by (1) modifying product characteristics, (2) using alternative breakdowns of the scope of work, (3) re-sequencing work and adding or removing work from a process sequence, (4) selecting alternative means and methods used by a trade, (5) changing worker- and crew skill particulars as well as the assigned number of trade resources. In previous studies by Bardaweel (2018), Jabbari et al. (2020a), Singh et al. (2020), and Tommelein (2022) the objective for adjusting work density is to minimize the workload peak (operable takt). In takt planning, this peak must fall below the calculated takt (customer or demand takt) in order to guarantee process completion within its allowable duration. However, to define zones so that the number of work hours are similar for all steps of all trades moving from one zone to the next (Frandson et al. 2013), there might be other objectives to consider. Workload leveling, described next, tackles this problem of identifying suitable objectives and adjusting work densities accordingly.

2.2.5 Workload Leveling

This section includes text from previously published and co-authored work in Singh and Tommelein (2023 a, b).

Across steps in a process and zones in the work space, workloads will vary depending on the nature of the work and how the work was structured. In general, variability in workloads is unwanted. Reducing or eliminating it using workload leveling helps to achieve a smooth workflow. Rather than zoning a work space by simply dividing space according to physical features of the structure being built, the WDM performs both workload leveling and zoning. Specifically, the WDM describes a quantitative way of zoning a work space.

The workload leveling problem is similar to resource leveling and resource-constrained project-scheduling problems (RCPSPs) in respect to their mathematical objective. Among them are resource allocation methods with the objective that resources required do not exceed resources available, resource leveling methods that reduce variability in the number of resources used (e.g., Colak et al. 2006, Davis 1974) and methods that strive for continuous resource use to mitigate any negative impact on productivity and cost (e.g., Harris and Ioannou 1998).

Although in the basic RCPSP model a reduction or minimization of the project duration remains the most studied effect, several extensions of RCPSP consider other effects or combinations thereof, such as variabilities in the project environment and resource capacity (Chakrabortty et al. 2017, Hartmann and Briskorn 2010). Resource leveling and likewise workload leveling are desired because variability makes it difficult to size crews and can cause abrupt changes in work sequence, mismatches in the supply of information or resources, trade stacking, shortages of workers with the necessary skills, etc. In a system with sequential handoffs, predecessors constrain the work of successors. The manifestation of variability can have a progressively worsening impact on downstream performance (e.g., Tommelein et al. 1999).

Some resource leveling methods try to reduce fluctuations in the number of resources used, whereas others strive for continuous use of resources to improve productivity and reduce cost (e.g., El-Rayes and Jun 2009, Hegazy 1999). The mathematical formulation of a resource leveling method may have as its objective to minimize resource variability or to lower resource peaks. When CPM is used, this could be done by shifting noncritical activities within their available floats while keeping the project duration fixed (Franco-Duran and de la Garza 2019, Kastor and Sirakoulis 2009, Lu and Li 2003, El-Rayes and Jun 2009).

The mathematical formulation of a resource allocation method may prioritize critical activities on the CPM schedule over others. In contrast, takt planning and the WDM have no prioritization for resource allocation or leveling as all activities (i.e., steps in a process) are critical. In that sense, steps within a process have no float. However, each step has a capacity buffer to ensure enough people on the crew are ready so that, in case work takes slightly longer than anticipated, they will be available and able to complete their step within the customer takt (Frandson et al. 2015; Tommelein 2020, Tommelein 2022). In addition, takt plans include buffers between processes and at the end of processes. The judicious use of buffers prevents delays that could reverberate through the schedule.

Additional metrics may be applied in the WDM to meet objectives related to variation of workloads across steps and zones. However, given the novelty of the method, how to best formulate a multi-objective optimization algorithm remains a research question. In real-world scenarios, a multitude of constraints and preferences from the physical site and the project team including the trades can affect the preference for one solution over another.

The primary objective for all the stakeholders in a project typically centers around cost. However, the influence of production design decisions and workload leveling on costs remains an unexplored area of research. Sections 3.1.2 and 3.1.3 define objectives and metrics for workload leveling in detail. In the following section, I will explore current practices in modeling, estimating, and managing costs for takt and other location-based methods.

2.3 Modeling, Estimating, and Managing Cost for Takt Production

2.3.1 Current Practices

Cost modeling involves "formulating a cost model to estimate cost at some level of abstraction of a component or a system under design." (Nguyen 2010). Cost models are designed with a specific purpose in mind—to generate a cost estimate while considering relevant assumptions and abstraction related to their intended application. The intended application for takt production includes gauging quality of a production plan to meet the cost objectives.

In practical terms, cost models utilize various inputs, including product quantities and unit costs. These inputs are processed using mathematical relationships, historical data, and knowledge-based rules and heuristics to produce cost estimates. The format of these estimates varies and is driven by the unique requirements of the user, which can be influenced by factors such as the maturity of the design, industry standards, organizational practices, and contractual obligations.

In many regions across the world, particularly in the field of construction and civil engineering, it is common practice to structure cost reporting for projects using a Work Breakdown Structure (WBS) (ICMS 2021). The cost of a product, such as an installed component, is typically calculated as the sum of the material cost and all resources required for its installation, including labor and equipment (Gordian RS Means Data 2017).

The Construction Specifications Institute (CSI) is responsible for creating and maintaining classification standards that are most widely adopted in cost estimation and scheduling practices in the United States (CSI 2023). These standards include:

1. Uniformat (2010): Based on the hierarchy of system elements (e.g., Substructure, Shell, Interiors), Uniformat is useful in the early design phases, such as Conceptual Design or Design Development. It aligns well with the needs of owners and designers.
2. MasterFormat (2020): Based on the hierarchy of trades and materials (e.g., Concrete, Masonry, Metals), MasterFormat is valuable in detailed Design Development and Construction Document Creation. It suits use cases related to crafting specifications for construction contract documents, a requirement for construction managers, general contractors, and specialty contractors.
3. OmniClass Construction Classification System (OCCS 2019): Based on the various forms of information generated throughout a project's lifecycle, OmniClass is useful beyond design and construction, by including commissioning and facility management. This system aligns with the needs of owners and facility managers. OmniClass also integrates other existing systems, such as MasterFormat and UniFormat, to cater to diverse reporting systems.

Traditionally, cost models were primarily used to assess the cost impact of design or design changes, and this led to the establishment of these classification standards as industry norms. However, as the demand for comprehensive decision-making tools in project management expands beyond design-cost considerations, newer classification standards are emerging, highlighting the necessity of tailored models for distinct end-goals. For example, the ICMS (2021) has the capacity to model life cycle costs and carbon emissions. Furthermore, the Total Cost of Ownership (TCO) standard by the National Institute of Building Sciences (Weidner and Herndon 2023) incorporates costs related to the end of useful or functional life.

As project management moves from traditional planning and control towards a production-oriented approach, it becomes increasingly important to develop cost models and management systems that support production-based planning and control. Next, I will examine the challenges associated with cost modeling.

2.3.2 Challenges for Production Based Cost Modeling

The construction industry uses cost models as essential tools for project management. However, these models, like all models, are built upon simplifications and assumptions. These models often overlook crucial production factors, such as idle time, production organization, and waste. While they serve the purpose of simplifying cost estimations for contractors, they fall short in capturing the intricacies of actual production dynamics that extend beyond mere inputs and outputs.

To provide context, the construction industry typically utilizes widely recognized classification systems such as the MasterFormat (2020) in conjunction with historical cost databases such as the Gordian RS Means Data (2017). This constrains practitioners to model based on pre-defined assemblies and dimensions. The scope of these cost models is typically confined to materials, labor, equipment, general conditions, overhead, and profit. Moreover, they are often tailored to a fixed set of resource inputs, batch sizes, assumed productivity levels, and worker competencies. For direct work activities such as material receiving and handling, site mobilization, site movement, breaks, and cleanup, these activities are typically treated as abstracted data points and cannot be readily modified to reflect actual project-specific conditions. The rigidity of the cost models can limit their ability to account for the variability present in real-world construction projects. The cost databases provide regional averages which contractors use as a target price to beat, but do not use to plan production with.

In practice, costs associated with batch sizing decisions, such as setup and mobilization costs, depend on planning decisions. For instance, in takt production, the objective is to reduce batch sizes to reduce process lead time and have more granular control, as advocated by studies such as Linnik et al. (2013). While a reduction in batch size is expected to increase direct costs due to extended setup times, it also has the potential to decrease overhead costs when process concurrency can be increased. However, the nuanced cost implications are often beyond the reach of prevailing deterministic cost modeling and estimation methods, as they are not designed to do so.

In summary, the use of cost models to support production management methods, including takt production, faces several significant challenges. These challenges include oversimplification of critical production factors, limitations imposed by classification systems and historical databases, and the inability to capture the cost dynamics associated with flexible batch sizing decisions.

2.3.3 Shift from Deterministic to Stochastic Cost Modelling

Lean construction academics persistently advocate for a departure from the prevailing deterministic and transformation focused cost modeling. Instead, they call for the adoption of a cost model more adept at efficiently overseeing production systems. The conventional practices in cost modeling are predominantly grounded in economic theory, a foundation that has been subject to critique due to a range of flawed assumptions, as highlighted e.g., by Koskela and Tommelein (2009). Specifically, some of these assumptions bear relevance when contemplating cost modeling within the context of takt production. Two noteworthy assumptions can be identified:

The first assumption involves the abstraction of any internal industrial organization within the production process. Economic theory assumes that a productive organization is determined by the relationships between costs and prices, and any internal industrial organization of the production is abstracted away. In other words, conventional models tend to oversimplify the intricacies of how production systems are structured and operate. This is also true in construction, where the internal production processes depend on many factors that can be changed to achieve different outcomes. Assumption of a fixed internal organization makes it impossible to model the time-cost trade-off at the level of production design, e.g., in planning decisions in takt production.

Using the Parade of Trades game, Tommelein et al. (1999) showed that it is possible to reduce waste and shorten project duration by reducing the variability in workflow between trades. By modeling sequential dependence and process duration variability on a stochastic discrete-event-simulation, they illustrate the detrimental impact such variability has on a system's performance. Their model also highlighted the shortcomings of using a deterministic modeling tool such as the CPM for field-level planning. In CPM, modeling the dependence of ongoing activities between trades or operations on a daily-basis is challenging, as these relationships are often not documented in the CPM network. Additionally, the variability within and between activities is not considered in the network.

Several simulation-based stochastic models for construction time-cost trade-off problems have been developed for decision-making (Odeh 1992, Feng et al. 2000, Srisuwanrat and Ioannou 2007, Rybkowski et al. 2008, Eshtehardian et al. 2009, Kim and Kim 2016, Dargham et al. 2019). These models demonstrate greater realism compared to deterministic models by exhibiting characteristics not observed in deterministic approaches. Furthermore, they enable managers to incorporate variability, their own level of risk acceptance, and a degree of optimism into the decision-making process. Eshtehardian et al. (2009) emphasize that the actual cost and time of each option is usually not known to planners. Furthermore, it is impractical to determine the precise relationship between time and cost for the given options in either discrete or continuous terms. This is due to the absence of precise data prior to task completion and the vulnerability of these relationships to uncertain external and internal factors.

The necessity of accounting for imprecise data and the influence of uncertain factors is critical for developing realistic models. Tommelein (2020) demonstrated how a probability distribution can be used to describe the variability in the output of a process under normal operating conditions, referred as process capability. In such situations, takt production relies on collaboration and communication for assessing process capability. This involves understanding standard work, normal operating conditions, conducting first run studies if possible, and asking people who will know the best possible estimate for the relevant conditions. Tommelein also suggests buffering against remaining variability to achieve reliable workflow and in the longer term making effort to improve process capability.

The second assumption revolves around the notion of optimal productive efficiency, thereby positing that no waste is generated during the production process. This assumption does not necessarily align with the realities of production systems including construction, where some level of waste may be inherent. Critical evaluation of economist Stigler's 1976 paper by Koskela et al. (2023) identifies three main shortcomings: Stigler (1) underestimated the significance of waste by claiming that waste is not a useful concept in economic theory, (2) restricted waste to the context of market exchange, and (3) disregarded waste arising from decision implementation. Koskela et al. call for a new decision-making framework that encompasses inefficiencies before, during, and after decisions, labeling them as background waste, decision-related waste, and foreground waste. Their framework aims to address all aspects of waste in decision-making behavior under scarcity. Koskela and Ballard (2021) argue that the emphasis of cost management should be directed towards reducing costs, as opposed to simply estimating them. Waste reduction, one of the four methods they suggest to control and reduce costs, underscores the importance of acknowledging waste in cost models.

By elucidating the assumptions, we gain a clearer understanding of the limitations of current cost modeling practices and the necessity for more adaptable models, especially in the context of takt production. A new approach for cost modeling acknowledges the intricacies of construction production, internal organization, and inefficiencies. This approach will produce tools and methods that enable project teams to make better management decisions. As a result, project outcomes become more accurate, precise, and sustainable.

2.3.4 Parametric Cost Estimation

Researchers have extensively studied the effectiveness of parametric cost estimation models, especially in situations where project scope and data are limited. Hegazy and Ayed (1998) have illustrated the utility of parametric cost estimation models under such conditions. These models rely on carefully selected parameters that accurately capture the project's unique characteristics, facilitating more accurate estimation of cost.

In recent years, several studies have expanded the horizons of parametric cost estimation by incorporating ML and other advanced data analysis methods. Studies by researchers such as Melin (1994), Elmousalami (2020), and Yang et al. (2022) have highlighted the efficacy of parametric estimation even when the available information is scarce or incomplete. Such studies have demonstrated the ability of parametric models to adapt and provide accurate estimates in challenging data environments.

Furthermore, parametric estimation models offer valuable insights for project analysis by enabling the exploration of how various parameters impact project costs. This provides the users of such models to test scenarios and do simulations that can inform decision-making processes and optimize resource allocation strategies (Elfaki et al. 2014).

2.3.5 Process and Activity Based Costing

Traditional costing methods often struggle to capture cost fluctuations resulting from changes in process design. In response to this, Process- and Activity-Based Costing (ABC) methods have received significant attention within the lean construction community. Researchers, including Kim and Ballard (2001), Staub-French et al. (2002, 2003), Kern and Formoso (2006), Nguyen (2010), Kim and Kim (2016), and others have explored these methods for cost modeling and estimation.

Staub-French et al. (2002, 2003) introduced an integrated approach to modelling that explicitly links features, activities, resources, costs, and the estimator's decision-making rationale. This approach involves the upfront creation of generic activity and resource specifications, streamlining their application by estimators, and also making the application easily reproducible and scalable. The proponents of such integrated models contend that it saves both time and effort in comparison to traditional estimating practices. Furthermore, it lays the foundation for representing project scope, schedule, and associated costs. This, in turn, empowers project teams to explore diverse design, cost, and schedule alternatives, thus averting inefficiencies that could lead to cost overruns and schedule delays.

Nguyen (2010) developed the Process-based Cost Modeling (PBCM) framework, that offers an alternative approach and accomplishes the following:

1. Considering Process-Related and Product-Related Costs: PBCM ensures that both process-related costs (e.g., material handling, transportation, site logistics, and installation) and product-related costs are explicitly presented to designers when analyzing design alternatives.
2. Specifying Cost Changes due to Process and Product Design: The PBCM framework considers product and process design features, enabling it to quantify cost changes resulting from changes in product design (e.g., materials, shapes, or dimensions) and changes in process design (e.g., sequencing, logistics, or construction methods). This framework aids (integrated) project delivery teams in exploring various production system design alternatives while having a clear understanding of the cost implications.
3. Providing Rapid Cost Feedback during Design or Planning Phases: The PBCM framework facilitates timely and accurate cost feedback during the design and planning phases, supporting decision-making processes. It involves three phases: (1) collecting process and cost data, (2) mapping this data to Building Information Model (BIM) objects, and (3) providing cost feedback during design.

The process necessary for implementing such a framework, as undertaken by Nguyen (2010), involves process mapping using data collected through observations and interviews. I use a similar approach of process data collection by mapping processes for the WDM. This mapping enables users to visualize sequence and dependencies within the process. This, in turn, allows for the analysis of variability within and between process steps, offering insight into the performance impact of production system design decisions. By incorporating variability into a stochastic model, it becomes possible to conduct time-cost trade-offs aimed at achieving desired goals such as cost reduction, waste reduction, and project duration optimization (Feng et al. 2000).

The development of the PBCM framework by Nguyen (2010) and its application in a case study, Nguyen et al. (2018) aimed at enhancing design-related decisions during the pre-construction phase. Applying this framework during the construction phase, especially for specialized areas such as takt production, presents an unexplored opportunity.

2.3.6 Cost modeling in Target Value Delivery (TVD)

Target Value Design (TVD), also known as Target Value Delivery (Ballard 2011), constitutes a comprehensive set of management practices applied throughout a project's lifecycle. It aims to ensure that the project aligns with operational requirements, customer values, and is delivered within the confines of an allowable budget and other pertinent constraints (LCI 2023). TVD takes inspiration from the concept of target costing (Ballard 2011), a practice rooted in the manufacturing industry, where for several decades it has been instrumental in securing cost predictability during new product development. In 2004, Ballard and Reiser documented the first successful implementation of the concepts and techniques from target costing on a construction project in the United States. TVD has evolved over the last two decades, tailoring target costing principles to cater to the unique challenges of the construction industry—an industry historically grappling with the successful delivery of projects in terms of cost, quality, and timeliness (Ballard 2011, Morris and Ballard 2024, Zimina et al. 2012).

TVD, rooted in lean principles, transcends the traditional target metrics of project success that are limited to keeping the project on time, on budget, and at desired quality. It champions the enhancement of delivered value while simultaneously eliminating waste, thus seeking to improve upon the targets themselves. At the heart of TVD lies cost modeling, a mechanism for formulating the anticipated market cost. This market cost estimate is aligned with the client's allowable cost at various stages of design maturity and during construction. Thus, the cost model serves as a compass, guiding the project team towards their target value, both in the design and construction phases.

The ability of the cost model to provide an accurate market cost estimate is critical for high-quality decision-making. The level of detail and accuracy of the estimate evolves as the project advances. During the construction phase of a TVD project, elements such as a 'contract target' item and work package 'cost targets' form integral components of the general contractor's cost control and reporting mechanisms (Zimina et al. 2012).

All project delivery systems operate within three fundamental domains: the project organization, the project's operating system, and the commercial terms binding the project participants (Thomsen et al. no date). TVD fosters the involvement and investment of participating organizations by focusing on commercial terms, including contracts, risk management, and remuneration structures. These elements shape relationships between individuals and organizations, often employing relational contracts structured around a pain-gain share mechanism (Zimina et al. 2012). Illustrating the multifaceted approach of TVD, the case study of the Cathedral Hill Hospital project by Nguyen (2010) highlights various strategies to restructure the project's operating system toward a TVD environment. These strategies include: (1) Collocation and collaboration of the team, (2) Set-based design to incorporate multiple design alternatives, (3) Frequent sharing of incomplete information, (4) Simultaneous design of product and process, (5) Three-dimensional (3D) design or modeling and digital prototyping, and (6) Specialty contractor and supplier participation in the design process.

The three domains of the project delivery system collectively enable project teams to conduct trade-off analyses between product and process design alternatives. Conventional cost modeling methods fall short in their ability to perform such intricate trade-offs. Research on TVD (Do et al. 2014, Zimina et al. 2012) demonstrates its effectiveness in managing project cost overruns, by steering design and construction decisions and conducting trade-off analyses when evaluating the impacts of alternatives. TVD serves as a framework for addressing the complexities of cost management in construction projects.

2.3.7 Cost Modeling for Takt Production

2.3.7.1 Primary Impacts of Takt Production

As described in Section 2.2.2, takt production offers many potential benefits to construction project planning and control. Numerous case studies, including those by Court (2009), Frandson et al. (2013), Vatne and Drevland (2016), Binninger et al. (2018), Dlouhy et al. (2018), and Kujansuu et al. (2019), have demonstrated the benefits of takt production over traditional methods. These benefits include the reduction of non-value adding time and shortened production lead times (e.g., Frandson et al. 2013, Binninger et al. 2018), decreased waste, increased worker productivity, and improved flow (e.g., Linnik et al. 2013, Lehtovaara et al. 2021a, Vatne and Drevland 2016). These benefits are a result of enhanced concurrency, standardized and repetitive tasks, reduced variability, improved collaboration, communication, and streamlined workflow. Figure 2.2, from

Linnik et al. (2013) outlines some of these benefits and their associated cost impacts resulting from the implementation of takt production.

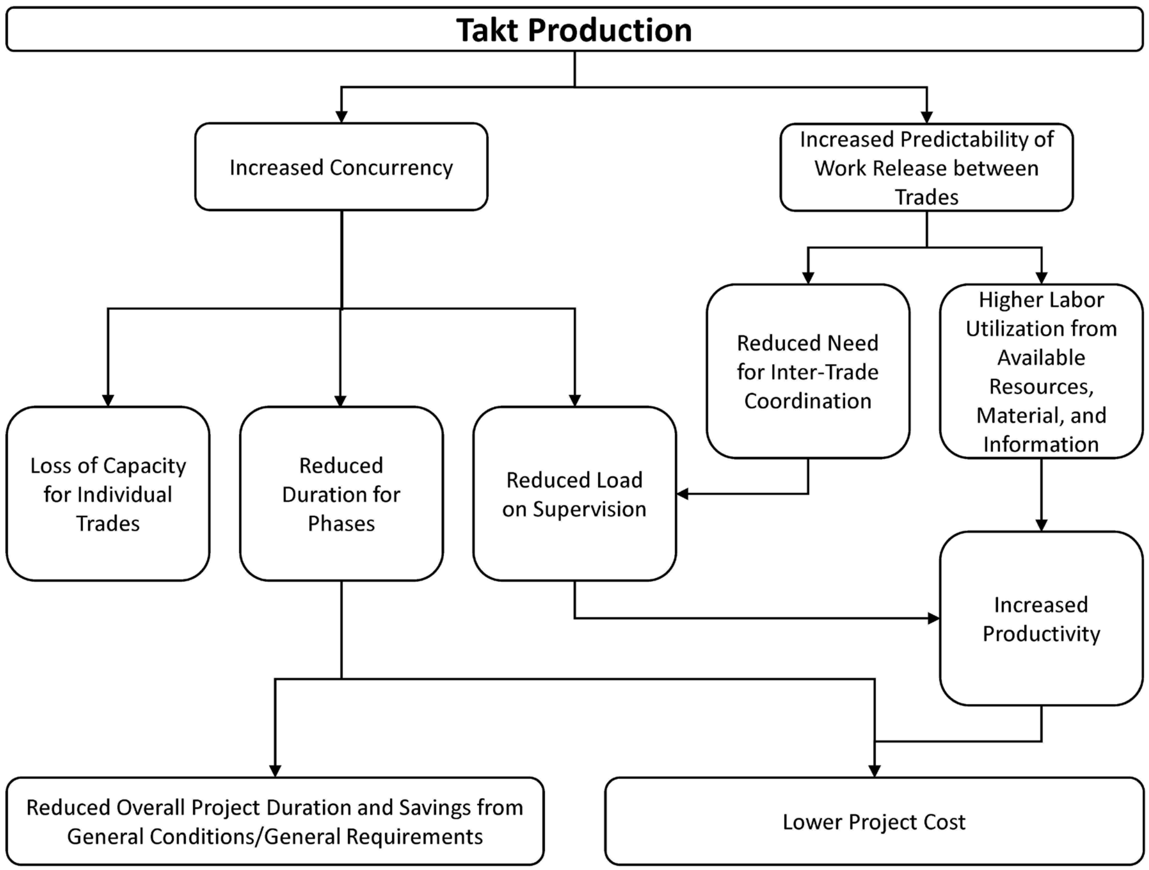


Figure 2.2: Benefits and costs from takt production (after Figure 1 in Linnik et al. 2013).

Mordal's (2014) case study highlighted reductions in construction time and costs, particularly for projects featuring a higher degree of repetitive work. Note however, that while some research reports have shown significantly reduced project duration, the evidence regarding effects on costs, quality, and safety remains limited, as evidenced by Kujansuu et al. (2019).

Studies underscore the significance of reducing project duration as a primary objective in implementing takt production (as emphasized by Lehtovaara et al. 2021b). Shortening the start-to-finish times can potentially yield cost savings by reducing overhead costs (also referred as indirect or soft costs). In construction cost estimating, overhead cost falls under general conditions. General conditions include costs for a variety of expenses that are not directly linked to construction, e.g., project management staff, temporary facilities, and are needed for the duration of the project. Linnik et al. (2013) argues that this reduction in duration may lead to increased direct labor costs. However, if takt can be consistently met, it can also bring about sufficient reductions in general condition costs. Their study reported a case where the framing phase saw a 7-month plan reduction. As the bottleneck step, the framing trade incurred double the labor costs to meet the takt. Nevertheless, the project achieved net savings of $12 million from reduced general condition costs.

One common objective of takt production is to minimize WIP to enhance process flow, as observed in studies such as Linnik et al. (2013). WIP is a type of inventory that accumulates anywhere within processes and in contrast to stock (another type of inventory) that accumulates between two or more processes (Hopp and Spearman 2008, p. 230). These inventories are useful as buffers against variability and allow processes to perform as planned and meet customer demand. Minimizing WIP without dealing with the existing variability can negatively impact performance. Research by Lehtovaara et al. (2021a) on takt production strategies for promoting flow underscores the work by Little and Graves (2008) on the importance of finding an optimal balance in managing WIP and improving flow. They caution against reducing WIP beyond a limit of diminishing returns, as it can result in a high need for control efforts and WIP starvation, leading to increased costs and reduced performance. Although the initial benefits of improving flow are evident, a sole focus on reducing WIP may yield diminishing returns over time. To have a better understanding of production design decisions, such as WIP, and their impact on cost, a comprehensive cost model is needed.

2.3.7.2 Opportunity Cost of Takt Production

The cost implications of completing a project early or facing delays extend beyond the scope of construction expenses, bearing significant importance for the client. Lehtovaara et al. (2021a) draw attention to a challenge within the domain of takt production, namely a lack of universally applicable Key Performance Indicators (KPIs) that hinder contractors' ability to optimize flow efficiency in alignment with clients' objectives. The authors adopt an operational strategy framework, as defined by Pound et al. (2014), which underscores the importance of designing, implementing, and controlling demand, time, cost, inventory, variability, and capacity to attain the client's financial and marketing goals. This framework is applied to takt production, enabling the creation of a production system that harmonizes with the project's scope and enhances flow effectiveness.

Pound et al. (2014) introduced five KPIs designed to assess the effectiveness and value-creation potential of a takt production system. Among these KPIs, two—lead time and batch-specific lead time—hold relevance in translating takt production's impact on the client's financial and operational outcomes. Lead time signifies how swiftly the entire production process can be completed, from start to finish (Hopp and Spearman 2008). Short lead times offer clients the advantage of faster returns on their investment but often entail more concentrated cash flows. Batch-specific lead time measures the time needed to complete a specific segment of production, such as an individual apartment in a building that can be completed in shorter lead time and be operationalized for quicker revenue generation. This KPI supports paced handover and early utilization of spaces. To reduce lead times, minimizing variability, non-value-adding activities, and unnecessary buffers becomes crucial.

In this context, a cost model can be utilized for calculating the marginal cost associated with a day of production. This calculation can help determine the value of lead time reduction for the client in terms of opportunity costs related to building operations.

2.3.7.3 Cost Impact of Capacity Buffer

The strategic deployment of capacity buffers (swing capacity) is an important component of takt production strategy for managing variability and enhancing plan reliability. This involves assigning additional manpower or equipment beyond the minimum required to meet customer demand, thus keeping the step cycle time below the takt. The difference between the estimated cycle time and the takt is the capacity buffer, which accommodates unanticipated variability and ensures reliable handoffs between steps by completing tasks within the customer takt.

Capacity buffers are assigned to proactively address production challenges, ensure quality management for reliable handoffs, and facilitate continuous improvement, albeit with potential additional costs (Horman and Thomas 2005). Although capacity buffers may, initially, decrease resource efficiency by using more input to produce the same output, over time, they enhance overall production efficiency by providing rapid responsiveness to resolving problems and reducing their cascading effects. Longer term considerations of continuous improvement and learning from the past should be targeted towards standardization and reducing variability to reduce the need for capacity buffers.

In the construction context, the use of capacity buffers is frequently avoided due to perceived initial cost increases (Lehtovaara et al. 2021a). However, a comprehensive assessment of the actual cost impact remains a relatively unexplored area of research.

When considering the risk of capacity loss due to workload variations across trades and zones within a takt plan, Linnik et al. (2013) suggests potential strategies, such as adjusting workloads or identifying alternative productive uses for any excess capacity. Furthermore, Tommelein (2020) studied the application of capacity buffers to enhance system performance. Through simulations of a takted version of the Parade of Trades game, she compared the simulation outcomes between judiciously providing capacity buffers and simply adding capacity. To assess performance, three key metrics were introduced: (1) project duration, (2) time on-site for each trade, and (3) cumulative lost capacity for each trade. These metrics encompass both project and trade performance aspects. While cost of waste is not directly quantified, these metrics can be incorporated in a cost model.

2.3.7.4 Impact of Subcontracting- and Labor Hiring Practices

The established practices within the construction industry present challenges when it comes to the implementation of takt production. The successful adoption of takt production is heavily contingent on subcontracting- and labor hiring practices. However, in practice, takt is often implemented in conjunction with traditional contracting and hiring approaches. A hybrid approach can cause a misalignment between trades' expectations of their contractual obligations and the realities of takt planning and execution. Such discrepancy can render it economically unviable for trades to adhere to a takt plan.

A noteworthy study by Vatne and Drevland (2016) proposes a revision of the wage system as a means to fully leverage the benefits of takt production, for instance, by transitioning from piece-rate compensation to an hourly pay structure. The study posits that reducing project lead time can potentially yield cost reductions by minimizing overhead costs. Regarding direct labor and equipment costs, they suggest the possibility of cost savings by shifting from piece-rate compensation to hourly rates. While the potential impact on worker behavior in response to this shift remains an area for further exploration, it is essential to acknowledge that, apart from the rate structure, the daily work routine can also become more streamlined when adopting takt.

Keskiniva et al. (2022) studied the contractual complexities associated with takt production. They created a conceptual foundation for the development of subcontract clauses suitable for takt production and underscore the importance of effective communication between trades and general contractors for the viability of takt production. Their recommendations are outlined as subcontract requirements developed to better fit the takt production model, encompassing various aspects such as collaborative takt planning workshops, daily takt meetings, and other on-site gatherings. They emphasize the need for maintaining a consistent workforce presence at the construction site, completing work packages in a single cycle within the takt timeframe, establishing clear responsibilities concerning material transportation, rigorous adherence to the takt schedule, and digital production status reporting, if necessary. Furthermore, they advocate for the use of stage payments to incentivize trades to align with takt production and ensure work packages are completed in a single cycle. Leveling of workload may cause workers to wait, and the cost implications of the waiting and how it is compensated should also be explicitly addressed within subcontracts. Furthermore, subcontracts should possess the flexibility to accommodate changes in the takt plan as required.

TVD illustrates how contractual terms and remuneration mechanisms can influence the dynamics between individuals and companies involved in construction projects (Zimina et al. 2012). Integrated Project Delivery (IPD) is a system that aligns the commercial incentives of project participants (Thomsen et al. no date). IPD, combined with TVD, forms a project delivery system often referred to as Lean Integrated Project Delivery (Do et al. 2015). In these projects, TVD relies on relational contracts, such as the Integrated Form of Agreement (IFoA), which are executed earlier than traditional contracts and structured around a shared pain-gain mechanism. This mechanism aligns the interests of stakeholders, fostering a collaborative foundation upon which relationships can thrive. The implementation of similar contractual and financial incentives—either through the modification of existing contracts or the creation of new ones—has the potential to provide a more transparent understanding of the cost impact of takt production on projects and their various stakeholders.

The learnings from the study of cost impacts for takt production decisions on the project and the stakeholders is developed as a cost model for takt production in Section 3.3.

2.4 Data-Driven Project Production

A comprehensive review of the theoretical landscape reveals a compelling case for the adoption of data-driven approaches in production planning and control. This review allowed me to make an informed choice in the technology to be used in this research. Section 2.4.1 starts by highlighting existing research that underscores the need for data-driven production planning and control in the construction industry. Section 2.4.2 explores a range of technologies capable of supporting such a data-driven system. It includes an overview of existing technologies within the construction industry. The selection of technology for the research begins by narrowing down specific technology types, namely positioning- and vision-based tracking technologies, and subsequently analyzing technology solutions within those types. Final selection ends in a comparative analysis grounded in specific characteristics tailored to the research's requirement and preference criteria. The technology requirement criteria for the research included spatial accuracy, capture frequency, processing time, and range, while the preference criteria focus on cost, availability, scalability, coverage, and permeability. I selected the 360° Camera-based tracking for the research. However, the data-driven production planning and control framework developed later in this research (Chapter 4), is created with the idea of interchangeability of technology. Section 2.4.3 describes the need for a process-based Common Data Environment (CDE) and Section 2.4.4 defines basic Machine Learning (ML) concepts.

2.4.1 Need for Data-Driven Production Planning and Control

The need and opportunities for data-driven project production planning and control has become evident in recent years. Research studies conducted by Bardaweel (2018), Jabbari et al. (2020a) and Tommelein (2022), alongside my own collaborative work with Tommelein (Singh and

Tommelein 2023a), have collectively demonstrated the role of quantifying and visualizing work density in enabling new data-driven methods of production planning.

However, these studies consistently encountered the challenge of not having readily accessible data and are currently obtained primarily from scratch. Even with the support from project owners and general contractors, collecting production rate estimates and associated means and methods from the involved trades is met with resistance. This resistance comes from the trades' concerns over sharing sensitive production rate information and worries about it being used to create time commitments. In case the trade is unable to meet the production rates, they have concerns about it being used against them in case of a project delay or cost overrun. As a result, trades often share data reluctantly or include buffers to cover uncertainties. Even when the data is collected successfully, the collection process yields subjective estimates grounded in the trades' experiential knowledge.

Furthermore, investigations into production control, as exemplified by the studies by Bae et al. (2014), Yang et al. (2015), and Keskiniva et al. (2021), which relied on real-time data collection for progress monitoring and reporting, expose the inefficiencies and susceptibility to errors in existing methods. The conventional practice of physically visiting construction sites and manually documenting progress, undertaken either by the project management team or relying on information provided by the trades, is challenging as it is proved to be labor-intensive, time-consuming, devoid of standardization, and fraught with inaccuracies. These challenges become increasingly daunting when multiple trades are concurrently engaged on a site, necessitating heightened coordination, particularly during phases such as interior finishing. To promptly identify deviations from the project plan and support informed decision-making, the need for spatiotemporal data pertaining to resources, including trades and their respective locations, becomes evident, reinforcing the need for an automated data-driven approach.

The emergence of objective, standardized, and an increased numbers of data streams from construction sites makes it possible to use data-driven approaches to extract valuable insights. For systems where empirical models do not exist, and that are typically nonlinear, dynamic, multi-scale in space and time, and high-dimensional (when the number of variables is close to or larger than the number of observations), researchers are turning to data-driven approaches. These approaches from data science, ML and engineering mathematics are enabled by the unprecedented availability of data and computational resources(Brunton et al. 2019). Increasing access to data and data-processing reinforce the opportunities of using data-driven approaches for production management.

The identified needs and opportunities for application of data-driven approaches in construction underscores the urgency of collecting and structuring production data. Organization of production data in alignment with spatiotemporal dimensions promises to streamline the application of the WDM for production planning while simultaneously establishing a foundation for production control. The final goal is the development of a framework and computer-based tool capable of automating near real-time data-driven production control. Over time, as historical data accumulates, this tool will significantly augment the efficacy of the production planning using prediction models.

2.4.2 Technologies Supporting Data-Driven Methods

This section explores the potential technologies to support a data-driven production planning and control system. Through this exploration, I narrow down the type of technology suitable, and then select the technology solution within those types. Figure 2.3 depicts the exploration and selection process, starting from the top (Section 2.4.2.1) and narrowing down to the bottom (Section 2.4.2.5). Section 2.4.2.1 gives an overview of software and hardware technologies that: (1) can support data-driven methods and (2) technologies that exist in construction. Sensor-based tracking technologies lie at the intersection of the two groups. Section 2.4.2.2 and Section 2.4.2.3 then talk about the two main groups of sensor-based tracking technologies: (1) positioning-based and (2) vision-based. Section 2.4.2.4 presents technology solutions among the two sensor-based technology groups and selects five of these solutions best fit for this research: (1) 360° camera, (2) surveillance camera, (3) laser scanner (a term used interchangeably with Light Detection And Ranging (LiDAR)), (4) Indoor Positioning System (IPS), and (5) Global Positioning System (GPS). Section 2.4.2.5 presents a Choosing by Advantages (CBA) analysis for the five solutions by matching them with the requirements ("musts") and preferences ("wants") of the research (Suhr 1999). This analysis ends in the selection of 360° Camera as the technology to develop a data-driven production planning and control system.

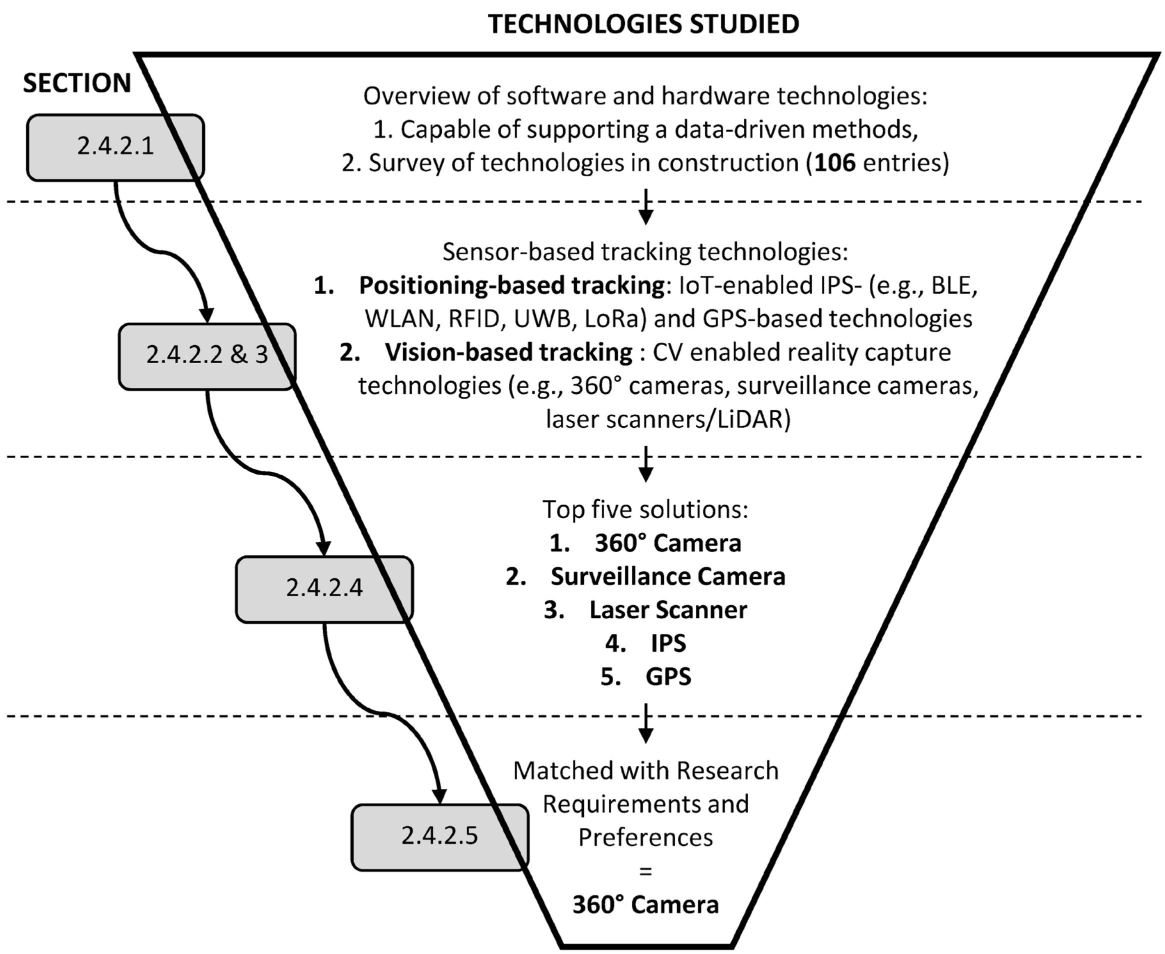


Figure 2.3: Data capture technology exploration and selection process.

2.4.2.1 Overview of Existing Technologies

The exploratory review of software and hardware technology for this research included identifying existing sources of data being collected on construction sites, how they can be useful, and where research is needed to fill the gaps to meet research objectives.

Tommelein and Singh (2019) conducted a study for a large global data center construction program, surveying the technologies being used by the general- and specialty contractors involved in the program. Their report documents an array of 106 distinct software and hardware technologies actively deployed in preconstruction and construction. The report shows that there exists an expansive landscape of prevailing technologies in construction. It also details the specific types of data these technologies capture or manage. The technologies are evaluated in a comparative analysis based on their purpose, perceived value addition, level of operational effort, cost implication, and the phase of implementation. Findings from this report, which are integral to our research for selecting the technology to collect data, are detailed in Appendix A.

In the selection of data collection technologies for this research, I placed a particular emphasis on choosing existing technologies, such as those employed in construction project management, scheduling, and labor tracking. This choice acknowledges the inherent complexities associated with introducing new technologies to construction sites, along with the challenges of replicating results in the real-world construction environment.

An extensive review of technologies for on-site location tracking using various types of sensor-based technologies. This also includes technologies that are fit for the purpose but not being used in construction. From this review, two promising technologies surfaced: (1) positioning- and (2) vision-based tracking.

Positioning-based tracking leverages Internet of Things (IoT)-enabled IPS- and GPS-based technologies to track the location of objects. Vision-based tracking primarily uses computer vision (CV) to recognize objects. The use of CV for image recognition has witnessed growing adoption due to (1) easy and affordable access to requisite computation power, (2) availability of structured data, and (3) development of algorithms. CV provides a nonintrusive way to detect work-related tasks. The inputs for a CV system can be sourced from various reality capture solutions, including but not limited to 360° cameras (image or video capture), surveillance cameras (image or video capture), and laser scanners (point cloud capture).

The literature on other sensor-based technologies, such as inertial, pressure, sound, and light sensors, was not reviewed in detail because these technologies are still in a nascent stage of development. Their ease of application, community of knowledge, accessibility, and cost are less supportive compared to positioning- and vision-based solutions. However, despite the limited research, some studies have explored the use of these sensors in the construction context. Simões et al. (2020) provide insights into a broad spectrum of indoor navigation technologies. These encompass low-cost inertial sensors, capable of estimating pedestrians' positions without necessitating the implementation of additional infrastructure within building units. Sound systems, which emit audible and inaudible sounds, offer the unique ability to embed coding that conveys information to the system without causing disruption to human users. Additionally, light-based systems, which utilize both natural and artificial light sources, serve to delineate points of interest within location systems. Transmitted light signals can also incorporate coded information, functioning as a language for relaying instructions to the localization system. Other examples of research include the work of Rashid and Louis (2020) and Akbal and Tuncer (2022) who used audio signals and support vector machine (SVM) models to identify activities in modular construction and construction sites, respectively. Slaton et al. (2020) used accelerometer sensors as input for convolutional neural networks (CNN) and long short-term memory (LSTM) ML models to recognize heavy equipment activities. Alwasel et al. (2017), Rashid and Louis (2019), and Bangaru et al. (2021) used data from inertial measurement units (IMUs) and various neural network (NN) models to classify activities of masons, heavy machinery operators, and scaffold builders, respectively. Studies have also shown the power of using data from an array of sensors, especially common when coming from the equipment and machinery on-site. Fischer et al. (2023) used data from sensors already installed on the rotary pile drilling rig, which included sensors that can measure pump pressure, rotary torque, winch forces, and mast inclination. They used this data on hybrid deep learning model for hierarchical classification and activity recognition.

The next two sections provide a detailed review of the two promising tracking technology technologies: (1) positioning- and (2) vision-based tracking.

2.4.2.2 Applications of Positioning-based Tracking

A positioning system serves as a tool for ascertaining the spatial coordinates of an object in space. These systems are designed to operate continuously and in real time, with the primary objective of delivering accurate location data (Zafari et al. 2019). The applications of positioning systems are diverse and encompass various activities, including the detection and tracking of humans and equipment (Simões et al. 2020).

Positioning system technologies can be organized into two categories: (1) outdoor and (2) indoor. For outdoors, GPS is well established and widely used. GPS encounters limitations when employed indoors. Construction materials in the building attenuate the GPS signals and make them lose power, leading to diminished signal reception and accuracy. With limitations of GPS working indoors and sensors for local positioning becoming affordable, the last decade has seen increased adoption of IPS technologies in manufacturing and other production-based industries.

In construction, the use of IPS technologies remains largely confined to research initiatives. Zhao et al. (2019), Zhao et al. (2020), Badihi et al. (2019), Park et al. (2018), and Dror et al. (2019) show research with promising applications of Bluetooth Low Energy (BLE) tracking systems for real-time positioning and tracking in construction work spaces. Various wireless technologies have been applied in building construction and similar projects. Li et al. (2017) and Woo et al. (2011) used a Wireless Local Area Network (WLAN) for safety hazard zoning and labor tracking, respectively. Fang et al. (2016) used Radio Frequency Identification (RFID) for construction management. Cheng et al. (2010) used Ultra-Wideband (UWB) for the analysis of lean principles by tracking resources. Kim et al. (2021) used long range (LoRa) radio frequency for indoor localization for safety performance assessment for construction workers.

The advent of Industry 4.0 technologies (Lasi et al. 2014) and the proliferation of radio frequency-based indoor positioning, often interchangeably referred to as indoor localization, have the potential to bridge the knowledge gaps of this research.

Some researchers have used positioning time-series data and movement trajectory of resources on jobsites to produce position density or heat maps for construction projects exists. These maps signify how much time an entity spends at one position on the map, with “higher density” or “heat” meaning more time spent. Li et al. (2017) divided a construction site into a series of uniform grid cells, known as bins. They developed an algorithm to count how many movement points fall into each bin and used the frequency to plot the density map. Badihi et al. (2019) and Zhao et al. (2020) developed an end-to-end BLE-based positioning system capable of tracking individuals, material, and tools. They found it difficult to locate a single point on the floor plan which led to the generation of heat maps based on density of captured points. Thus, even when using a tracking system with low accuracy for single point coordinates, heat maps can be used to know the general location of the tracked entity in terms of rooms or areas on a floor plan.

Golovina et al. (2021) converted heat map data (continuous data) into grid density maps (discrete data by grid cell) or directly collecting frequency of a worker in a cell on the grid map for a time duration longer than a particular value. This duration is akin to the "measurement interval" used by Zhao et al. 2020.

To test the application of position tracking using grid-based indoor positioning sensor data, fellow students and I (Singh et al. 2021) worked with a BLE dataset provided by Mohammadi and Al-Fuqaha (2018). These datasets contained Received Signal Strength Indicator (RSSI) values collected from mobile phones, with gateway devices placed strategically within a library building. The dataset also included the actual location coordinates within a grid system. To predict positions within the library, we applied an Ensemble ML model, comprising of Random Forest Classifier, Gradient Boosting Regressor, Random Forest Regressor, and Random Forest Classifier. This Ensemble achieved an impressive accuracy of 0.88 when considering a grid cell size of 3 m x 3 m. This result was an improvement (for the same grid cell size) compared to the model trained by Mohammadi et al. (2018), who also collected the raw data. Mohammadi et al. used a semi-supervised deep reinforcement learning model, which achieved accuracies of up to 0.57 for the same grid cell size (3 m x 3 m) and up to 0.97 for a larger grid cell size (9 m x 9 m). This shows that depending on the required positioning accuracy (e.g., grid cell size), a different type of ML model might be suitable.

Positioning-based tracking technologies for data collection along with data-driven methods for analysis present, is found to be useful in connecting production with the spatiotemporal dimensions. This way of measuring actual production in a data-driven way will have profound implications for enhancing the accuracy and efficiency of construction production planning and control.

2.4.2.3 Applications of Vision-based Tracking

Vision-based tracking systems, powered by light sensors with varying characteristics, have emerged as a transformative technology with applications in construction progress monitoring. The recent review of existing vision-based progress monitoring methods by Reja et al. (2022) and Pal et al. (2023) underscores the role of vision-based monitoring in construction progress monitoring and management.

As detailed by Simões et al. (2020), these systems can be employed in two primary setups: infrastructure-based and mobile device-based. In infrastructure-based setups, strategically positioned cameras are utilized to monitor large visual fields, enabling the detection, and tracking of construction-related targets. These can be part of surveillance camera system. Conversely, mobile device-based setups focus on expanding the visible area around the user and visually identifying reference points and information.

Vision-based technologies, with a primary focus on CV as the data analysis method, have emerged as effective tools for addressing a wide array of challenges within the construction industry. These technologies are being applied for progress monitoring, material and machinery detection, worker tracking, and safety monitoring (Jacobsen and Teizer 2022). The successful application of vision-based tracking hinges on tailoring system parameters to suit the specific requirements of the given task. Key parameters include the source of image capture, the frequency of image acquisition, the speed of image processing, and more. Consequently, the choice of data-driven model and the anticipated performance may vary according to the nature of the construction application. E.g., in a spectrum of processing speed requirement, on one end, for robots to move autonomously and safely maneuver around an unstructured construction environment, it is essential for the robot to conduct comprehensive analyses of the surrounding environmental conditions in a short span of time.(Wang et al. 2022). On the other end, to provide situational awareness for construction workers and progress tracking systems, the data can be collected and then later processed at the end of the day or later (Hamledari et al. 2017). Versatility of these systems highlights their potential across various construction applications.

A challenge in employing CV in construction-related applications is the need for extensive and diverse datasets for training, testing, and validation (Yang et al. 2015). Utilizing a dataset from a single construction site is often insufficient for providing the necessary contextual diversity. Data from multiple sites can offer a larger and more varied representation of features that influence production performance, such as project type (residential, commercial, industrial), structure type (horizontal and vertical), building materials (concrete, steel, wood-frame, masonry), and various local factors related to geography and regulations. Relying on data from a single project can lead to overfitting, resulting in model performance limitations due to the lack of generalization to different properties and contexts.

To address this challenge, researchers have undertaken various approaches to improve the data collection process by reducing the associated effort, time, and cost. For instance, Asadi et al. (2018) developed a mobile robotic platform that integrated Simultaneous Localization and Mapping (SLAM) and object recognition, albeit limited to labeled images from a single construction site. Hamledari et al. (2017) introduced a set of vision-based modules designed to automatically detect elements such as studs, insulation, electrical outlets, and different states of drywall sheets. To compensate for the limitations of data availability, they drew upon multiple image databases captured by smartphones, unmanned aerial vehicles (UAVs), and publicly accessible internet sources to validate their models. Kim et al. (2016) presented a recognition system for a construction site, employing a scene parsing method with 42 test images and 169 training images. Wang et al. (2022) grappled with a shortage of labeled datasets and thus collected and labeled their own data to develop a semantic segmentation model for enhancing visual comprehension of construction sites. Advancements in automation using computer programs and robots, and identification of existing data sources increases the pool of data available to train the vision-based tracking systems.

Data sources for images from actual construction sites tend to be surveillance videos and photographs used for documentation. For instance, Fang et al. (2018) have leveraged far-field surveillance videos to detect workers without hard hats. Such sources are inherently limited to the areas within their field of view.

Another prevalent vision-based tracking technology is the laser scanner, often used synonymously with LiDAR. These scanners produce a three-dimensional point cloud, a discrete collection of data points in space. While laser scanners are a primary method for creating point clouds, image cameras can also produce similar results through photogrammetry, the process of aligning and overlapping multiple images.

Using laser scanning for as-built and geometric modeling has become a widespread application in construction (Pătrăucean et al. 2015). Moreover, research as early as Turkan et al. (2012) have demonstrated the effectiveness of laser-scanned point clouds in tracking construction progress. Armeni et al. (2016) introduced a method for semantically parsing a building’s point cloud through a hierarchical approach: beginning with raw point cloud data to define spaces (such as rooms) and progressing to identify structural and architectural elements (such as walls and columns).

A promising alternative to laser scanning is 360° imaging, also known as omnidirectional imaging. Companies specializing in 360° imaging have access to millions of photographs captured across thousands of construction projects, possibly providing complete site coverage. The prevalence of 360° images extends beyond construction, finding applications in safety training, advanced driver assistance systems (ADAS), unmanned ground rovers, autonomous robotics, and drone navigation systems (Eiris et al. 2020, Ibrahim et al. 2023, Lee et al. 2022, Wang et al. 2022). 360° cameras are particularly well-suited for use in confined spaces, as demonstrated by Humpe (2020) in bridge health inspections, as well as in situations demanding a wide field of view, as highlighted by Premachandra et al. (2020) in the detection and tracking of moving objects at intersections. Chow et al. (2021) used a mobile data collection system equipped with a 360° camera and LiDAR technology. They employed SLAM to reconstruct the site using LiDAR data and deep learning algorithms to detect defects from collected 360° images. Given the specific requirements of this research in terms of coverage area, frequency of image capture, and time efficiency, 360° images emerge as a fitting input source for tracking construction progress.

Leading 360° imaging technology solution providers in construction, such as StructionSite (2022b) (an American start-up, now acquired by DroneDeploy), OpenSpace (2022), and Cupix (2023), describe themselves as ML-driven photo documentation tools capable of autonomously generating navigable photo representations of construction sites. In essence, these solutions serve as the construction industry's equivalent of Google Street View. They are increasingly being integrated into standard operations within construction businesses, serving as a system of record and enabling remote site management. Moreover, commercially available 360° cameras, lightweight and affordable, can be readily mounted on hard hats, seamlessly becoming part of the regular workflow without disruption. The image capture comprises of a time-lapse sequence of images from two fish-eye cameras. Following the capture, image processing stitches images from these two cameras together. Visual Simultaneous Localization and Mapping (VSLAM) and other proprietary CV-based object detection techniques position the stitched images on a floor plan (StructionSite 2022a). VSLAM, a well-developed technology with approximately a decade of development, relies solely on images to determine the position of a moving camera and construct a representation of the explored area (Fuentes-Pacheco et al. 2015). VSLAM enables 360° imaging technology companies to map the trajectory and image nodes onto user-provided two-dimensional (2D) floor plans. The turnaround time for processing images from a typical construction site is usually a matter of a few hours, generally completed within a single day (ENR 2022). The processing time is a function of the walk duration (which translates in the video size), the number of active customers (which translates into the number of videos uploaded to be processed), and available bandwidth on the cloud-based computation.

Furthermore, these solution providers are increasingly investing in CV for automated classification of objects and structures, as well as quantification of work performed on-site. StructionSite's (2022b) SmartTrack, OpenSpace's (2022) ClearSight, and Cupix's (2023) Cupix Vista are three commercially available 360° image-based progress tracking products. Internally, each of these providers has embarked on the task of labeling their captured data to support the classification and segmentation of various scopes of work. Depending on the company, different scopes of work are at various stages of operationalization. These scopes include framing and drywall, ceiling grid and tile, soffits, mechanical, electrical, plumbing, and others.

The integration of existing vision-based technologies in construction (360° camera, surveillance camera, and laser scanner) with advancements in CV and other data-driven methods present a promising solution for construction production planning and control.

2.4.2.4 Technology Solutions for Positioning- and Vision-based Tracking

The previous three sections detailed my analysis of an extensive review of tracking technologies to align with the research objectives and existing technologies in the construction industry. I identified two promising groups of technologies from this analysis: (1) positioning-based tracking and (2) vision-based tracking. The next step in this research is to narrow down the specific technology solutions within these two groups.

For the positioning-based tracking group, I used insights from the preliminary literature review in Section 2.4.2.2 and a survey of existing IPS solution providers (Appendix B) to identify various indoor positioning technologies. These include BLE, RFID, UWB, WLAN, and ZigBee, many of which have been used for construction applications. However, I did not find any solution that provides an out-of-the-box tracking hardware solution dedicated to construction applications or software that connects spatiotemporal tracking data to production parameters. Most available solutions offer kits with components to configure a custom IPS or are dedicated to industrial applications such as proximity monitoring.

Different types of indoor positioning technology utilize various radio frequency ranges to communicate, impacting their performance. However, the components of an IPS-based system architecture are mostly similar and include beacons/tags for data transmission, gateways/receivers for data collection and aggregation, a central hub/cloud for data processing and storage, an analyzer module for data analysis and redundancy removal, a pre-processing module for filtering incorrect data points, and a positioning module for determining beacon coordinates relative to the reference gateway (Zhao et al. 2019). These systems use various algorithms for positioning, which can affect performance and depend on the system architecture. Since no commercially available solution exists, several decisions must be made, such as designing the system architecture, selecting the multilateration metric for ranging (e.g., RSS, AoA, ToF), creating a deployment strategy, identifying sources of noise and interference, creating post-processing filters, and performing installation and calibration (Mackin 2018).

To narrow down the specific technology solutions for positioning-based tracking group, I included all the IPS technology solutions as one alternative, representing the indoor category. If this alternative is selected as the most suitable, further selection of radio frequency range, system architecture, and algorithms for positioning will be determined. For the outdoor category, I selected GPS as an alternative.

In construction, total stations or theodolites are ubiquitous instruments used for positioning objects on construction sites for surveying and construction purposes. However, this type of positioning should not be confused with the positioning-based tracking referred to in this research, as it is not used for continuous tracking but for single-application-based positioning. The terrestrial data sensing part of a total station uses electro-optical scanning instruments, thus falling under the vision-based tracking group. The traditional laser scanning workflow of a total station is vastly different from the emerging laser scanning techniques (such as LiDAR). Although the traditional laser scanning methods are useful for surveying and similar applications, newer workflows have proven to be a better fit for construction progress monitoring (Golparvar-Fard et al. 2011).

For vision-based tracking group, I used the study conducted by Golparvar-Fard and colleagues for Oracle Industry Lab (Golparvar-Fard et al. 2023) which provided an extensive review of vision-based reality mapping. The study provides insights for contractors and owners on how to select which reality mapping tool, process, and team that is right for their job. The landscape of reality mapping technologies encompasses various options with differing resolutions, speeds, costs, and visual deliverables, presenting a challenge for architecture, engineering, and construction (AEC) firms, as well as project owners and operators.

The study employed a range of hardware technology solutions, including LiDAR and structured light depth cameras, stationary and mobile laser scanners, structured light technology, laser-scanner mounted on autonomous robots, and reality mapping in both 2D and 3D with perspective and 360° images and videos. This hardware diversity caters to varying measurement accuracy and specific needs in different use cases, offering solutions for higher accuracy, visual photorealism, and repetitive captures, such as weekly progress monitoring (Figure 2.4). The study also emphasized the need for different types of expertise, from professional surveyors to certified drone operators and field engineers using 360° cameras, based on project phases, team roles, and team sizes.

Stationary LiDAR	LiDAR mounted on robot	Mobile LiDAR	Structured light	Autonomous drone	Manual drone	360° video	Smartphone video	
✓	✓	✓	✓	✓	✓	●	●	As-build documentation for marketing and design for real estate
✓	✓							Surveying during installation
✓	✓	✓						Survey-grade QA/QC (flatness and plumbness; Floor Flatness (FF) and Floor Levelness (FL) ; contouring)
✓	✓	✓		✓	✓	●	●	Day-to-day QA/QC (pre concrete pour, rebar spacing, placement of components such as embeds, conduits)
✓	✓	✓	●	✓	✓	✓	✓	Progress tracking
✓	✓	✓				●	●	Scan2Drawings
✓	✓	✓						Scan2BIM
✓	✓	✓		✓	✓	✓	✓	Safety inspection
✓	✓	✓		✓	✓	●	●	Logistics planning

✓ **Today's high-frequent use-cases**

● **Emerging use cases**

Figure 2.4: Today's high-frequent use cases and emerging use cases for various reality mapping solutions. (after Figure 6 in Golparvar-Fard et al. 2023).

Figure 2.4 shows that LiDAR, in various form-factors, already provides high-frequent use cases on construction sites, whereas 360°- and smartphone videos are the next most used solutions. Using the trends seen in the figure, the study highlighted a desire to move toward portability of tools (e.g., a preference for using smartphone and 360° video captures) and increasing autonomy during the reality mapping process. 360° cameras can capture the entire environment in a single click, offering high-quality, immersive 360° imagery and videos. This is desirable for the project team as they can spend more time on analyzing actionable insights from captured data for decision-making rather than spending time collecting and processing it.

For further analysis, the study compared the engagement time by full-time employee (FTE) (on y-axis) versus the time from the start of the capture to results (on x-axis), considering single and multiple captures, for each solution (Figure 2.5). The FTE engagement time (setup and data capture time) includes tasks such as placing tags for automated registration, surveying 3D locations, and setting up devices on tripods. The time from the start of the capture to results includes setup, reality capture, data transfer, processing, and web-based viewer preparation, but varies for solutions that provide images and videos versus those that directly capture point clouds with LiDAR. The FTE engagement time varied based on the chosen reality mapping solution and whether the capture was initial (colored circle) or repetitive (connected grey circle). Among all solutions, the FTE engagement time required per capture reduces after the first capture as the initial setup takes extra time. This reduction can be significant for some solutions where the initial setup can take a large part of the FTE engagement time. This is especially true where autonomy is used, as is the case for LiDAR mounted on robots and autonomous drones.

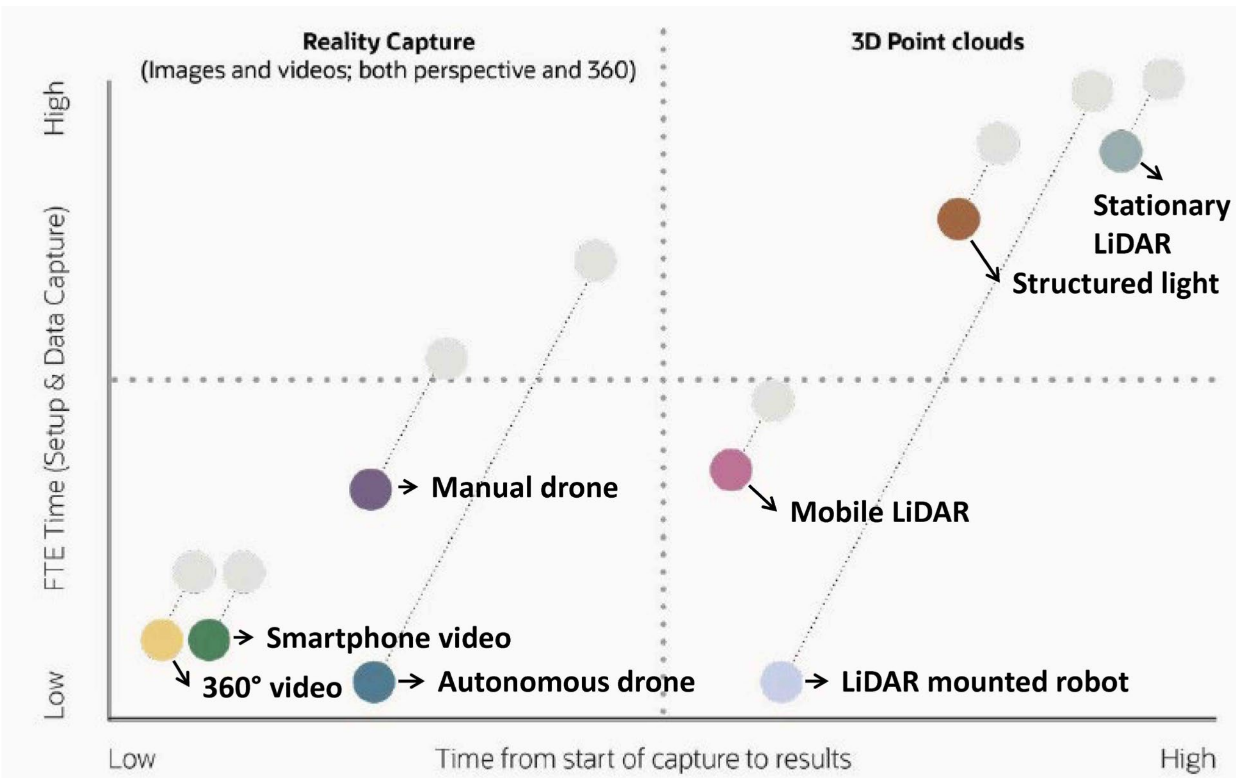


Figure 2.5: Full-Time Employee (FTE) time analysis of technology solutions (after Figure 8 in Golparvar-Fard et al. 2023).

The FTE time and the time from capture to results from the user's perspective are important factors to consider when selecting a technology solution. Considering both FTE time and the time from capture to results, 360° video performs the best, followed by smartphone video, drones, whereas laser scanning (LiDAR and structured light solutions) performs the worst.

Figure 2.6 illustrates the relationship between the cost of hardware and FTE time required f (on y-axis) versus the time from the start of the capture to results (on x-axis), considering single and multiple captures, for each solution. The data points consider both the initial setup and capture costs (colored circle), as well as costs during repetitive captures (connected grey circle). The findings reveal that readily available hardware solutions, such as smartphones and 360° cameras, offer cost-effective options for reality mapping. LiDAR and other laser scanning solutions are known for high precision, but they come at higher costs.

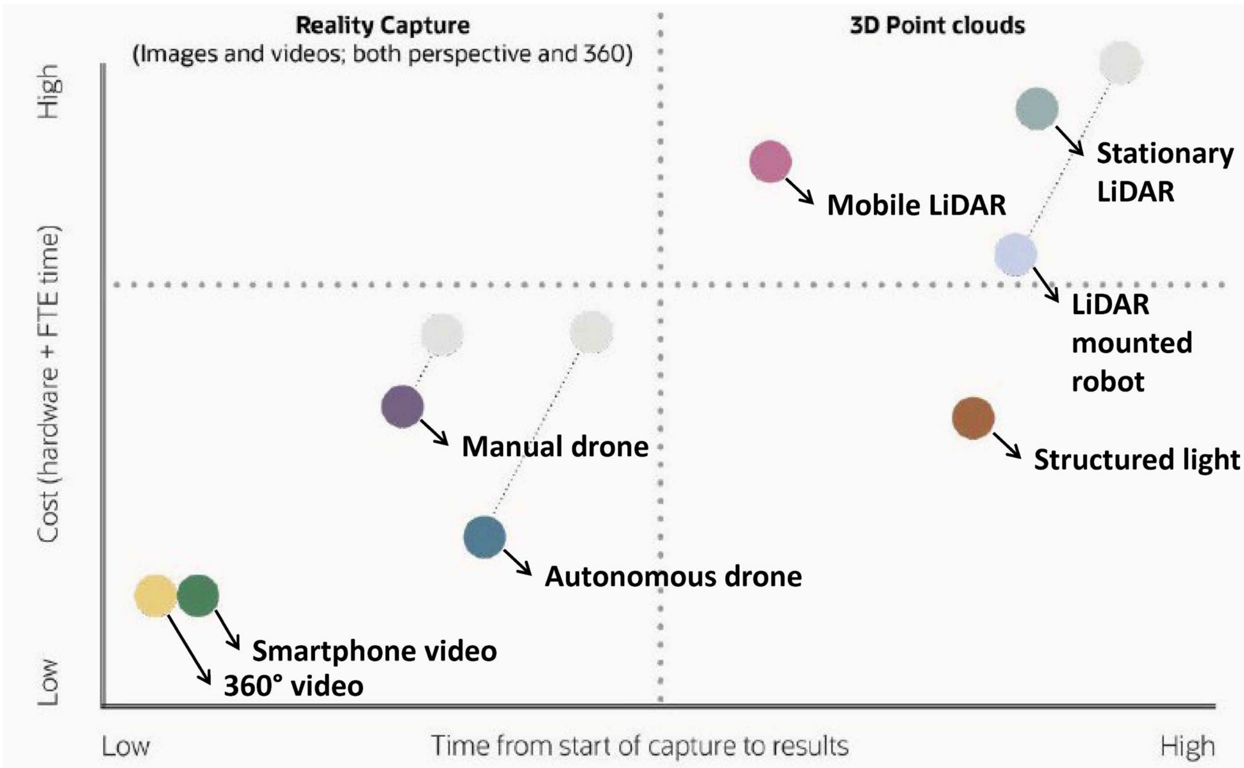


Figure 2.6: Cost analysis of technology solutions (after Figure 9 in Golparvar-Fard et al. 2023).

The study also emphasizes that certain autonomous robotic platforms, especially ground robots, may require human supervision in the short term to ensure operational safety. Additionally, while the figure suggests potential FTE time reductions with autonomous platforms, these time reductions may not be fully realized in the initial months of implementation.

The study concludes that the accuracy of reality mapping results can be enhanced through better planning and reliable autonomy in the mapping process, however use of drones or ground robots is costlier. In terms of time (total setup, data capture, and capture to results time) and cost (total cost of hardware and employee time), 360° video surfaces is the best solution. Ultimately, time, cost, and specific requirements of the use case (e.g., accuracy) are the main factors to consider when comparing and selecting the most appropriate technology solution.

Among the positioning-based and vision-based tracking groups analyzed, I selected five technology solutions best fit for this research: (1) 360° camera, (2) surveillance camera, (3) LiDAR, (4) IPS, and (5) GPS.

2.4.2.5 Selection of Technology Solution

I used CBA to make an objective decision of selecting one technology solution among the selected five in the previous section. CBA is a decision-making system, developed by Jim Suhr (1999), that provides a rational and objective approach to compare the advantages (beneficial differences) of each option. CBA follows eight steps: (1) identify alternatives, (2) define factors, (3) define must-

(requirements) and want (preferences) criteria for each factor, (4) describe the attributes of each alternative, (5) decide the advantage of each alternative, (6) decide the importance of each advantage (IofA), (7) evaluate cost data, and (8) make a recommendation.

Table 2.1 depicts the CBA analysis I conducted in selecting technology solution for this research. The data gathered at each step of the analysis is described next.

Step 1 Identify Alternatives: The five potential technology solutions considered as the alternatives are: (1) 360° Camera, (2) Surveillance Camera, (3) LiDAR, (4) IPS, and (5) GPS.

Steps 2 and 3 Define Factors and Criteria: The factors used to compare the alternatives, grouped into must criteria and want criteria are:

Factors with must criteria:

- **Spatial Accuracy** refers to the degree to which the reported positions of an object (or point) measured by the system correspond to its true position in physical space. The technology should accurately determine the spatial position of detected objects within a small-sized room (about 1 m or 3 ft). This spatial position size is determined by the spatial resolutions of a step in a production plan. These objects include construction work put in place within the duration of a day: items as small as specific fixtures and devices (e.g., urinal in a bathroom, lighting fixtures, door hardware), but not including smaller parts (e.g., nuts and bolts).
- **Capture Frequency** refers to how often data can be captured and processed by technology. The frequency is dependent on the project's needs, with more complex control requirements necessitating more frequent data capture. For takt production, a daily capture frequency is essential for single day takt, whereas weekly capture suffices for most projects. This frequency is crucial for a system to match the data capture frequency with control frequency at minimum.
- **Processing Time** refers to the duration from data capture to the availability of processed information. The processing time should not exceed one day for planning and control decision-making.
- **Range** refers to the maximum distance over which the system can accurately and reliably detect objects. The technology must be capable of accurately detecting objects within a large room, offering a minimum effective range of about 10 meters (32 feet). This range ensures that the technology can cover the typical dimensions of large spaces without compromising on spatial accuracy.

Factors with want criteria:

- **Availability** refers to how familiar and readily available the technology is to the construction industry to avoid implementation delays. Preferring solutions that are readily accessible to the construction industry and are already integrated into existing operations.
- **Scalability** refers to the ability of a system to adapt and perform efficiently as the scale of its application changes. This could mean expanding its operational capacity to cover larger areas, accommodate more tracked objects, or handle increased data volumes without a significant drop in performance or accuracy. Preferring technologies that can be easily scaled for larger projects or across multiple projects. Cost, time, and effort related to implementation literacy, equipment set-up, data capture, and data processing should not increase nonlinearly with increasing implementation.

Table 2.1: Choosing By Advantages (CBA) analysis for selecting technology solution for the research.

	Vision-based Tracking Systems						Positioning-based Tracking Systems			
Factor (Criterion)	**Alternative 1: 360° Camera**		**Alternative 2: Surveillance Camera**		**Alternative 3: LiDAR**		**Alternative 3: IPS**		**Alternative 3: GPS**	
Spatial Accuracy	Att.: Low to High (depends on the accuracy of the algorithm, e.g., SLAM)		Att.: Low to High (depends on distance from subject) (Chen et al. 2021)		Att.: Very High (~1cm-10cm) (Golparvar et al. 2011, 2023)		Att.: Moderate to High (~1m or better with UWB) (Zafari et al. 2019)		Att.: Low (Not suitable for indoor)	
Must be at least ~ 1 m (3 ft). Higher accuracy is better.	Adv.: Higher accuracy for indoors.	Imp.: 70	Adv.: Higher accuracy for indoors.	Imp.: 70	Adv.: Much higher accuracy for indoors.	Imp.: 100	Adv.: Much higher accuracy for indoors.	Imp.: 80	Adv.:	Imp.:
Capture Frequency	Att.: Varies (daily or less, usually weekly) (Golparvar et al. 2023)		Att.: Continuous (Chen et al. 2021)		Att.: Low (Golparvar et al. 2011, 2023)		Att.: Continuous (Zafari et al. 2019)		Att.: Continuous	
Must be at least daily. More frequent capture is better.	Adv.: Considerably higher frequency with minimal setup time.	Imp.: 75	Adv.: Much higher frequency with minimal setup time.	Imp.: 90	Adv.:	Imp.:	Adv.: Much higher frequency with considerable setup time.	Imp.: 85	Adv.: Much higher frequency with least setup time.	Imp.: 100
Processing Speed	Att.: Few hours (Golparvar et al. 2023)		Att.: Few hours to real-time		Att.: Hours to days (Golparvar et al. 2011, 2023)		Att.: Few hours to real-time (Zafari et al. 2019)		Att.: Few minutes to real-time	
Must be less than a day. Shorter processing is better.	Adv.: Shorter processing time.	Imp.: 70	Adv.: Shorter processing time.	Imp.: 70	Adv.:	Imp.:	Adv.: Much shorter processing time.	Imp.: 75	Adv.: Much shorter processing time.	Imp.: 80
Range	Att.: Moderate range, but extended through multiple positions.		Att.: Moderate		Att.: Moderate to Large (0.5-350 m) (Golparvar et al. 2023)		Att.: Moderate to Large (~10m with UWB to 15km with LoRa) (Zafari et al. 2019)		Att.: Large (Outdoor)	
Must be at least ~ 10m (32ft). Larger range is better.	Adv.: Similar range but extendable.	Imp.: 60	Adv.:	Imp.:	Adv.: Larger range but limited positions.	Imp.: 60	Adv.: Much larger range.	Imp.: 65	Adv.: Extremely large range.	Imp.: 70
Availability	Att.: High (Chow et al. 2021, Golparvar et al. 2023)		Att.: High		Att.: Moderate (Golparvar et al. 2023)		Att.: High DIY to low commercial		Att.: High	
Preferably part of existing operations. More accessible is better.	Adv.: Several commercially available solutions, but less common in operations.	Imp.: 40	Adv.: Several commercially available solutions already being used.	Imp.: 45	Adv.: Several commercially available solutions being used, but need more literacy.	Imp.: 40	Adv.:	Imp.:	Adv.: Several commercially available solutions, but less common in operations.	Imp.: 40
Coverage	Att.: High (Golparvar et al. 2023)		Att.: Very Low (limited to placement and numbers of cameras)		Att.: Low (limited to number of captures) (Golparvar et al. 2023)		Att.: Moderate to High (Zafari et al. 2019)		Att.: Not suitable for indoor	
Preferably able to cover most of indoor floor plan. Larger coverage is better.	Adv.: Significantly higher converge through multiple positions.	Imp.: 55	Adv.:	Imp.:	Adv.: Slightly higher converge through multiple positions.	Imp.: 40	Adv.: Higher coverage but limited to position of tracked resources.	Imp.: 45	Adv.: Higher coverage but limited to position of tracked resources.	Imp.: 45
Scalability	Att.: High (Golparvar et al. 2023)		Att.: Very low		Att.: Low (Golparvar et al. 2023)		Att.: Low to Medium (Zafari et al. 2019)		Att.: High	
Preferably easy to scale. Higher scalability is better.	Adv.: Very easy to scale as only connected to one resource for coverage.	Imp.: 55	Adv.:	Imp.:	Adv.: Repetitive usage needs extensive efforts to scale.	Imp.: 40	Adv.: Network and configuration complexity increases with scaling	Imp.: 40	Adv.: Easy to scale but needs linearly scaling one-time configuration.	Imp.: 50
Permeability	Att.: Low but covered through multiple positions (needs multiple point of view)		Att.: Very low due to fixed position (needs multiple point of view).		Att.: Low due to fewer positions (needs multiple point of view)		Att.: High with certain technologies like UWB (Zafari et al. 2019)		Att.: Not applicable for indoor	
Preferably works accurately through obstructions. More permeable is better.	Adv.: Can work around obstructions through many multiple positions.	Imp.: 40	Adv.:	Imp.:	Adv.: Can work around obstructions through few multiple positions.	Imp.: 30	Adv.: Performs best through obstructions.	Imp.: 55	Adv.: Does not work indoors.	Imp.: 0
Total IofAs		465		275		310		445		385

- **Coverage** refers to the spatial area or volume within which the positioning system can accurately and reliably work. It represents the operational boundaries of the system, indicating where it can be effectively used. For building construction, the technology should be able to cover complete floor plans in terms of connectivity, or set-up, or battery power. It is not a requirement as multiple implementations of the system can be used to increase the coverage.
- **Permeability** refers to the ability to maintain functionality and accuracy in environments where physical obstructions or materials might interfere with or attenuate the signals used for positioning. Additionally, given the dynamic nature of construction environments, where the layout and structure continuously change, it is essential to use technologies that can adapt to these evolving conditions while maintaining accurate positioning. Preferring solutions that remain effective in the presence of physical obstructions common on construction sites.

The factors and their assigned criteria are represented in the left most column in Table 2.1.

Step 4 Describe Attributes: The attributes for each alternative, corresponding to each factor, are represented in Table 2.1. The least preferred attribute (underlined in Table 2.1) per factor is selected.

Step 5 Decide Advantages: The advantages of each alternative with respect to the attributes are represented in Table 2.1. This is done by identifying the advantage of each attribute relative to the least preferred attribute.

Step 6 Decide Importance: The IofA values are represented in Table 2.1. It is based on the selected paramount advantage per criterion (circled in Table 2.1) and the established scale of importance for the criterion. The scale of importance (values between 0 to 100) depends on the maximum IofA value given to the alternative with the paramount advantage. Factors that have must criteria have higher maximum IofA value than the factors with want criteria. Based on the maximum importance and the relative advantage, an importance value is assigned to each alternative. Finally, the importance values are summed up to calculate the total IofA value for each alternative.

Step 7 Evaluate Cost: Cost includes the total cost of hardware, software, and employee time required to run the system. Preferring solutions that are economically efficient, either by being low in cost or not incurring additional costs to the contractor’s existing operations.

Calculating total cost is difficult for comparison as each solution has a wide range of operational decisions to make, such as the type of hardware used, number of sensors used (especially with IPS and GPS that need individual sensor per object being tracked), type of software used, in-house versus contracted service used. To simplify the cost analysis, I categorized the cost range into 5 categories: (1) very low, (2) low, (3) moderate, (4) high, (5) very high, and then assigned a score between 1 to 5 (increasing from very low to very high cost) to each alternative. Based on these cost categories, I found: 360° Camera to be very low cost (Chow et al. 2021, Golparvar-Fard et al. 2023) with a score of 1, Surveillance Camera to be moderate cost with a score of 3, LiDAR to be high cost (Golparvar et al. 2011, 2023) with a score of 5, IPS to be low to moderate cost (Zafari et al. 2019) with a score of 2.5, and GPS to be low cost with a score of 2. Figure 2.7 shows the cost versus IofA analysis where the five alternatives are plotted with cost score on x-axis and total IofA value on the y-axis.

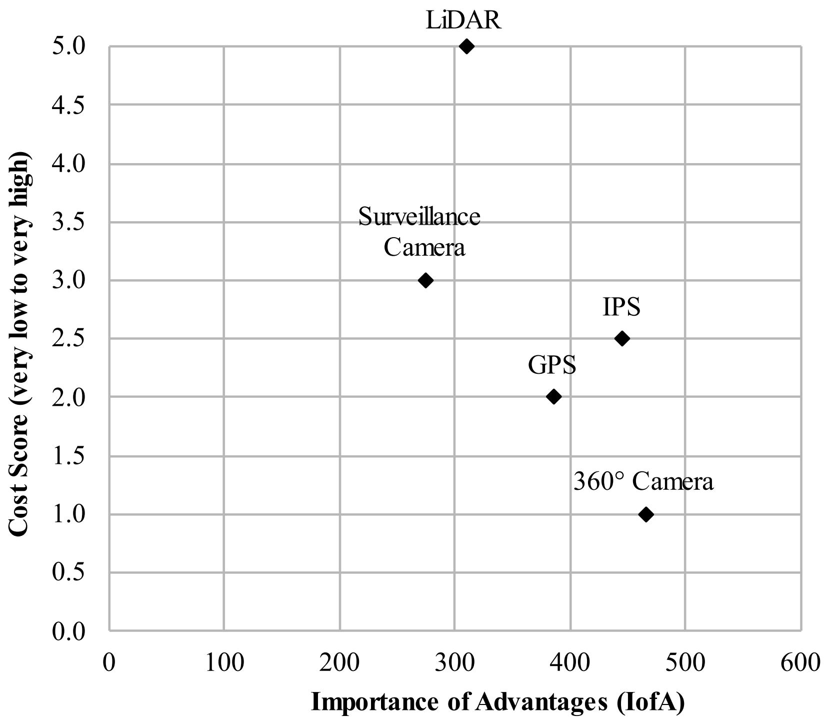


Figure 2.7: Cost versus importance of advantages analysis for Choosing By Advantages (CBA) in technology solution selection.

Step 8 Make Recommendation: Using incremental analysis on the cost versus IofA graph (Figure 2.7), slope of increments from one alternative to the next is calculated. Analysis between 360° Camera (alternative 1) and all other alternatives gave negative increments (\$/IofA), suggesting 360° Camera to be the most suitable technology solution. This is due to the 360° Camera's IofA value of 465, highest among all alternatives, and cost score of 1, lowest among all alternatives.

Apart from the final recommendation, I also analyzed other alternatives for their strengths and weaknesses. Table 2.1 provides context for evaluating other technology solution against individual criterion. Surveillance cameras for instance, due to their limited field of view results in constrained coverage and presents deployment challenges throughout a construction site. The dynamic nature of construction sites, with ongoing work, means a camera's fixed field of view may get obstructed, necessitating repositioning. Chen et al. (2021) suggest using BIM to optimize camera placement by accounting for changes in obstacles and working areas, which improves coverage compared to experience-based camera placement. Despite this, the need for constant reconfiguration and the use of a BIM complicates deployment. However, when limited to a specific location, surveillance cameras offer excellent solutions for tracking due to their wide availability. Limiting tracking to a single location also significantly reduces their cost as a single camera can be used.

LiDAR scanners deliver unmatched accuracy but often provide more spatial resolution than necessary, coming at the cost of slow setup and data processing time. The slow turnaround discourages frequent data capture, affecting coverage and scalability. In future, a cost effective and reliable autonomous (drone or robot mounted) laser scanning solution can overcome these challenges in terms of time and coverage (Golparvar-Fard et al. 2023). Another approach to improving the scanning performance is moving towards mobile hand-held lidar based technology (Blinn and Issa 2017).

IPS is a close second to 360° camera in terms of its importance, with an IofA value of 445, but at a slightly higher cost. IPS meets most of the criteria but falls short for construction due to several reasons. IPS has not become popular in construction mainly because implementing a hardware-based IPS solution, which requires attaching sensors to workers, poses significant logistical and social hurdles.

To understand the "availability" factor, I conducted a supplementary survey of commercially available tracking technology solutions aimed to complement the technology selection with a detailed list of available software and hardware for positioning- and vision-based tracking in construction (Appendices A and B). This survey's analysis shows that current IPS solutions lack dedicated tracking hardware for construction and do not seamlessly link tracking data with construction production. Most solutions are kits for custom IPS setups or are designed for industrial use, such as proximity monitoring in warehouses. Additionally, the need for frequent reconfiguration and calibration of beacons and receivers on dynamic construction sites makes it a labor-intensive and costly process. In contrast, some 360° camera-based solutions have been successfully applied in construction, suggesting a more straightforward path for industry adoption.

Understanding IPS, including its communication modes, system architecture, data collection formats, and existing solutions, was vital for developing the data model in Section 4.1. As the construction industry increasingly incorporates IoT sensors into tools, equipment, and worker environments (Lasi et al. 2014, Park et al. 2018), this understanding ensures the data model's flexibility. It allows for the integration of IPS tracking data in the future, through a framework and data model that is agnostic to the data source.

In summary, integrating vision-based tracking technologies, particularly 360° camera imaging, has the potential to transform production monitoring and management in the construction industry. Enhanced by ML and automated work- or object detection, these technologies promise real-time, comprehensive project insights, streamlining decision-making and enhancing project performance. The tools and methods developed in this research are grounded in an extensive review of technology and aligned with the research objectives of a data-driven production management.

2.4.3 Data Environment and Unit of Observation

To develop a standard data model that can be generalized for all types of projects and used with other AEC applications, it is necessary to consider the broader applications outside the scope of applications in production planning and control. A fundamental aspect of such data-centric model is to determine the unit of observation and establish a CDE.

The unit of observation pertains to the entity described by the data collected and analyzed. It represents the object around which information is gathered. By adopting a standardized unit of observation, we can create a CDE, which serves as the framework for collecting, managing, collaborating, and sharing information. To facilitate a seamless exchange of information among the various stakeholders in AEC projects and programs, the scope of the CDE must extend beyond individual applications and incorporate production systems across the value chain.

While efforts have been made to codify construction information within a CDE, as highlighted by Soman and Whyte (2020), several challenges persist. Beyond the hurdles associated with software utilization and information sharing, their work underscores the intricacies of collecting and disseminating construction process information. Construction process information often lacks the structured and detailed attributes found in product information. While product information can be meticulously organized, process information is typically represented in the form of Gantt chart-based network models within scheduling software, which are then linked to the BIM. However, detailed process information is frequently presented in an unstructured manner, such as method statements in PowerPoint presentations and PDF documents. Collecting information in these unstructured formats presents implications for data quality, including inconsistencies, difficulties in data retrieval and analysis, and challenges in ensuring accuracy and reliability for decision-making processes.

With regard to construction process information, Nguyen (2010) previously shed light on the limitations of traditional product-based cost modeling and advocated for a more comprehensive approach through PBCM framework. In line with the PBCM framework, this research proposes to adopt a process based CDE for the production planning and control within the design and construction industry. Compared to traditional product based CDE, this process based CDE should ideally employ process steps as the fundamental unit of observation, facilitating a more holistic and effective framework for managing and optimizing construction processes.

2.4.4 Machine Learning (ML) Concepts

The field of ML lies at the intersection of computer science and statistics and is described as a collection of algorithmic systems designed to enhance their performance by gaining experience (Jordan and Mitchell 2015). ML constitutes the domain of knowledge that strives to establish computational relationships between observed data and various computational rules. A hallmark of ML is its capacity to infer and derive these computational rules based on empirical evidence. These computational rules have two fundamental categories of algorithms, supervised learning and unsupervised learning (Russell and Norvig 2010).

Supervised learning pertains to the task of learning from example input-output pairs, wherein a supervised ML algorithm deduces a function from labeled or annotated training data (Hastie et al. 2009, p. 9). This data-driven method is fundamental for predictive modeling tasks, which can be broadly categorized into regression tasks, where the goal is to predict continuous values, and classification tasks, where the objective is to assign discrete labels to input data. In contrast, unsupervised learning thrives without the limitations of pre-existing labels and can be used for dimensionality reduction, simplifying datasets by reducing the number of variables while preserving essential information, and clustering, grouping data points into clusters based on similarity (Hastie et al. 2009, p. 486). Situated between these two types of algorithms is semi-supervised learning, an intermediary approach that fuses elements of both supervised and unsupervised techniques. Within the domain of ML, an array of algorithms emerges, each serving as a tool in data-driven investigations. These algorithms include, but are not limited to:

- **Supervised learning:**
    - **Regression:** Linear Regression
    - **Classification:** Logistic Regression and Bayesian Networks
    - **Regression and classification both:** Support Vector Machine (SVM), Random Forest, Decision Trees, and Neural Network (NN), encompassing Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and many more
- **Unsupervised learning:**
    - **Dimensionality reduction:** Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE)

- **Clustering:** k-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and k-prototypes

As listed above, some supervised learning algorithms can be applied to both classification and regression tasks. Additionally, certain algorithms, such as NN-based algorithms, are versatile enough to be used for both supervised and unsupervised tasks.

Applications of many, if not all, types of common ML algorithm exist in construction engineering and management. Apart from the ML assisted position- and vision-based tracking work discussed before, several applications have been directly related to project and production planning and control of construction work. Jacobsen and Teizer (2022) conducted a bibliometric analysis, revealing a wide range of NN applications in construction. Amer et al. (2021) introduced a novel approach utilizing natural language processing (NLP) and ML (with Transformer architecture) to automate the linkage between look-ahead planning tasks and master-schedule activities, streamlining project coordination and payment application reviews. Amer et al. (2023) present an Implicit Logic Checker (ILC) that leverages ML to optimize lookahead plan revisions, reducing overall plan durations in construction projects. Gondia et al. (2023) focus on proactive safety management through Ensemble ML algorithms, enabling the prediction of safety risk leading indicators to enhance safety performance and minimize injury-related costs.

Effective training and evaluation of ML models necessitate the division of the dataset into distinct subsets, including the training set, an optional validation set, and the test set. The training set serves as the dataset for model training, whereas the validation set plays a pivotal role in identifying the optimal model configuration through the exploration of varying hyper-parameters, referred as hyper-parameter tuning or optimization (Schratz et al. 2019). Finally, the test set serves as the litmus test to assess the model's performance. A robust ML model should exhibit the ability to generalize its performance to unseen datasets. In this context, the model's performance must extend beyond the training set and encompass the validation and test sets, which remain unobserved during the training phase. The inability to achieve good performance on both the training and test sets indicates underfitting (Russell and Norvig 2010, p. 709). Conversely, a model that excels on the training set but falters significantly on the test set indicates overfitting.

Challenges involving the inference of a natural state from a finite set of data samples, in a high-dimensional feature space, highlight a critical trade-off concerning the number of features to be selected. The selection of a reduced number of features tends to produce a simpler model that may struggle with underfitting, as described earlier. Conversely, opting for a greater number of features tends to produce a more intricate model that can struggle with overfitting. As the dimensionality of the feature space (i.e., the number of features) increases, the feature space grows exponentially. In such high-dimensional spaces, data samples become sparsely distributed, making it difficult to produce generalizable models.

In the process of developing a ML model, it is crucial to consider quality and quantity of training dataset, desired output, generalization, etc. in making decisions relating to feature selection, algorithm choice, balancing overfitting and underfitting, and selecting appropriate evaluation metrics. Practical considerations including computational resources and execution time, along with ethical concerns and bias mitigation, are equally important for model effectiveness and fairness. I have incorporated these considerations in the data schema design for this research (Chapter 4), data collection and data preprocessing (Chapters 5 and 6), and finally selecting the appropriate ML models (Chapter 6).

2.5 Conclusions

The literature review provided the essential theoretical background on project-based production in construction, location-based production systems such as takt production, cost modeling for takt production, and the tracking technologies and ML models supporting data-driven production planning and control in the construction industry. Traditional methods for construction project planning and control have significant limitations in addressing workflow reliability and flow evenness due to their focus on transformations at individual activity level rather than the overall process. Adopting lean principles, project production theory, and a flow-based approach offers a more holistic approach, emphasizing workflow reliability, waste reduction, and global efficiency.

Location-based production planning and control methods, particularly takt production, align with desired outcomes by focusing on spatial continuity and efficient resource utilization. The WDM allows for workload leveling and zoning, essential for effective takt production implementation with a data-driven approach. Based on the existing literature on the WDM and location-based project production planning, Chapter 3 describes the development of a visualization and computing support tool named ViWoLZo for data-driven production planning.

Cost modeling for takt production is complex, with existing models often oversimplifying critical production factors and failing to account for real-time adjustments and variability. The shift towards stochastic cost modeling is emphasized, better capturing the complexities and dynamics of construction production systems. Insights from this review are incorporated into Chapter 3 to create a framework for implementing cost models for production planning and control.

Data-driven methods can significantly improve production planning and control by providing real-time insights and enhancing decision-making processes. ML algorithms are highlighted for their potential to process and analyze large datasets, leading to better predictions and optimization of construction workflows. However, the construction industry faces challenges in collecting accurate and reliable data, which hampers the adoption of data-driven methods. The benefits include streamlined production processes, reduced errors, and enhanced overall project performance. Positioning-based and vision-based tracking technologies are promising solutions for real-time tracking and data collection on construction sites. The CBA method identified 360° camera-based tracking as the optimal choice, based on factors such as spatial accuracy, capture frequency, processing time, range, etc.

A process-based CDE is needed to organize and manage data effectively, facilitating seamless data flow and improving collaboration among project stakeholders. With robust data management, including collection, transformation, and storage, ML can create smarter, more efficient production planning and control, driving better project outcomes and reducing costs. Chapter 4 introduces a comprehensive data-drive production framework that incorporates the complete data pipeline and a novel process-based data schema.

In summary, the reviewed studies highlight the growing importance and potential of integrating data-driven approaches in construction. The findings underscore the need for structured and standardized production data collection, aligned with spatiotemporal dimensions, to enhance production planning and control. This literature review sets the stage for the subsequent chapters, which will develop a comprehensive framework (Chapter 4), computer-based tools to automate and enhance data-driven production control in near real-time (Chapter 5), and train ML models on actual site data to predict work density for future data-driven production planning (Chapter 6).

Chapter 3 Location-Based Project Production using Work Density Method

This chapter introduces the Work Density Method (WDM) for location-based project production planning together with a visualization and computing support tool, named ViWoLZo. ViWoLZo stands for Visual Workload Leveling and Zoning, as the tool computes work density, which is then used for workload leveling and zoning to create a plan. To support the decision-making and what-if analyses, and replace conventional subjective approaches to planning, several metrics and a framework for cost modeling are also suggested to gauge the quality of the plan. Refer to Section 2.1.4 for project production terminology used in this chapter.

Section 3.1 starts with describing the workload level and zoning problem, the WDM, and introduces ViWoLZo. The work density data needed was not readily available, hence Section 3.2 outlines what data to collect, the development process, and application of ViWoLZo, in the B33 case study project. Section 3.3 builds on the learnings form ViWoLZo by summarizing the suggested production parameters, production planning and control metrics, flow metrics, and workload leveling and zoning metrics, that can be used to gauge quality of a production plan and measure the performance of actual production. Section 3.4 adds an important aspect of decision-making by including the impact on cost. The section provides a descriptive framework for modeling cost of production system design. Section 3.5 shares findings and topics worth discussing and Section 3.6 ends the chapter with the conclusions.

This section includes text from previously published and co-authored work in Singh et al. (2020), Singh and Tommelein (2023a, b), and Tommelein et al. (2022).

3.1 Work Density for Production Planning

3.1.1 Work Density Method

In Section 2.2.4, I defined work density using the theoretical definition provided by Tommelein (2022). Numerically, work density is the quantity of scope of work (products) to be worked on in a given area divided by the rate at which a particular step can perform that scope of work, as shown in Equation 3.1. Work density can also be specified by other means, as will be discussed later.

$$\text{Work Density } [\tfrac{time}{area}] = \text{Quantity } [\tfrac{units}{area}] \text{ / Production Rate } [\tfrac{units}{time}] \tag{3.1}$$

Work density is specific to what work is to be done and where (e.g., install sink 4 in bathroom 3). For a production system comprised of processes, each process comprises steps, each one pertaining to a certain scope of work (and associated quantities). Hence, work density is tied to a step. For example, does the sink installation step include putting the sink fixture in place, mounting the faucet, and connecting it to the plumbing system, or is this work divided into multiple steps? For each step and location by location, the type and scope of work together with a crew size and a corresponding production rate must be defined. Once these are defined, work density can be calculated using Equation 3.1. When different scopes of sequential work are aggregated into one step (e.g., put the fixture in place and connect it to the plumbing system) it is assumed that their corresponding work density values may be added together. That is, if a crew takes a certain amount of time to perform one step in a given area, and another amount of time to perform another step in the same area, then it would take that crew the sum of those amounts of time to perform all the work in a single step in that area, i.e., work density maps are assumed to be additive. Should that assumption not hold, a single production rate for that crew and for that single step may be provided to account for the aggregated scope of work.

The WDM is a process planning method based on units of work density as the means to time the use of work space. The method requires as input (1) a linear sequence of S trade steps in a process (e.g., in Figure 2.1: process includes four steps T1 to T4, thus $S = 4$), (2) the number of zones Z in which to divide the work space with zones being mutually exclusive and collectively exhaustive (e.g., in Figure 2.1: six zones from Floor 1 Zone 1 to Floor 1 Zone 2, all the way to Floor 2 Zone 3, thus $Z = 6$), and (3) a work density map for each step (the map is a matrix of work density values, as explained and illustrated later in Section 3.2).

These inputs are defined using production parameters:

- Set of steps $\{s_1, s_2, \dots s_k, \dots s_S\}$ where S is the number of steps in the process
- Set of zones $\{z_1, z_2, \dots z_m, \dots z_Z\}$ where Z is the number of mutually exclusive and collectively exhaustive zones, in which to divide the work space
- The cells of the work density map contain work density of the scope of work physically located inside the cell. Work density for step s_k in cell (i, j) is represented by $w_{i,j}^{s_k}$.

Given these inputs, a planner divides the work space into Z zones by selecting cells in the matrix of grid cells, thus deciding which cells make up a zone. Then, for each step and each zone, the work densities of cells are added. The resulting cumulative work density, called the workload or step cycle time, describes the time a trade needs to complete their step-worth of work in the given zone. The workload for step s_k in zone z_m is given by Equation 3.2. The workload for each step zone-by-zone may be depicted in a histogram. For a process, the workload peak of the histogram or the operable takt, is defined as the maximum time needed to complete any step in any zone. The operable takt, denoted as *T(Z)*, is a function dependent on the zone definition, as specified in Equation 3.3.

$$W_{z_m}^{s_k} = \sum_{\forall\, cell\ (i,j) \in z_m} w_{i,j}^{s_k} \tag{3.2}$$

$$T(Z) = \max_{\substack{\forall k,\ s_k \in S \\ \forall m,\ z_m \in Z}} \left(W_{z_m}^{s_k} \right) \tag{3.3}$$

The duration of a process is determined by the duration of its steps. If steps are sequential then the process duration will be the sum of each step's duration. With the number of steps, the number of zones, and the operable takt as the duration of each step, the process duration D can be computed using Equation 3.4.

$$D = (S + Z - 1) \times T(Z) \tag{3.4}$$

To reduce the process duration, it may be possible to divide the work space into zones and accordingly perform multiple instances of the process concurrently in different locations. Dividing work space into zones, in general—although not always, as Jabbari et al. (2020a) noted—decreases the workload peak and thus decreases the process duration (Equation 3.4). See Section 3.4.4 for example where process duration can increase with increasing number of zones.

Figure 3.1 illustrates the derivation of Equation 3.4. For a process with S number of steps $(s_1, s_2, \dots s_k, \dots s_S)$, taking at the operable takt of *T(Z)* time in each of the Z number of zones $(z_1, z_2, \dots z_m, \dots z_Z)$, the process duration is D (given by Equation 3.4).

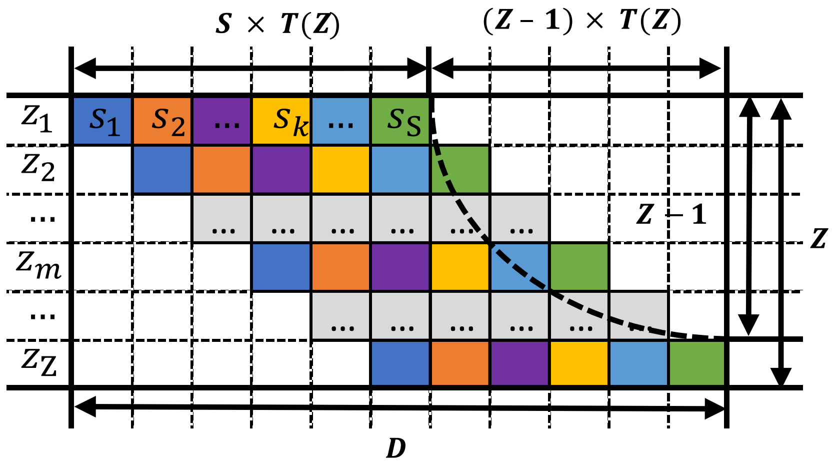


Figure 3.1: Takt production parameters of a takt plan.

The resulting takt plan must meet all constraints, e.g., the duration D must fall within schedule milestones. The planner may redefine the process, change zone boundaries, use a different value for Z and re-zone, or adjust workloads by applying various throttles until a satisfactory result is achieved. This throttling is the two-dimensional equivalent of line balancing of assembly lines in manufacturing (readers can find more detail on assembly line balancing in, e.g., Chapter 8 of Baudin (2002).

It is important to note that using operable takt *T(Z)* in Equation 3.4 gives the minimum process duration possible for a takt plan with the given workloads. *T(Z)* defines the lower bound for the takt of a plan, i.e., all step's workloads in all zones are estimated to be less than or equal to this amount of time. Similarly, Equation 3.4 can be used in reverse by assuming the maximum allowable duration D of a process (e.g., defined by schedule milestones) and knowing the number of steps S and the number of zones Z, one can calculate the time for customer takt T_c. T_c defines the upper bound for the takt of a plan, i.e., every step's worth of work must be completed within this amount of time. Whether or not that customer takt can be met depends on how steps and zones are defined, and how much concurrency is feasible. As given by Equation 3.5, the final process design selected in the plan should have a takt T, that is equal or greater than the operable takt $T(Z)$ to reliably complete all steps within the takt, and equal or smaller than the customer takt T_c to be able to meet the maximum allowable process duration D.

$$T(Z) \leq T \leq T_c \tag{3.5}$$

Selection of a takt T that minimizes the process duration while accommodating anticipated variabilities in the production system is a balancing act left to the planner, as discussed in Section 3.5.1. This balance can be achieved using a workload histogram. Figure 3.2 presents a workload histogram illustrating the distribution of workload across a four-step process (S1, S2, S3, and S4) spanning three zones (Z1, Z2, and Z3). The x-axis represents the zones, and the y-axis quantifies the workload in terms of time per step per zone. Due to varying amount of work in different zones, there is workload variability for a step across the zones, and due to varying process capability, there is workload variability for the steps in a zone.

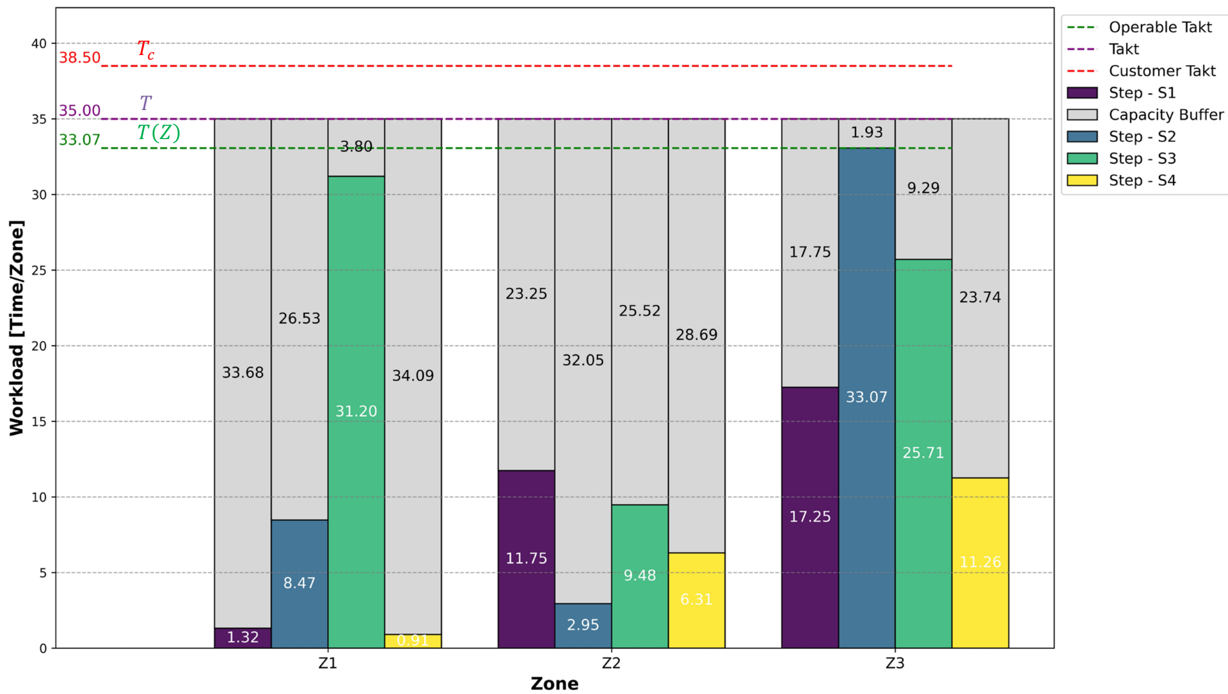


Figure 3.2: Workload histogram with operable takt, takt, and customer takt for an example four step process and three zones.

The horizontal lines across the histogram in Figure 3.2 mark critical takt terms from Equation 3.5. The operable takt *T(Z)*, delineated by a green dashed line, is set at 33.07 time units from the maximum workload for S2 in Z3. The customer takt T_c, shown by a red dashed line, is at 38.50 time units per zone, calculated based on the customer demand (e.g., using Equation 3.4). Using Equation 3.5, the takt T, indicated by a purple dashed line, is set slightly higher than the operable takt and lower than the customer takt at 35.00 time units.

For selecting the takt, planners need to balance the performance for individual trades versus the system. Trades need to decide if their process capability can reliably meet the decided takt, while the process can meet the customer demand. To achieve this balance, trades can use inventories (buffers), extra capacity or time (Formoso et al. 2021). Out of these, buffers are the most important way to mitigate against variability, with capacity buffer being the most relevant for takt (Tommelein 2020), as further discussed in Section 3.5.1.5. The capacity buffer, represented in gray vertical bars, indicates the additional time allocated to manage unforeseen variability in each step and ensuring they operate within the planned takt, thus optimizing the production process and meeting customer expectations.

3.1.2 Desired Outcomes and Objectives of Workload Leveling

In lean production, takt plays a key role in synchronizing processes and operations. The workload for a step in a given process may be less than, more than, or equal to the takt required by the customer. By matching workloads to the takt, planners eliminate waste stemming from unevenness and overburden (chapter 9 in Frigon and Jackson Jr. 2009). Thus, workload leveling tries to minimize the three types of wastes identified in the Toyota Production System (TPS), muda (waste of resources or wastefulness), mura (unevenness), and muri (overburden) (Womack et al. 1990). By avoiding overburdening of resources beyond their process capabilities by absorbing variability through capacity buffer, and avoiding unevenness by reducing workload variability across zones, takt achieves a more predictable production plan, which is also simpler to control (Ballar and Tommelein 2021).

In construction, takt can be implemented at two levels of planning: (1) at the strategic level to meet the project deadline and (2) at the operational level to meet phase- or process milestones and to generate evenness in workflow and avoid trade stacking. This research focuses on the operational level, dealing with workload leveling and zoning for phase or process planning. Given a process and a zone definition, each step (belonging to a single trade) has a workload. As work tends to be distributed non-uniformly across a work space, workloads will vary across steps and zones. Workload leveling tries to achieve a steady flow of work for processes, trades, crews, etc. This research identifies the following desired outcomes of workload leveling:

1. Meet customer deadlines by reducing the process- or phase duration under the target through increasing concurrency.
2. Achieve constant crew size (Ballard and Tommelein 1999) by reducing the variation of workloads across zones, thus improving trade flow (Sacks 2016).
3. Increase worker utilization (reduce the time workers wait on work) by providing timely handoffs of zones and reducing the need for inter-trade coordination.
4. Increase space utilization (reduce the time work waits on workers) by reducing the variation of workloads across steps in each zone and designing for spatial continuity (Alves and Formoso 2000), thus reducing overproduction waste (Linnik et al. 2013) and improving process location flow.
5. Reduce workload variability by reducing the variation of workloads across steps and zones.
6. Reduce process step variability by standardizing work and adding a capacity buffer (underloading) to each individual step.

These desired outcomes can be formalized as objective (functions) to optimize the result of the workload leveling and zoning procedure. In a real-world scenario involving multiple parties with conflicting objectives, it is essential to understand how production planning and control decisions affect different objectives. Understanding the impact and trade-offs between different objectives can be achieved by applying metrics and understanding their relationship to the objectives.

3.1.3 Workload Leveling and Zoning Metrics

Workload leveling and zoning metrics aim to measure the distribution of workloads across steps and zones in a location-based production design method such as takt production. The metrics will assist in evaluating the quality of levelness of workload according to the desired outcome from a production system design. By selecting a combination of metrics representing different desired outcomes, the user can quantitatively compare process-plan alternatives while trading off objectives. The following metrics are implemented in ViWoLZo (Figure 3.7 and 3.10, described later):

1. **Workload** for a given step and zone, defined as the cumulative work density. The workloads of a given step can be viewed across zones or, alternatively, workloads in a given zone can be viewed across steps. In either case, the objective may be to reduce variation to improve respectively trade location flow and process location flow.
2. **Workload peak *T(Z)*** of a process (Equation 3.3), defined as the maximum workload across all steps and all zones. This identifies where the process bottleneck(s) is (are) and therefore is an indicator of the speed of the process. The objective may be to lower the peak, either to achieve a given target value or minimize it.
3. **Duration *D*** of a process (Equation 3.4 when takt planning is used), defined as the overall time required for the process to complete. An objective may be to lower the duration, either to achieve a given value locked in by schedule milestones or to reach some other target value.
4. **Average of workloads** of all steps for all zones in a process (Figure 3.10). An objective may be to lower the average to achieve an overall lower workload distribution. Average workload across all zones and steps is given by Equation 3.6 and is used in calculating other metrics including variance, standard deviations, coefficient of variation, and workload-peak-to-average ratio.

$$\overline{W} = \frac{\sum_{k=1}^{\mathrm{S}} \sum_{m=1}^{\mathrm{Z}} W_{z_m}^{s_k}}{(\mathrm{S} \times \mathrm{Z})} \tag{3.6}$$

5. **Variance and standard deviation of workloads** of all steps for all zones in a process. An objective may be to reduce the variance and standard deviation to achieve a more uniform distribution, i.e., with less variability. Variance of workload across all zones and steps, denoted by σ^2 (sigma squared), is given by Equation 3.7. Standard deviation, denoted by σ (sigma), is defined as the square root of the variance. Variance and standard deviation are useful in visualizing the spread and shape of the data distribution (Figure 3.10) and used in calculating the coefficient of variation.

$$\sigma^2 = \frac{1}{(\mathrm{S} \times \mathrm{Z})} \sum_{k=1}^{S} \sum_{m=1}^{Z} \left(W_{z_m}^{s_k} - \overline{W}\right)^2 \tag{3.7}$$

6. **Coefficient of workload variation** is a quantitative way of measuring relative variability of the workload distribution. Hopp and Spearman (2008, p. 268) suggested this coefficient as a better alternative to variance and standard deviation, which measure absolute variability. It provides a measure of variability independent of the scale of the data. For example, a standard deviation of 5 hours would indicate low variability in a process with a week-long takt but would represent a very high level of variability for a day-long takt. The coefficient, denoted by c_w, is the standard deviation divided by the average given by Equation 3.8.

$$c_w = \frac{\sigma}{\overline{W}} \tag{3.8}$$

7. **Number of workers** assigned to a crew for a given step (crew size shown in Figure 3.7) and total number of workers involved in the process. An objective may be to employ a certain number of workers, e.g., to keep a constant crew size, or to balance employees across multiple projects. A user may want to explore how changes in this number result in alternative workloads of a specific step and impacts other metrics.
8. **Workload-peak-to-average ratio** of a process: calculated by dividing the workload peak by the average of all workloads. An objective may be to reduce the ratio, i.e., to bring the peak closer to the average. This can be done by lowering the peak, or increasing the average, or both. The ratio has a lower limit equal to 1, as the maximum value will always be greater than or equal to the average. Workload-peak-to-average ratio across all zones and steps is given by Equation 3.9.

$$W_{\frac{P}{A}} = \frac{T(Z)}{\overline{W}} \tag{3.9}$$

9. **Average-of-workload-range** of a process by steps: calculated by taking the average of the ranges of workloads, i.e., for a given step the difference between the maximum and the minimum workload across all zones. An objective may be to lower this average by narrowing the ranges. Average-of-workload-range of a process by steps is given by Equation 3.10.

$$\overline{W}_{range\ by\ steps} = \frac{\sum_{k=1}^{S}\left[\max_{\forall m,\ z_m \in Z}\left(W_{z_m}^{S_k}\right) - \min_{\forall m,\ z_m \in Z}\left(W_{z_m}^{S_k}\right)\right]}{S} \tag{3.10}$$

Optimizing these mentioned metrics can yield benefits related to reducing the peak and variation of workload distribution. These benefits can be grouped as following:

1. Lowering the workload peak T(Z) makes it possible to choose a lower takt, which in turn may result in a lower process duration D (Equation 3.4) to meet a customer's deadline.
2. Reducing the workload variability:
    a. Across steps in a zone generates better process location flow for that zone, which may help improve zone handoff between steps and increase space utilization.
    b. Across zones for a step generates better trade location flow for that step, which may help maintain a constant crew size and increase worker utilization.
    c. Across all steps and zones creates a more reliable process that is less prone to delay and generates predictable results.
3. Improving the ability to judge how much underloading is appropriate and thereby increasing crew confidence that they will be able to complete their work within the allotted time yet be productive. Underloading means planning with a takt higher than the workloads so that trades will have a designed-in capacity buffer to ensure timely handoffs. The step with the workload peak will have the least amount of underloading.

3.1.4 Visual Workload Leveling and Zoning (ViWoLZo)

This research contributed to the application of the WDM by improving the implementation procedure, data collection, data analysis, and the use of workload leveling and zoning metrics. These contributions came together through the creation of Visual Workload Leveling and Zoning (ViWoLZo) tool. ViWoLZo is visualization and computing support tool that allows planners to use work density for creating a takt plan by zoning a work space and leveling workloads across zones and steps.

The tool has evolved over two versions. I developed the first version (ViWoLZo-1) on the UCSF Block 33 case study project, published in Singh et al. (2020). I developed second version, ViWoLZo-2, by reconceptualizing ViWoLZo-1 published in Singh and Tommelein (2023a). ViWoLZo-2 eases the setup prior to tool use and offers the user more work structuring options and additional interface features. This dissertation describes ViWoLZo-2, and for simplicity, refers to it as "ViWoLZo". The case study-based development and application of ViWoLZo is described next.

3.2 ViWoLZo Case Study: Project B33

3.2.1 Project Context

ViWoLZo development was based on-site observations and data obtained during the construction of a building located in San Francisco, California, referred to as the UCSF Block 33 (B33) project. This building has a gross area of 31,500 m^2 (340,000 ft^2) and includes classrooms, laboratories, clinics, conference rooms, and administration offices. It is divided into (1) a 3-story North wing, (2) a 12-story tower, and (3) a 5-story South wing. The case study focused on the tower with repetitive floors 6 to 12, selected a typical floor among those 7 floors, modeled processes involving interior trades, and for that scope of work then created and customized a so-called "ViWoLZo zoning dashboard." This case study was part of the National Science Foundation grant number CMMI-1563511 for developing theory and application of takt planning in project-based production.

3.2.2 ViWoLZo Procedure

Figure 3.3 depicts the process planning procedure supported by ViWoLZo. The figure includes a Setup section and a Workload Leveling by Process section, respectively shown on the left and right, and it is divided into five horizontal swim lanes. Swim lanes depict the tasks the user performs (shown as rectangles with a solid border) and decisions the user makes (diamonds) using ViWoLZo's dashboard, as well as the tasks ViWoLZo performs in the background (rectangles with a dashed border) and the data output it presents on the dashboard (trapezoids with a dashed border). The procedural data flow (what types of data are used and when) is depicted by arrows. The next section expands on the data and the format in which it is input into ViWoLZo.

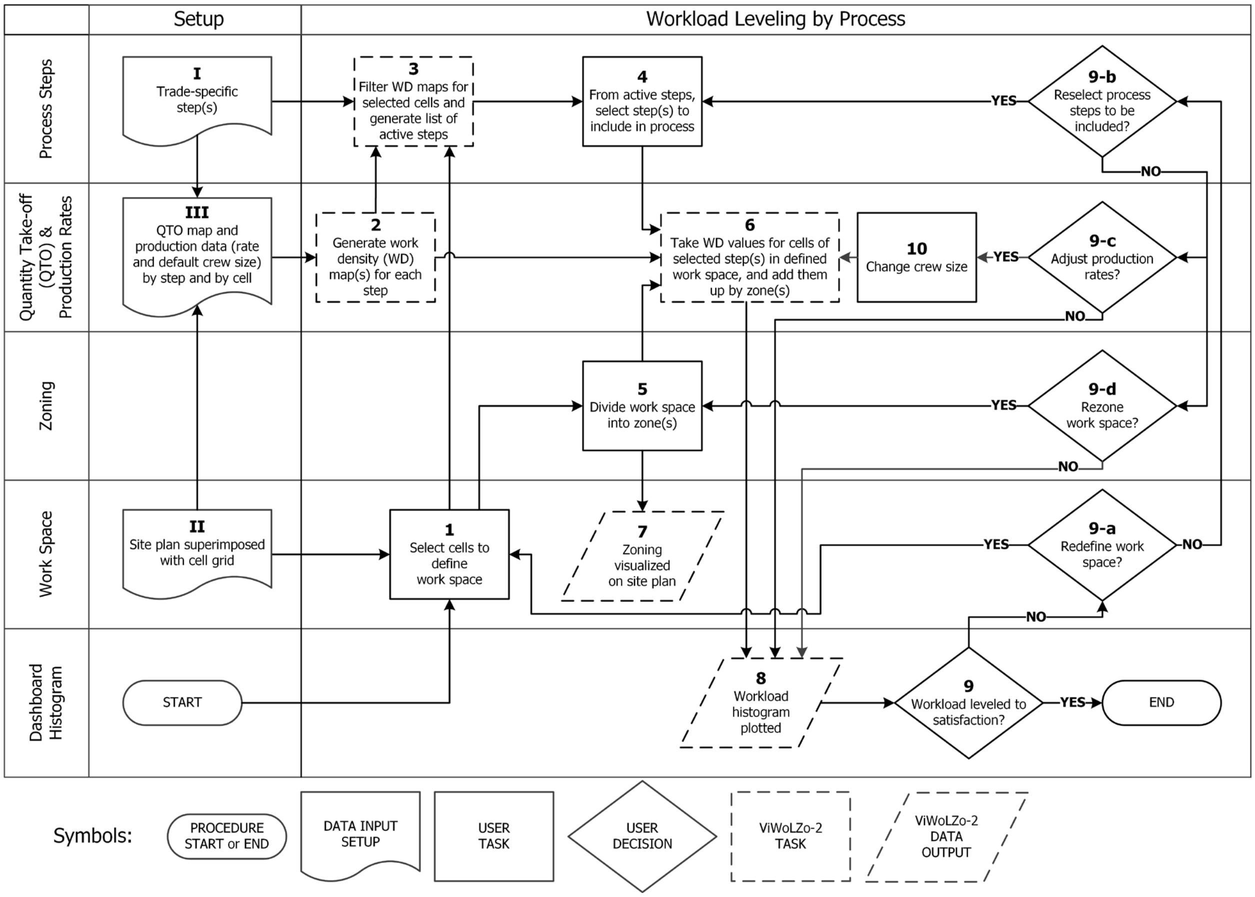


Figure 3.3: ViWoLZo procedure (Figure 1 in Singh and Tommelein 2023a).

3.2.3 Data Collection and Organization

Because of ViWoLZo's novelty, the required input data was not readily available and had to be collected from the B33 project team. All trades involved in the process being planned therefore participated, gaining a shared understanding of the process flow(s) to follow through different types of spaces.

Different types of spaces will be visited by different trades, one trade at a time. Each trade must identify their own operations' steps depending on the scope of work they have in a space. These steps (Figure 3.3 input I) will later help to define the process. Spaces are differentiated based on, for example, knowledge about the materials needed to build them out, means and methods, and trade practices, as well as practices of personnel responsible for inspections. Definition of process steps in this input and superimposing the cell grid on the site plan (Figure 3.3 input II), explained in the next section, both reflect knowledge of building construction sequencing.

The size of a crew with their production rate and the actual work they are to perform in each step (Quantity Take-Off (QTO) by grid cell in different spaces) are required inputs (Figure 3.3 input III). For each step in the process, ViWoLZo then generates a work density map. These three inputs and their relation to work density maps are described next.

3.2.4 Work Density Maps

3.2.4.1 Defining Process Step Sequences

A project is viewed as made up of different space types according to the nature of construction work to be done and the trades involved. Given the product design, the planner (ViWoLZo user) collaboratively with trade partners involved in a certain phase of the project (the Team) must decide on the scope of steps (i.e., what work is to be performed by each trade) and arrange steps sequentially in processes, typically with a phase comprising multiple processes plus perhaps some work not belonging to any process at all. The identification of information related to the processes and the steps within them will likely require iteration. This information is input for ViWoLZo (Figure 3.3 input I).

3.2.4.2 Defining the Cell Grid

Orthogonal lines (grid lines) divide the site plan, resulting in a grid that defines cells by size and coordinates (Figure 3.3 input II). Cells are the basic, granular units that will make up a zone, that is: a ViWoLZo user will choose a single cell or aggregate multiple cells to define a zone.

The choice of the grid's mesh size and uniformity of spacing affects the setup work needed and the flexibility the ViWoLZo user subsequently will have. Grids can be defined in different ways. In exploratory research, Bardaweel (2018) used a grid with uniformly spaced grid lines, that is, with all cells referring to physical space of the same length and width. In contrast, the ViWoLZo grid can be non-uniformly spaced, that is, the physical distance between horizontal or vertical grid lines may vary. This makes it possible—if desired—to align the grid with architectural features such as walls of rooms or open spaces, possibly where a zone boundary is anticipated.

Furthermore, trade know-how to achieve the desired performance- and safety levels must be considered, that is, cells should not be too small. The finer the mesh of the grid (i.e., the more cells the work space is divided into), the greater the number of possibilities the user has for workload leveling and zoning, increasing the likelihood of achieving a lower workload peak. The advantage of having more possibilities must be assessed against the cost in setup time and effort needed to define grid lines and obtain QTOs for each cell (both of which are one-time costs) and in computation needed to determine workloads (a recurring cost, though tiny in comparison with other costs).

In the development of ViWoLZo, the person setting up the tool drew grid lines that reflected in-wall inspection requirements (thick lines in Figure 3.4) and that aligned with walls surrounding the structural core's vertical shafts. Recognizing inspections as the downstream customer for the processes being planned, some of the sequencing was anticipated by drawing additional grid lines (thin lines). The same person then obtained quantities of work, crew sizes, and production rates.

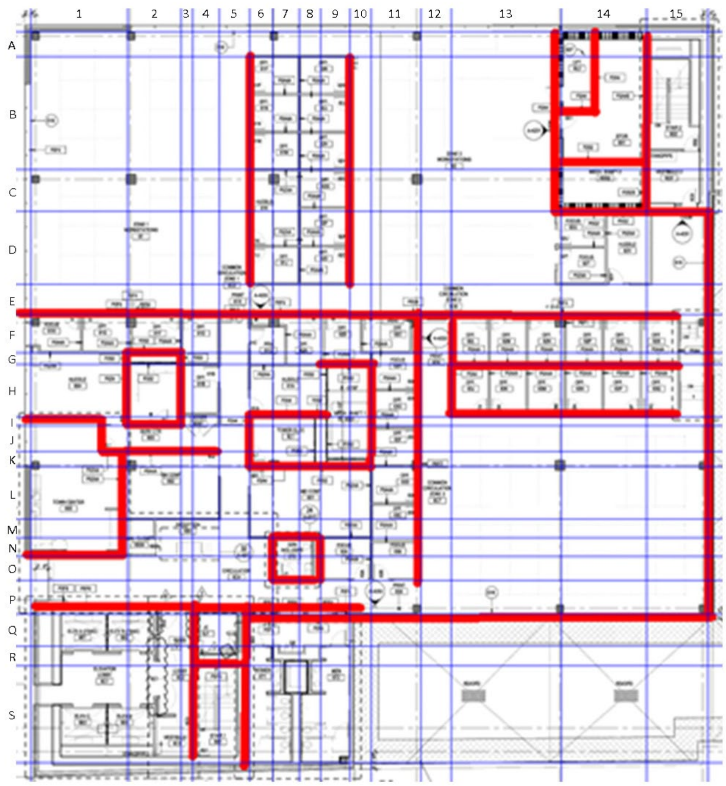


Figure 3.4: Boundary preferences (thick lines) resulting in nonuniformly spaced cell grid (thin lines) (Figure 2 in Singh and Tommelein 2023a).

3.2.4.3 Quantity Take-Offs

The setup of ViWoLZo requires QTO data (Figure 3.3 input III) for the calculation of work density. When working with many different scopes of work or with many grid cells, manually getting such data for each cell may be tedious. The take-off program On-Screen Takeoff 3 (OST) (version 03.95.02.51) helped to automate the process. OST allows the user to define each cell (the OST program calls these “zones”, but these are not to be confused with the term “zone” as defined in this paper) to match the grid identified in ViWoLZo. Then, OST automatically calculates QTOs per cell for export in spreadsheet format.

3.2.4.4 Production Rates and Work Density Throttles

The trades provided crew sizes and corresponding production rates associated with their scope of work for each step in each process (Figure 3.3 input III). The trades’ historical databases and the foremen or project managers’ experience provided this experience-cased data. They serve as default input values in ViWoLZo.

A user who wants to increase or decrease a workload associated with a step may assume that production rates vary linearly with crew sizes. A change in crew size then means applying a multiplier to change the production rate and hence the work density (Equation 3.1). However, recognizing that several other throttles may be applied and that throttles are inter-related, ViWoLZo also allows the user to manually adjust crew sizes or production rates in the database that lists steps (separate from the ViWoLZo dashboard).

3.2.4.5 Work Density Map Generation

A given step's work density map represents how much time the crew will need to complete their work in different parts of the work space, granularized cell by cell. With steps defined during work structuring, crew sizes and production rates collected from trades, and quantity maps, ViWoLZo generates a work density map for each step, cell by cell (Figures 3.5 and 3.3 task 2) using Equation 3.1. In ViWoLZo, the unit of work density is working hours per cell area.

Figure 3.5 depicts a work density map generated for ceiling grid and tile work in rooms. Each cell contains the work density value for that scope of work, shaded darker as the density increases. Details of this map remain hidden from the user but are used in ViWoLZo's workload calculations that will be displayed on the dashboard.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.27	0.00
B	0.00	0.00	0.00	0.00	0.00	5.29	0.00	2.39	2.92	0.00	0.00	0.00	0.00	6.09	0.00
C	0.00	0.00	0.00	0.00	0.00	5.38	0.00	0.84	1.10	0.00	0.00	0.00	0.00	0.02	0.00
D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.50	1.96	0.00	0.00	0.00	0.00	6.49	0.00
E	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F	3.44	1.76	0.42	0.89	0.00	0.58	0.87	0.81	0.92	0.47	1.73	0.00	3.85	2.57	1.26
G	1.09	0.60	0.13	0.29	0.00	0.22	0.33	0.30	0.35	0.18	0.45	0.00	1.44	0.96	0.47
H	5.20	2.76	0.58	1.20	0.00	1.10	1.33	1.33	0.00	0.00	2.48	0.00	5.47	3.67	1.78
I	0.36	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.45	0.00	0.00	0.00	0.00
J	1.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.08	0.00	0.00	0.00	0.00
K	1.36	0.78	0.16	0.36	0.00	0.00	0.00	0.00	0.14	0.14	0.65	0.00	0.00	0.00	0.00
L	4.56	2.93	0.60	1.27	0.00	1.12	1.34	1.10	1.40	1.10	2.54	0.00	0.00	0.00	0.00
M	1.60	0.00	0.00	0.00	0.00	0.39	0.50	0.39	0.49	0.38	0.92	0.00	0.00	0.00	0.00
N	1.31	0.00	0.00	0.00	0.00	0.00	0.35	0.28	0.49	0.36	0.80	0.00	0.00	0.00	0.00
O	0.00	0.00	0.00	0.00	0.00	0.00	0.45	0.37	0.62	0.49	1.00	0.00	0.00	0.00	0.00
P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Q	0.00	0.00	0.00	0.00	0.00	0.73	0.73	0.61	0.73						
R	0.00	0.00	0.00	0.00	0.00	0.39	0.38	0.37	0.46						
S	0.00	0.00	0.00	0.00	0.00	1.92	1.89	1.69	2.22						

Figure 3.5: Work density map for ceiling grid and tile in rooms (Figure 3 in Singh and Tommelein 2023a).

3.2.5 Work Structuring in ViWoLZo

Work structuring means defining chunks of work with their relative timing and sequencing (Ballard 1999, Tsao et al. 2004). In line with Haghsheno et al.'s (2016) harmonization operations, e.g., (1) changing the time required by altering the number of workers, (2) combining several steps into one, and (3) changing or optimizing or replacing products and processes, work structuring using ViWoLZo offers the user a novel approach to:

- change the work space definition (Figure 3.3 decision 9-a)
- change the steps included in a process (Figure 3.3 decision 9-b)

- change the crew size to change the production rates (Figure 3.3 decision 9-c and task 10)
- change zone boundaries or the number of zones (Figure 3.3 decision 9-d)

What-if analyses may be conducted iteratively to produce the desired outcome, e.g., meeting the target process duration and meeting crew availability constraints.

3.2.6 Application Example of ViWoLZo

3.2.6.1 Zoning Dashboard

ViWoLZo's dashboard is the interface between the user and the underlying input data (Figure 3.3). The user can: (task 1) Select cells to define the work space (i.e., that part of the site plan that will be zoned), (task 4) Select the step(s) to be included in the process, (task 5) Divide the work space into zone(s), and then level workloads iteratively by re-configuring them (decisions 9-a, b, c, and d). The ViWoLZo tasks, user decisions, and outputs are illustrated next.

3.2.6.2 Work Space

The user-defined work space is that part of the site that is to be divided into zones while leveling the workload of all selected steps (e.g., for a process focused on interior finishes, the user may start with a floor plan but leave out service rooms and shafts, elevators, and stairs) in the work space. The user defines the work space using the ViWoLZo dashboard by selecting cells that ViWoLZo tags as active cells (cells with "X" in Figure 3.6). Correspondingly ViWoLZo tags each step with work in any active cell as an active step.

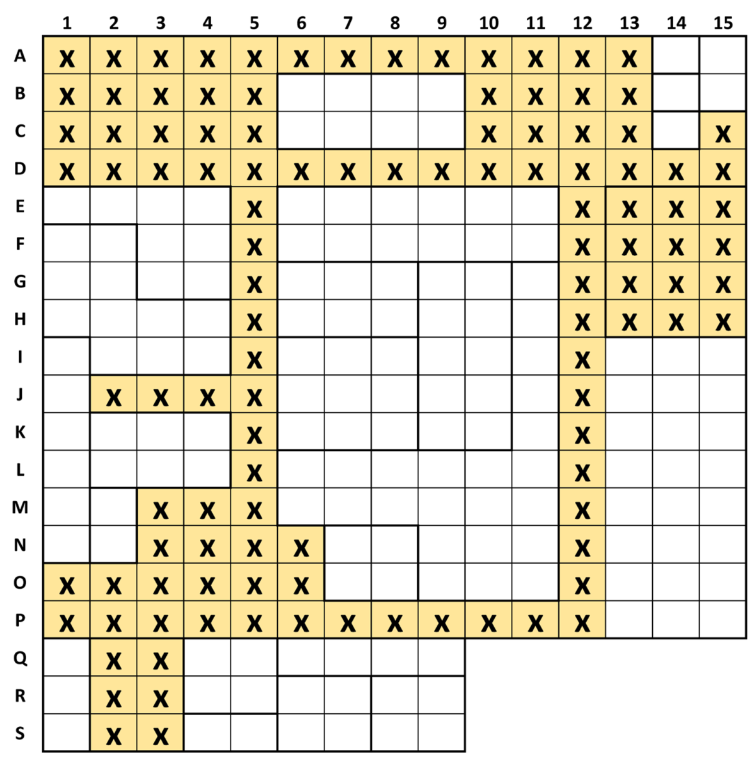


Figure 3.6: Screenshot of ViWoLZo work space definition area (Figure 4 in Singh and Tommelein 2023a).

3.2.6.3 Process Steps

Steps are identified by the project team and input into ViWoLZo (Figure 3.3 input I), but the user must select which ones to include in the process they choose to plan. By adding or removing steps and thereby redefining the process, the user can conduct what-if analyses.

The user clicks on "Select Steps" in the step selection area (Figure 3.7) and then on a pop-up window (Figure 3.8) chooses from a list of active steps ViWoLZo identified (Figure 3.3 task 3). In the background, ViWoLZo identifies the work density map by step and distinguishes them by space type (e.g., corridor, open space, office). Since a step can be present in more than one type of space, this distinction is necessary: e.g., step "PAINTER – Paint" is present in "Bathroom" as well as "Corridor", but the type of paint, number of coats, and thus the production rate can be different.

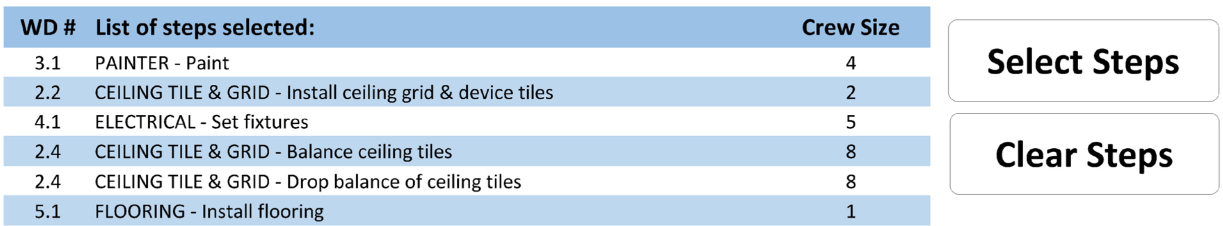


Figure 3.7: Screenshot of ViWoLZo step selection area (Figure 5 in Singh and Tommelein 2023a).

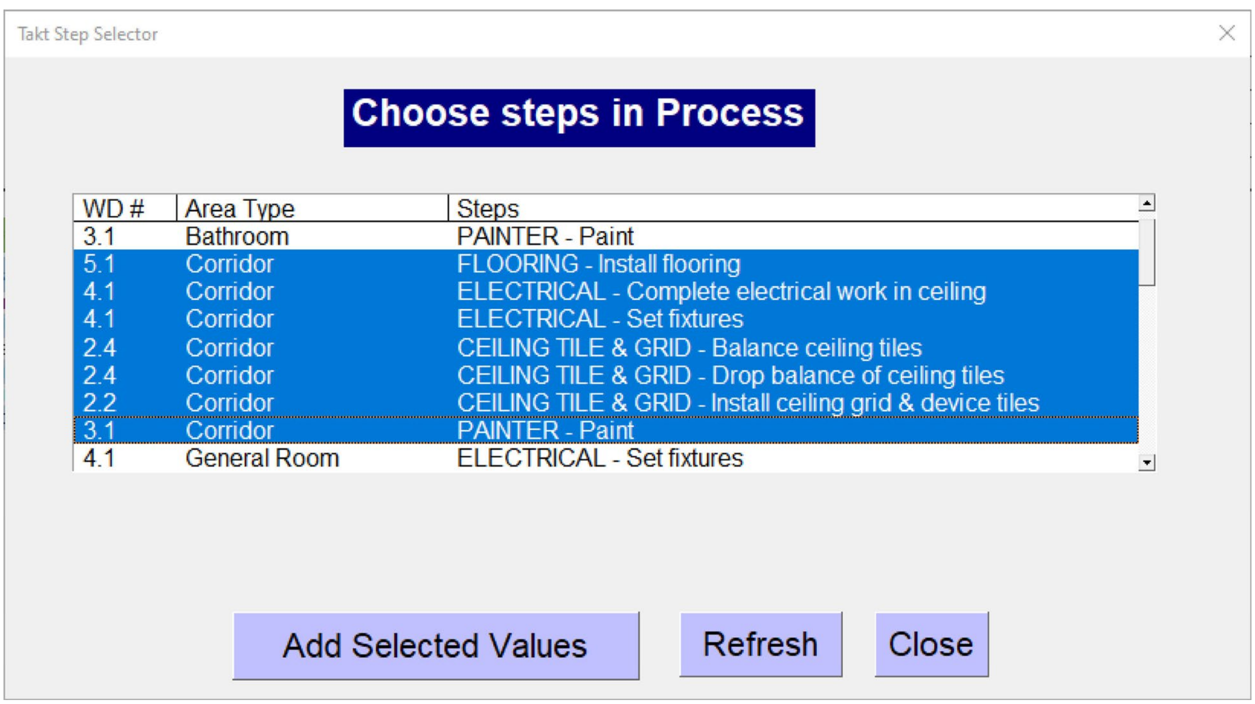


Figure 3.8: Step selection window of ViWoLZo.

After the user adds their selection ("Add Selected Values" in Figure 3.8), their selection then populates the list of steps selected (Figures 3.7 and 3.3 task 4) with the default crew size stored for the step. The user can modify this crew size by modifying the number corresponding to the step.

3.2.6.4 Zone Definition

The user next decides how many zones to divide the work space into and then, one by one, assigns a zone to each active cell (Figure 3.3 task 5). Accordingly, on the dashboard ViWoLZo automatically colors cells in the zoning map using their respective zone color (Four zones in Figures 3.9 and 3.3 output 7) and greying out cells that are not active or have not yet been assigned to a zone.

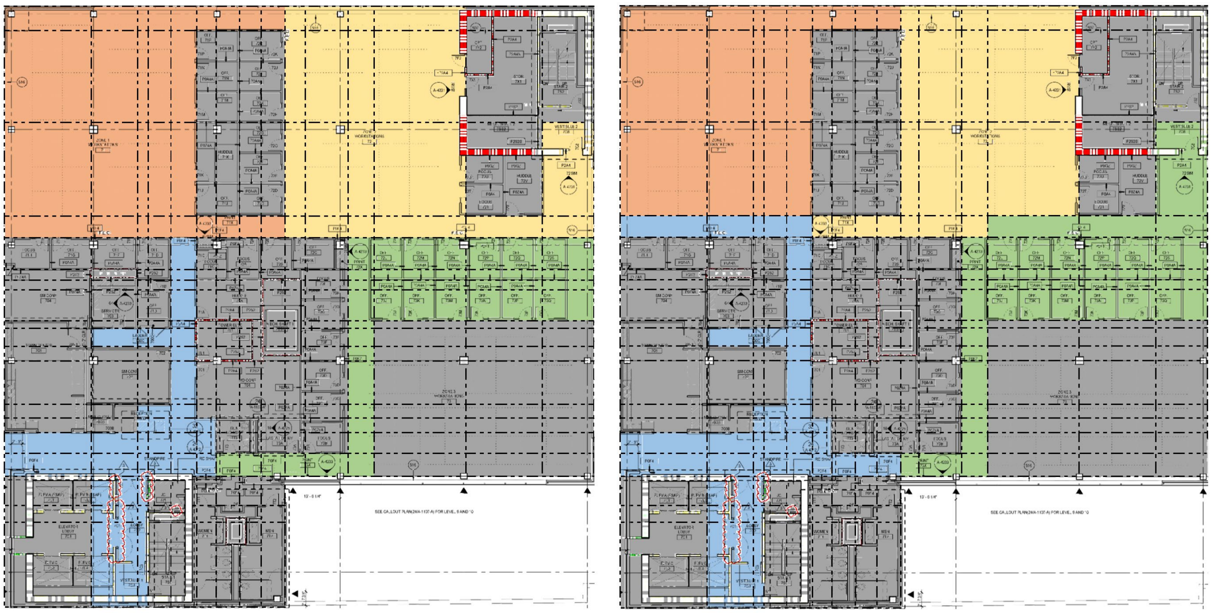


Figure 3.9: Screenshot of ViWoLZo plan dashboard with zoning before (left) and after (right) workload leveling (adopted from Figure 2 in Singh et al. 2020).

Each time the user makes a change, ViWoLZo takes the work density values for the selected steps and active cells and groups them for each zone (Figure 3.3 task 6). Then, using these values for each step in each zone, it plots a cumulative work density histogram aka. workload histogram or Yamazumi chart (Figures 3.10 and 3.3 output 8). For example, in Figure 3.10 (top) the workload for the step "PAINTER – Paint" in Zone 1 (Z1) equals 1.3 work-hours.

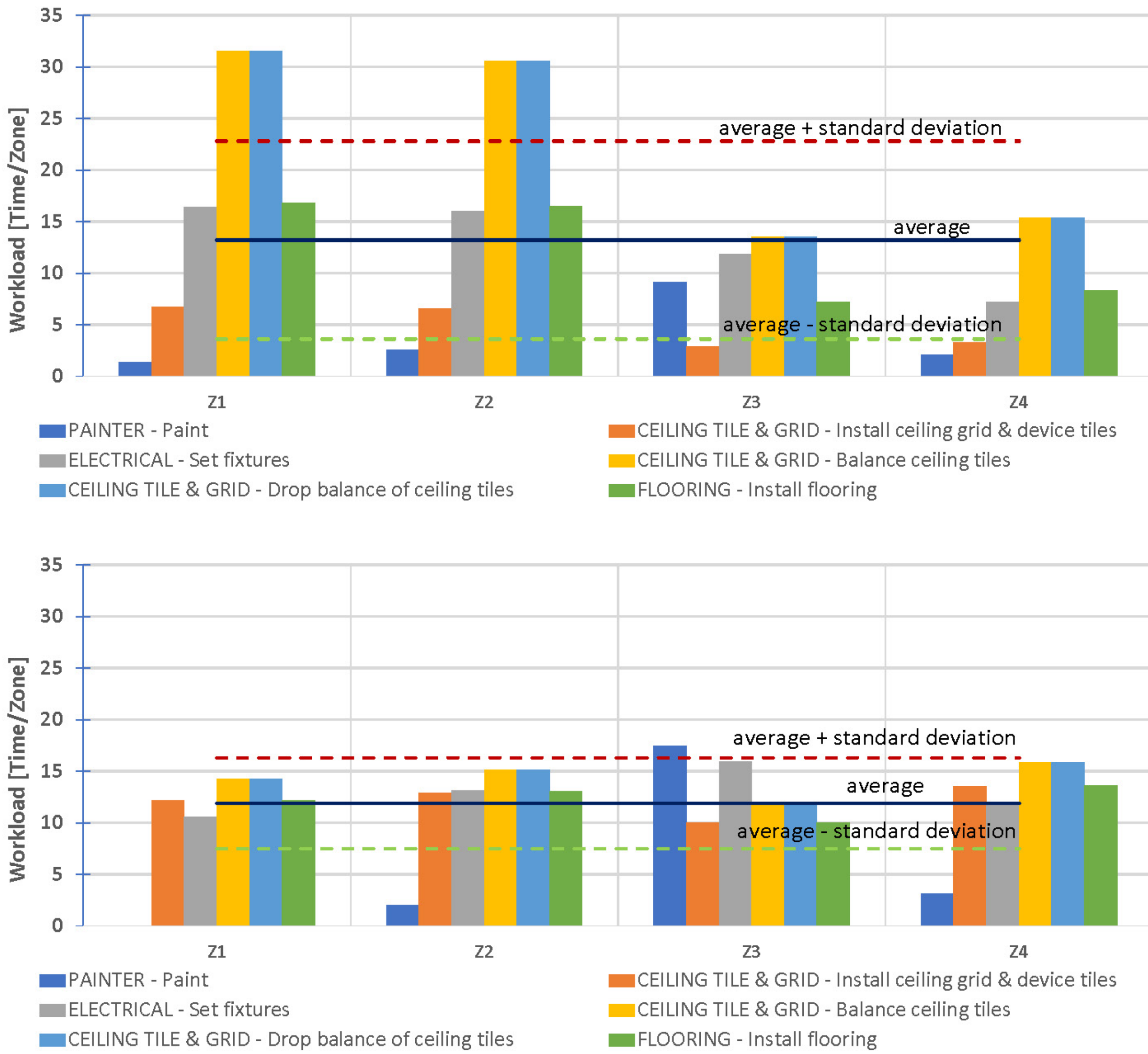


Figure 3.10: Screenshot of ViWoLZo dashboard with workload histogram before (top) and after (bottom) workload leveling (Figures 8 and 9 respectively in Singh and Tommelein 2023a).

3.2.6.5 Workload Leveling

With the real-time display of the workload histogram and informed by the metrics on the dashboard, the user can apply several means of leveling, individually or in combination, and account for any constraints or preferences specific to the site, trades involved, etc. When through trial-and-error, satisfactory workloads are reached, the process ends (Figure 3.3 decision 9).

Figure 3.9 (left) depicts an example work area before workload leveling and Figure 3.9 (right) after leveling. Figure 3.10 (top and bottom) depict the corresponding workload histograms, with the workload varying across zones and steps from 1.3 to 31.6 before leveling, and from 0.0 to 17.5 after leveling. In this example, the user made two changes. First, by re-zoning, keeping the number of zones at 4 and changing size and shape of zones by changing zone boundaries. Second, by changing the crew sizes for some steps in the “Step selection area” (Figure 3.7), adding workers in steps with high workloads and reducing workers in steps with low workloads, and the total number of workers increased by 1. With the two changes, the user reduced the value range and lowered the workload peak *T(Z)* from 31.6 to 17.5. Choosing that workload peak as the takt and leaving other variables in Equation 3.1 constant, the process duration *D* thus shortened from 284 to 157.

Recognizing that the workload also varies within a zone for different steps (e.g., the step "Install ceiling grid and device tiles" has a significantly lower workload than the other steps), the user reduced the corresponding crew size to increase their workload. A crew reduction may seem counterintuitive, but it is in line with the user's desire to pace the work so that all steps can be completed within the same amount of time as trades move from zone to zone and thereby improve the process location flow. No step has to be much faster or slower than other steps in the same process. This is what leveling is about.

This example illustrates only a few of the many ways to level workloads. For example, a low workload in a certain zone can possibly be increased by including more or different cells in that zone (increasing the quantity of work) or by decreasing the crew size (reducing the production rate) (Equation 3.1). If one step's workload is disproportionately larger than others', that step may be split into two or more steps, to be performed consecutively or not, so as to give the crew(s) more time to complete their work. Correspondingly, the number of steps will increase but the individual workloads for each one may decrease. The step increase will increase the process duration (Equation 3.4) but depending on the situation the workload decrease may shorten the duration, so the user will have to make the trade-off. If large discrepancies in workloads arise, the user will want to consider adding or removing steps from the process. These describe the kind of work structuring decisions project teams must make when planning at the process level.

ViWoLZo's real-time visual and quantitative depiction of workloads helps users make data-driven workload leveling and zoning decisions about the boundary of work space to zone, process steps to select, crew sizes, and the number and size of zones until a satisfactory solution is reached.

ViWoLZo, as described in this section, informs takt planning process with production parameters and workload leveling metrics. These metrics provide perspective of the project and individual trades. The next section provides a more in-depth description of these parameters and metrics related to the production system, identified through the development process of ViWoLZo.

3.3 Parameters and Metrics for Production Planning and Control

In Sections 3.1.2 and 3.1.3, I defined the desired outcomes, objectives, and metrics for workload leveling and zoning, as applied in ViWoLZo. However, continuous development, application, and improvement of ViWoLZo through the addition of new procedural steps and functionality, surfaced the need for additional metrics. To meet this need, I used key production system parameters identified in ViWoLZo to identify metrics. A metric is a measurable value used to evaluate the performance or success of a production system, whereas parameters are the configurable variables that define the system itself.

The identified metrics help users make production system planning and control decisions and measure the impact of the methods and tools developed in the research.

3.3.1 Key Production Parameters

Production parameters are configurable variables that detail aspects of the production system. The construction industry suffers from a lack of standardization in terms related to production parameters, complicating communication across and within organizations. Production duration remains the only widely reported parameter (Vatne and Drevland 2016). It is crucial, therefore, to identify and define terms with clarity.

Parameters used in ViWoLZo (Section 3.1.1) include the number of steps in a process (S), number of zones (Z), cumulative work density (referred to as workload or step cycle time)(W), workload peak or operable takt ($T(Z)$), customer or demand takt (T_c), takt T (as selected for the plan), and process duration (D). Examples of other parameters used in construction project production systems include project duration (Tommelein 2020, Srisuwanrat and Ioannou 2007), time on-site for each trade (Tommelein 2020), cumulative lost capacity for each trade (Tommelein 2020, Lehtovaara et al. 2021a), idle time (Srisuwanrat and Ioannou 2007), throughput rate, and quantity of WIP over time (Rybkowski et al. 2008, Lehtovaara et al. 2021a). These production parameters are presented as elements of a cost model in Figure 3.11 elements 1.a. to 1.g., described later in Section 3.4.3.

Looking at these parameters from the lens of manufacturing production system, as defined in Section 2.1.3 are:

- Number of zones (including zones that being worked on and not being worked on) is equivalent to WIP (a type of inventory that is partially transformed within any given process, not including stock in between processes).
- Cumulative work density (or workload) is cycle time of the step in a zone.
- Takt (as planned) is lead time for the step.
- Process duration, when calculated using planned takt, is process lead time.
- Project duration is project lead time.
- Throughput rate is as it is.

In ViWoLZo, users can use throttles to change these parameters. However, they need metrics to make throttle decisions or to extract actionable insights from these parameters.

3.3.2 Production Metrics

Based on the aforementioned production system parameters, I identified metrics for production planning and control. Metrics to measure the performance or success of a production system can be based on the anticipated performance for a plan or based on the actual performance for work completed. Therefore, I have separated the metrics for production planning and control, with certain metrics being common to both.

Metrics suggested for production planning, as defined in Section 3.1.3, include:

- Workload (cumulative work density) by step and zone
- Workload peak of a process
- Duration of a process
- Average of workloads for all steps and all zones in a process
- Variance and standard deviation of workloads for all steps for all zones in a process
- Coefficient of workload variation
- Number of workers

- Workload-peak-to-average ratio of a process
- Average-of-workload-range of a process by steps

Metrics suggested for production control used to evaluate the performance of a production system include:

- Work density to worker-hour ratio measures the ratio between estimated work density and actual worker-hours taken from the timesheets.
- Percent Plan Complete (PPC) measures the percentage of commitments completed to made (Ballard and Tommelein 2021). It measures workflow reliability.
- Tasks Made Ready (TMR) measures if the constraints for the work in the coming week are removed or not (Ballard and Tommelein 2021).
- Cumulative lost capacity for each step is the cumulative difference between takt (step lead time) and workload (step cycle time) for that step across all zones (Tommelein 2020).
- Service level measures customer delivery performance by calculating the probability of workload (step cycle time) being less than or equal to takt (lead time) (Hopp and Spearman 2008, p. 230).
- Handoff measures how many zones were (1) empty and cleaned, and (2) step in those zones completed 100% of their scheduled work (adopted from handover metric by Haugen et al. 2020).
- Returns measures how many crews had to return to a previous zone to finish incomplete work (adopted from Haugen et al. 2020).

PPC and TMR are taken from the LPS, with the intention to be used even when LPS is not being used. In a project where LPS is used for production control, other metrics provided by Ballard and Tommelein (2021) can also be used, including Tasks Anticipated, Commitment Level, and Frequency of Plan Failures.

This section described production parameters and recommended production planning and control metrics relevant to the WDM. These metrics provide perspective of the production, project, and individual trades. However, the financial implications of production decisions have yet to be formally modeled or assessed. Cost modeling and analysis using the WDM can provide insights into the time-cost trade-offs during production planning and control. The next section describes a framework developed to create such a cost model, and what the implementation of such cost model can look like.

3.4 Framework to Implement Cost Model for Production Planning and Control

Cost modeling is essential for planning and assessing the financial impact of design decisions. These models provide abstracted cost estimates for product design decisions and offer cost metrics for project planning and control decisions (Nguyen 2010). Traditional construction cost management systems utilize these models with historical cost data to calculate budgets that align with project owner's business goals. During project execution, traditional cost management focuses on cost control by monitoring actual performance against the budget and identifying variances. The Earned Value Method (EVM), an advanced and popular project control technique, integrates project schedule and cost. However, like traditional project planning methods, the EVM lacks concepts of flow and value generation. These traditional systems are designed for managing contracts but are not effective for production control (Kim 2002, Kim and Ballard 2002). The shift towards production-oriented approaches such as takt production highlights the need for more adaptive and nuanced cost models.

Takt production's aim is to improve construction project delivery by reducing scheduling complexity, project duration and variability, thereby necessitating cost models that can accurately reflect the related cost implications. Existing models depend on simplifications and assumptions that overlook the complexity of production dynamics (e.g., synchronization of process and trade flows) and do not consider the variability in the production system and its impact on the performance of the system. Creating a cost model suitable for takt production requires consideration of several production system design characteristics. The essential characteristics to consider include the resources required (number of workers, equipment, materials, space, etc.), production rate (work output by each resource within a given timeframe), process variability (uncertainty in production time), and support work (time and resources required to prepare for production tasks e.g., prefabrication, material delivery, set-up).

Challenges, as identified through the literature review in Section 2.3, include the oversimplification of production systems to an extent that the models become not fit for supporting production management decisions, the limitations imposed by commonly-used classification systems and historical databases, and the inability to capture the dynamic cost interactions associated with production planning. Existing cost modeling practices fall short in addressing the unique requirements of takt production and its impact on project and production costs across stakeholders.

This section describes the development of a framework that facilitates the implementation of cost models for construction project production systems. The framework takes a descriptive approach to be flexible to real-life differences coming from characteristics such as the production planning and control method used, type of project, involved stakeholders. The framework integrates decision-making parameters in takt production planning and control, with the goal of enabling a nuanced understanding of the impact of using takt and production related trade-offs. The section begins with an overview of the methodology used to develop the framework in Section 3.4.1, then describes the components of a project cost in Section 3.4.2, and elements of the cost model in Section 3.4.3, and ends with describing the use of the proposed framework through an example in Section 3.4.4.

3.4.1 Methodology for Framework Development

The methodology used to develop the framework for cost modeling includes the following steps:

1. Identify cost components: I started by identifying major cost components associated with construction projects. Some components are taken from the traditional cost estimation practices used in project management, such as labor, materials, equipment, overhead, etc. Additionally, some components are taken from the production management or lean perspective such as waste (eight types of waste considered by Womack and Jones (2003)), capacity, utilization, etc.

2. Identify and map elements of the cost model: I identified and mapped the elements of the cost model, with the intention to connect the production system to the cost components. These include:
    a. Map production parameters to production decisions: I mapped the production parameters, selected in Section 3.3, to the production decisions, identified in the WDM (Section 3.1) and ViWoLZo (Section 3.2).
    b. Identify the impact of production decisions: I mapped the production decisions from step 2.a to their impact on the production system and subsequently to their impact on the project.
    c. Map production to cost components: For each impact identified in step 2.b on the project and the production, I identified the corresponding impact on the cost components.
3. Develop framework: I developed a framework for cost modeling using the production-to-cost relationship. This involved connecting the components of the cost identified in step 1 to the production parameters and mapping identified in step 2.

The resulting cost modeling framework incorporates the relationships between production design and cost. The model can be used for continuous cost monitoring and control throughout takt production planning and control. Next, these three steps are described in detail, step 1 in Section 3.4.2, step 2 in Section 3.4.3, and step 3 in Section 3.4.4.

3.4.2 Components of Project Cost

The initial step in developing the framework for cost modeling involves identifying the components that contribute to the total project cost. To develop a simple, focused, and effective framework, I approached the development solely from the project's perspective (primarily that of the owner). This approach assumes the project as a temporary independent organization and simplifies the complexity typically associated with managing the network of cash flows exchanged among various stakeholders within a portfolio of projects. By concentrating on a single project, the framework specifically isolates its costs and benefits. This allows for a more precise measurement of performance based solely on the project's outcomes, rather than the broader organizational impacts, which would require understanding of information beyond the scope of the project.

Expanding the framework to include the viewpoints of other stakeholders, such as GCs and trades, necessitates a reevaluation of their perceived costs and benefits, potentially altering the framework significantly. It is important to note that the total project cost considered excludes fees associated with GCs and trades, as the framework assumes these fees to be fixed or unaffected by the performance of the production system.

The total cost of a project can be divided into various components, depending on the goal of the analysis. At a high level, costs are categorized into direct and indirect costs, a classification aligned with conventional cost estimating practices. Direct cost includes material cost component and cost for all the resources required for the installation of the material, i.e., the labor and equipment cost component (Gordian RS Means Data 2017). Indirect cost includes overhead cost component (also known as general conditions). This division helps to separate costs by their relationship to the scope and schedule of the project.

Considering value addition from lean perspective, the total cost can also be divided into: value adding costs and non-value adding costs. Value-adding costs include expenses that directly contribute to the creation or enhancement of the product with desired outcomes including product specifications, quality, safety, schedule, budget, etc., hence bringing value to the customer. Non-value adding costs include expenses that do not directly contribute to the product's value in meeting the desired outcomes from the customer's perspective. Hence, elimination of non-value adding cost should not change the value of the final product for the customer. However, categorizing costs strictly as value-adding or non-value-adding is not always straightforward. Some costs, while not directly contributing to the desired outcomes, are nonetheless crucial for maintaining the efficacy of the production system in its current state. For example, the use of capacity or inventory buffers to absorb variability might be categorized as non-value-adding. Yet, removing these elements could actually reduce the system's performance in achieving the desired outcomes. Therefore, a nuanced understanding of the role each cost plays in the production system is essential to truly optimize value from a lean perspective. Steady elimination of waste at all levels of the production system creates a more stable system (Womack and Jones 2003), reducing dependence on buffers and total cost

Additional high-level divisions of project costs include opportunity costs and contingencies. Opportunity cost pertains to the value of the next best alternative forgone by selecting a specific action or decision. In this framework, the only alternative opportunity considered is the early completion and operation of the project, or a part of the project, such as renting residential apartment units. This helps in quantifying the monetary impact of the early or late completion of the project, which might come from gain or loss of revenue. Contingencies represent a portion of the estimate reserved for unforeseen events or complications outside the original scope or estimate. Contingencies help in dealing with cost variability by acting as financial buffer to manage risk and unexpected issues during the project.

Delving deeper, direct costs are further split into material costs and labor and equipment costs. Material costs cover the price of materials within the project's design scope plus some buffer for wastage and damage, whereas labor and equipment costs pertain to the employment of labor and machinery directly involved in completing the project, whether on-site or off-site.

Although most of the direct cost is considered value adding, parts of it can be non-value adding. Costs that arise from wastage of material or inefficient use of labor and equipment, does not contribute to the project design scope, and does not arise from a trade-off that helps achieve a desired outcome, can be considered a non-value adding direct cost. E.g., a situation where material waste is accepted as part of a process due to the trade-off made to reduce the duration to meet project deadline, can be considered value-adding.

Common forms of non-value-adding direct costs encompass eight types of waste (called muda) considered by Womack and Jones (2003) including overproduction, wait, transportation, overprocessing, excess inventory, unnecessary movement, defects, and untapped employee creativity. Each of these costs represents a specific type of material or resource wastage. Material waste cost does not contribute to the project design scope. Over-production costs are associated with producing more than what is needed, leading to waste. Rework costs are incurred from correcting errors or redoing work not done correctly the first time. Un-utilized or underutilized capacity costs are incurred from maintaining capacity (labor and equipment resources) that are not constantly in use. This capacity, sometimes referred to as swing (or spare) capacity, can be used to handle variations in production needs by giving the ability to adjust production output up or down to match demand. In situations where it helps in coping with variations, it might help the production system stay on schedule and should be considered value adding until variations can be eliminated. Idle time costs are incurred when resources are not being used effectively, such as workers or equipment standing by without performing productive work. This can happen due to many reasons, e.g., the location of work not being ready as successor step are behind schedule. Unnecessary motion costs are associated with inefficient movement of workers or machinery to do their work.

Indirect cost, or overhead costs, is divided into staffing costs and hard costs. Staffing costs refer to salaries for administrative and management workforce who oversee processes and the project. Hard costs refer to costs such as rental for construction site facilities, utilities, or software licenses for design and project management.

Although most of the indirect cost is considered value adding, parts of it can be non-value adding. Indirect costs that do not ensure or improve efficient value addition from the direct activities, can be considered a non-value adding indirect cost. For example, staffing costs for redundant supervisory roles, excessive administrative procedures, or any form of bureaucracy that does not contribute to the final desired outcome. Hard costs for redundant, excessive, or overpriced rentals, utilities, or services that are above the industry standard without providing additional benefits would also be considered non-value-adding.

Understanding the composition of total project costs, which components are influenced by the production system's design and performance, how different components interact, and how trade-offs can affect them, can lead to comprehensive insight into production management.

3.4.3 Cost Model Elements

Figure 3.11 provides a flowchart for the identified elements of the cost model: production parameters, production decisions and their impacts on production, project, and project cost. The figure sequences the elements from 1 to 5, starting from the production parameters at 1 to the impact on the project cost components at 5. The first two elements are at the production level, whereas the last three are at the project level. Inside each element, individual boxes marked with letters (a, b, c, etc.) represent the examples for the element selected for demonstration. These examples are based on the scope and assumptions of a project with takt production from the perspective of the project or project owner.

The production parameters (Figure 3.11 elements 1.a. to 1.g.) are listed in Section 3.3.1 and defined in Section 3.1.1. Changing the parameters allows planners to make production decisions. The production decisions (Figure 3.11 elements 2.a. to 2.g.) are taken from the WDM, as defined in Section 3.1, and from ViWoLZo, as defined in Section 3.2, and include:

a) Workload leveling includes decisions related to the leveling (or balancing) of workloads across steps and zones in a process. It is described in Section 3.1.2 and illustrated on ViWoLZo in Section 3.2.6.5.

b) Zoning includes decisions related to the number of zones, part of work space to zone, and deciding zone boundaries. It is described in Section 3.1.1 and illustrated on ViWoLZo in Section 3.2.6.4.

c) Constant or variable crew size includes decisions related to the composition and size of the crew, how the crew changes with changing workloads, their estimated production rates, and assigning capacity buffers as time or additional capacity to deal with variability. It is described in Section 3.2.4.4 and illustrated on ViWoLZo in Section 3.2.6.5.

d) Clear handoffs include decisions related to defining the process boundaries (customer handoffs), and process map (step handoffs). It is described in Sections 3.2.4.1 and 3.2.4.5 and illustrated on ViWoLZo in Section 3.2.6.3.

e) Trade-stacking includes decisions related to number of trades working simultaneously in a zone, and thus related to defining the process map, i.e., the sequence of steps. It is described in Sections 3.2.4.1 and 3.2.4.5 and illustrated on ViWoLZo in Section 3.2.6.3.

f) Batch size includes decisions related to the size of the zones and definition of the scope of work in each step in the takted process, consequently affecting the workloads, the operable takt, and the temporal batch size (takt) and the spatial batch size (zones). It is described in Section 3.1.1 and illustrated on ViWoLZo in Section 3.2.6.

g) Buffer (type, size, and position) includes decisions related to deciding the type of buffers to use (e.g., time, inventory, capacity), and sizing and positioning the buffers according to the size and position of the (un)expected variability. It is described in Section 3.1.1 and discussed in Section 3.5.1.5.

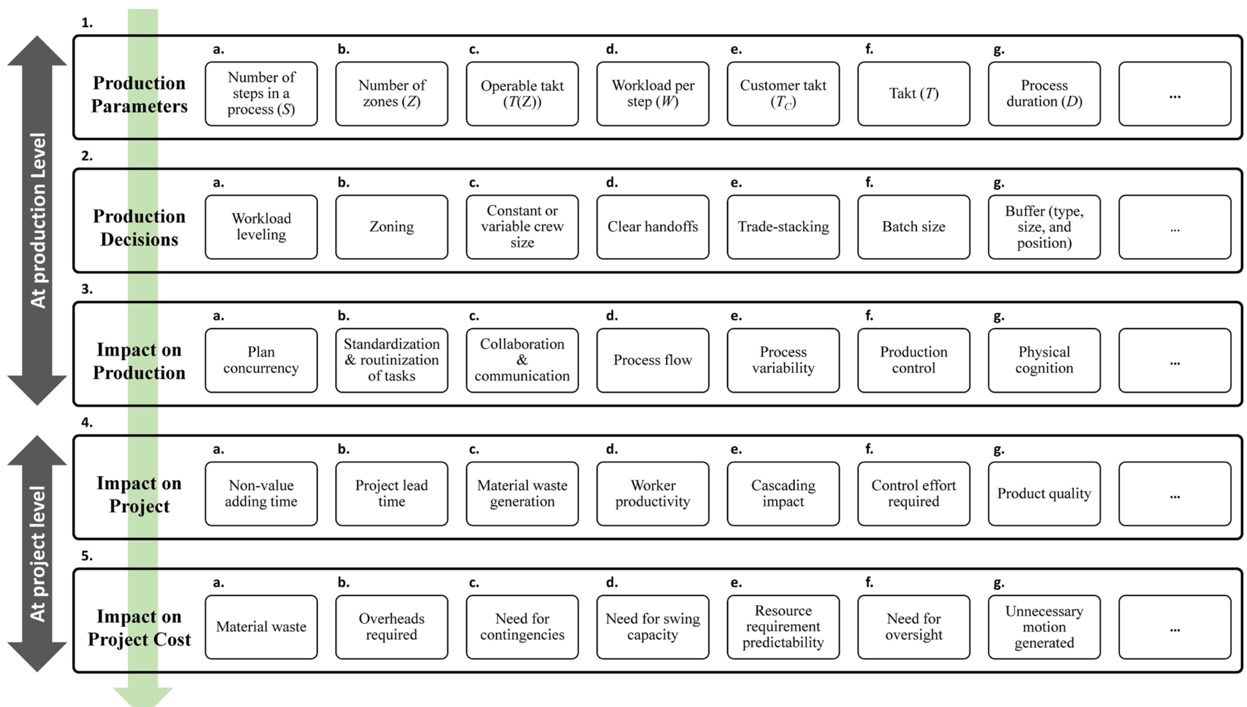


Figure 3.11: Elements of the cost model: production parameters, production decisions and impacts on production, project, and cost components.

Making production decisions has an impact on the production system and subsequently on the project, and project cost components.

The impact on the production system (Figure 3.11 elements 3.a. to 3.g.) include:

a) Plan concurrency is the degree to which execution of planned work is done simultaneously in multiple locations, without conflict or delay.

b) Standardization and routinization of tasks is changing uniformity in tasks to affect predictability and repeatability in production.

c) Collaboration and communication are facilitating better teamwork and information exchange.
d) Process flow is the quality of streamlining the sequence of steps and synchronizing processes and operations on a common takt.
e) Process variability is the fluctuations in the production process and its output.
f) Production control is the management of steps by location to keep the project on-schedule and under-budget and meet safety and quality standards.
g) Physical cognition is the worker's understanding of who is working where and when.

The impact on the project (Figure 3.11 element 4) include:

a) Non-value adding time is the time spent on activities that does not generate value for the customer.
b) Project lead time is the total duration from the start of the project till the delivery to the customer.
c) Material waste generation is creation of surplus materials and debris that are not utilized in the final product, resulting from inefficiencies, errors, damage, or excess procurement.
d) Worker productivity is efficiency of workers (often measured as value-added per employee) and is the output of their production rate (measured as the quantity of work done per unit time).
e) Cascading impact is the domino effect where an issue in one part of production affects subsequent parts.
f) Control effort is the amount of effort in terms of resources, including time, manpower, and financial investments, dedicated to monitoring and adjusting the production processes to address deviations from the planned.
g) Product quality is the measure of how well the product meets customer expectations and specifications.

The impact on the project cost components (Figure 3.11 element 5) include:

a) Material waste is the cost incurred due to excess materials used that are discarded or remain unused during the construction process.
b) Overheads required are the indirect costs related to management staff and hard costs to manage and support direct work.
c) Need for contingencies are funds set aside to cover unexpected expenses or changes in the project scope.
d) Need for swing capacity is the cost of maintaining additional capacity to accommodate variation in product and production.
e) Resource requirement predictability is the cost associated with the ability to accurately forecast the resources (labor, materials, equipment) needed over the course of the construction project to avoid delays and wastage.

f) Need for oversight is the cost related to supervisory activities that ensure production is on track as per specifications, on time, and within budget.

g) Unnecessary motion generated is cost associated with any wasted movement by workers or equipment that does not add value to the project.

The impact on the project cost components, like the examples above, can be connected to one or multiple components of project cost identified in Section 3.4.2. The cost model element described here are examples relevant to takt production. The structured flowchart can be extended to other examples as needed.

3.4.4 Framework for Cost Modeling with Zoning Example

The framework to implement the cost model for production planning and control combines the relevant production system with components of project cost by connecting the elements at each level (1 through 5).

Figure 3.12 illustrates use of the framework through an example where zoning decisions are made for a takt production system. The framework starts from element 1 (top), which represents a list of production parameters, and sequentially moves down each element until element 5 (bottom), which represents the impact on cost.

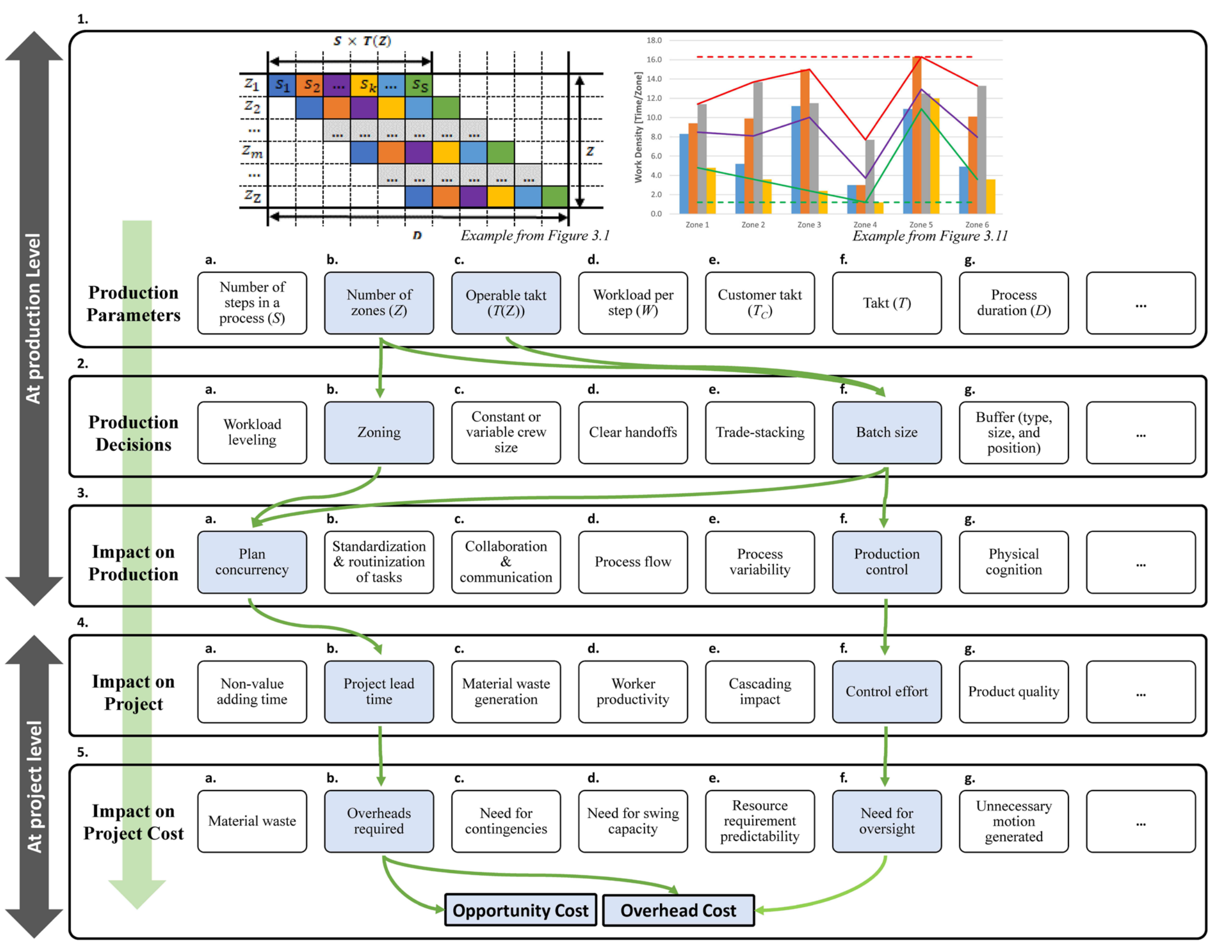


Figure 3.12: Framework for cost modeling with takt production zoning example.

When multiple trades must perform work in a work space (that can include multiple floors, a single floor, or a part of a floor), but only one trade can occupy the space at a time (to avoid trade stacking), the process duration required to finish the work with trades operating one after another equals the sum of the time each trade needs for their scope of work. A planner may divide the work space into zones, allowing them to work in sequence across these zones. According to the definition of production parameters (Section 3.1.1), *Z* represents the number of zones (Figure 3.12 element 1.b.) and *T(Z)* represents operable takt, a function of how the zoning is defined (Figure 3.12 elements 1.c.). Here other parameters are assumed unchanged, e.g., number of steps *S* is constant. A planner would use these parameters and make production decisions related to zoning (Figure 3.12 element 2.b.) and consequently decide the batch size (Figure 3.12 element 2.f.) in terms of the zone boundaries (spatial batch size) and the takt (temporal batch size).

Zoning- and batch size decisions impact the production system and project. Typically, though not always, increasing the number of zones results in smaller zones with smaller scopes for each trade, thereby reducing the batch size and decreasing the time needed for them to complete their tasks before moving on (takt). The collective time necessary for all trades to finish their tasks defines the process duration, given by Equation 3.4 in Section 3.1.1.

To demonstrate, Figure 3.13 (Figure 1 in Tommelein 2022) displays the schedule of a takted three-step process, with work space divided in one, two, or three zones, respectively. The figure indicates that increasing the number of zones improves concurrency (Figure 3.12 element 3.a.). Jabbari et al. (2020a, b) proved mathematically using the process duration equation, where even though *Z* increases, decreasing *T(Z)* reduces the process duration (*D*). Hence, this means the project lead time (Figure 3.12 element 4.b.), i.e., the total duration from the start of the project till the delivery to the customer, can be reduced to meet deadlines or reduce the project duration.

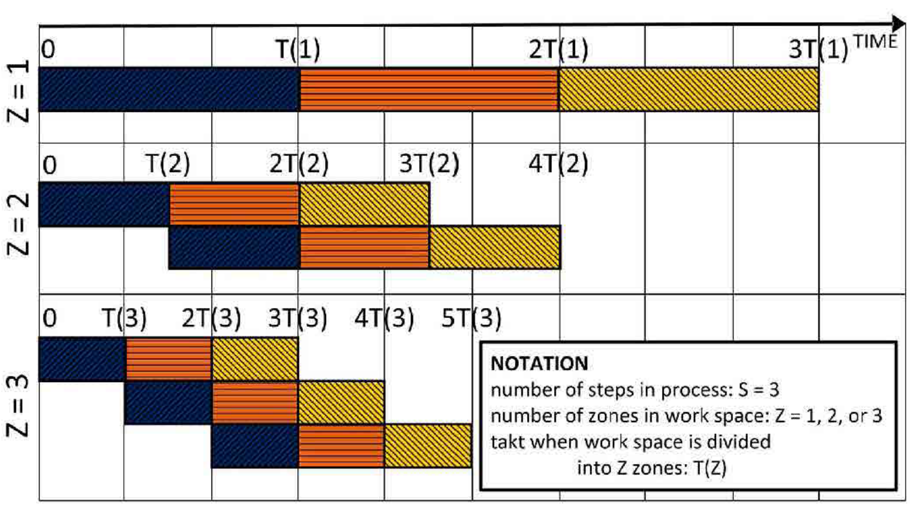


Figure 3.13: Three alternative takt plans of a three-step process with work space divided, respectively, in one, two, or three zones (Figure 1 in Tommelein 2022, used with permission).

Dividing the work space into more than one zone generally leads to a decrease in the *D* and should in turn reduce the project lead time. However, Jabbari et al. (2020b) caution about cases where the *D* does not decrease. One case when the distribution of work density is highly irregular, such as being concentrated in a small area that cannot be divided. Another case is when the number of zones keeps increasing. In this case the number of zones (*Z*) keeps increasing as *T(Z)* stabilizes and ceases to decrease with further increases in *Z*. Figure 3.14 demonstrates the behavior in this case, along with the behavior when zoning is repeated over multiple floors. Zones repeating over floors also act as additional zones and hence the advantage of partitioning a work space into smaller zones diminishes as the number of floors increases. An important limitation to note in Jabbari et al.'s algorithm is their constrained boundary conditions, including only continuous zones that are rectangular or "L" shaped. In real world, zones can be discontinuous and of any shape.

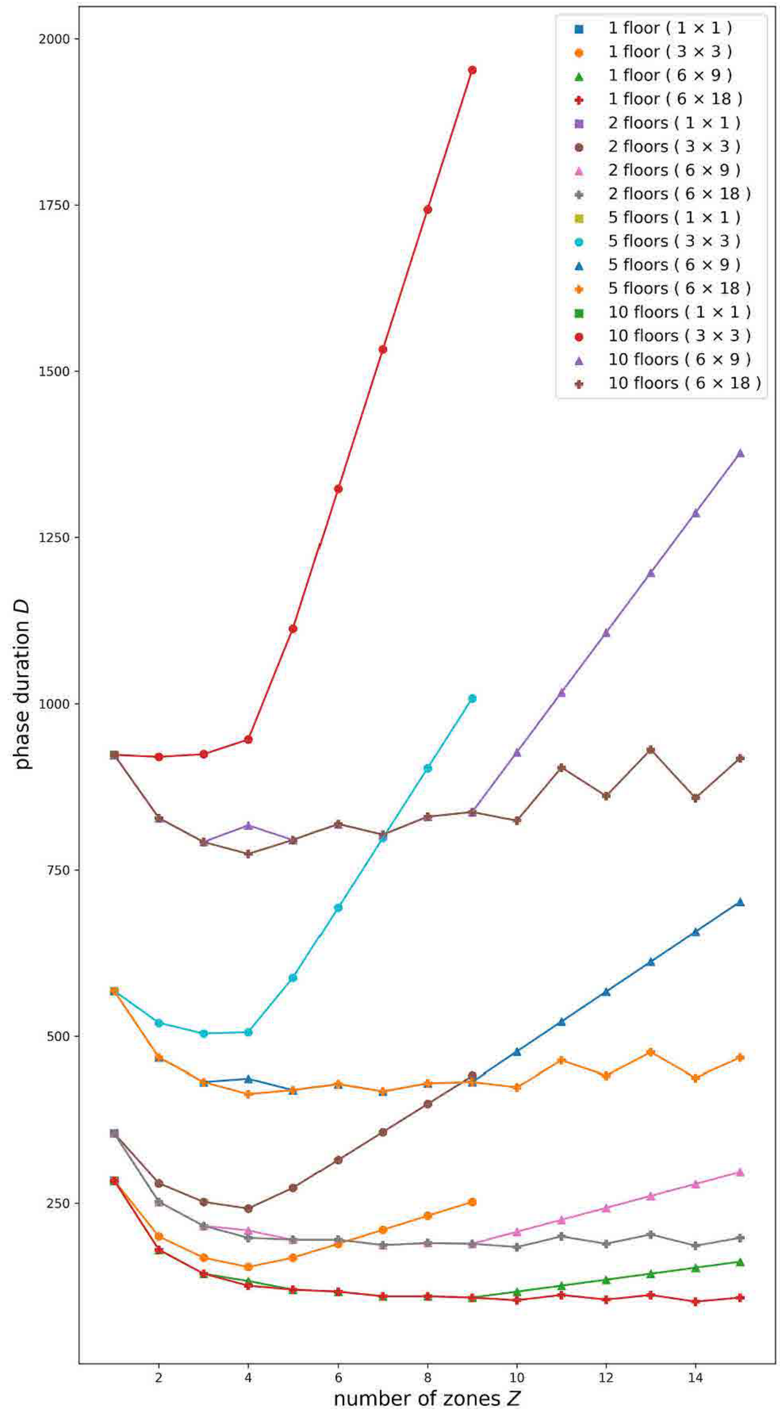


Figure 3.14: Phase duration vs number of zones for 1, 2, 5, and 10 floors (Figure 15 in Jabbari et al. 2020b, used with permission).

To study the impact on the production control side, Figure 3.13 displays how increasing the number of zones reduces the batch size, and hence creates opportunity to control production at a more granular level and more frequently (Figure 3.12 element 3.f.). This impact on production control comes with an increase in control effort required to keep project on track (Figure 3.12 element 4.f.). However, by introducing spatial continuity and limiting one crew in a location at a time, takt production can also reduce the degree of control complexity (Alves and Formoso 2000).

With the nonlinear behavior between Z and D, it is necessary to understand the sensitivity of production parameters in relation to their impact on project cost. In this example, the Z is converted to D, which in turn affects the overhead costs (Figure 3.12 element 5.b.). As the D decreases or increases with a change in zoning, the change in overhead cost (also referred as indirect cost) can be modelled by considering expenses that are dependent on time (generally linear dependence on time assumed for salaries and rent), e.g., project management staff. Control effort can also affect the overhead costs as it can change the level of oversight needed (Figure 3.12 element 5.b.), either through an increase in supervisory staff or software expenses to support their effort.

Change in project lead time can result in early or late completion of the project, and hence impact the opportunity cost of having the final product ready for operation (Figure 3.12 element 5.b). In mission-critical projects, often the speed to completion dominates the production decisions: owners prefer to make trade-offs that support timely completion of the project, even at a higher cost.

This example demonstrates how the framework can be used to help planners make trade-offs in complex decisions. Modeling the time-cost relationship even for a single decision parameter, despite presuming other parameters to be constant, can be intricate. It necessitates modeling with an awareness of the specific nuances of the project, stakeholders, and the production planning and control method employed. Employing this framework to establish a structured yet adaptable model is crucial for accurately capturing the cost dynamics in production systems. For a more structured and standardized implementation of this framework, creation of cost models based on this framework will be next.

3.5 Discussion

The development and application of ViWoLZo highlighted the effectiveness of leveraging work density to establish a data-driven production system, enabling objective decision-making and what-if analyses. By incorporating metrics and examining the influence of production system on the project costs, I further enhanced the approach. This section shares some critical observations, limitations, and assumptions derived from this chapter.

3.5.1 Learning from ViWoLZo

3.5.1.1 Increasing Plan Concurrency

A planner can shorten process durations by scheduling work to be done concurrently in multiple zones and ensuring there is no trade stacking. Alternatively, they may be able to achieve a shorter duration by getting more workers of the same- or different trades to work in the same location. If this leads to trade stacking or overmanning, however, then productivity can suffer, and the time gain may not be commensurate with the staffing increase. Should overmanning occur when reducing work density by increasing the number of workers, then consideration must be given to creating two or more crews instead of a single large one and starting them in different locations so each will have sufficient space to work effectively and efficiently.

In ViWoLZo, it is assumed that a simple multiplier suffices to model the relationship between changes in crew sizes and production rates. In reality, this relationship is much more complex. Currently lacking better models, ViWoLZo at least allows the user to manually adjust crew sizes or production rates.

3.5.1.2 Data Collection

The collection effort of the work density data ViWoLZo needs must be streamlined. Trades should participate in this effort, providing production data and assessing challenges and opportunities presented in the process being planned. I recommend that processes be defined in a pull planning session, with collaboration and data collection managed by a person internal to the project team (e.g., the superintendent). The collaboration should include a discussion of schedule trade-offs, buffering to accommodate uncertainties, etc. so that everyone on the team understands all data inputs and buys into the resulting process plans. Future research on this front can improve the data collection and setup process by standardizing processes and steps according to work space types.

Furthermore, the data collection process would benefit from the development of computer-support tools. Existing 3D modeling and other software do not appear to have the sought-after functionality to generate QTOs at the level of detail of grid cells. Research is needed to develop tools that can extract quantity data as needed for the application of the WDM.

Other ways of generating work density can be considered when QTOs are not available. Linnik et al. (2013) and Frandson et al. (2013) had trades produce color-ups to communicate their space needs and the time required to complete certain scopes of work. However, here I focus on a data-driven approach. Hence in the subsequent chapters, I describe a different approach—automating the data collection of actual work density from the site—using production tracking technologies.

3.5.1.3 Defining Cell Grid

Different types of spaces may lend themselves to different ways of defining grid cell boundaries. For example, when planning interior finishes work, it may be preferable to have cell borders aligned with architectural features such as walls so that each cell will fall within a single room. However, this is not always preferred. For example, if a wall needs to be worked on from both sides, assigning one of its sides to one cell and the other side to another cell could lead to incorrectly capturing work density and result in a work space zoning that is impractical. As illustrated in this chapter, an orthogonal grid may align well with plan features. However, other tessellations of the work space are possible and could be supported by a tool such as ViWoLZo.

3.5.1.4 Work Structuring

Work density values depend on how work gets structured: they are process specific. This means that they depend on how the scope of each step is defined and this scope can vary based on how steps are sequenced. Thus, when adding or removing steps or changing their order, the impact on work density should be considered by the user; ViWoLZo only goes by the work density maps provided as input. For example, a user can alter a work density map for a given step and scope of work by changing means and methods from stick-built to offsite assembly, in turn changing the onsite crew needed, the quantity and units of work, and the production rate. Work structuring can also be used to re-define processes by adding or removing steps, combining or splitting multiple steps by aggregating or separating their work density maps as appropriate. Though it was assumed earlier (Section 3.2.4), in general, it is unlikely that work density maps will be additive.

3.5.1.5 Workload Leveling and Capacity Buffering in Takt Planning

When using ViWoLZo for takt planning, deciding on capacity buffers is a crucial part of work structuring. Takt planning uses capacity buffers to alleviate any detrimental impact of process time variation on plan execution, e.g., production units may be underloaded by assigning them work up to 70 or 80% of their capacity (Frandson et al. 2015). The sizing of each trade's capacity buffer is decided after workload leveling when determining if the workloads of all steps in a process (including the workload peak *T(Z)*) are appropriately less than the selected takt. However, if a trade is greatly underloaded in specific zones, then the remaining crew time needs to be planned for workable backlog, skill development, improvement studies, etc.

3.5.1.6 Limitations of ViWoLZo

In its current implementation, ViWoLZo supports the zoning of only a single work space (though this space can be discontinuous) and one process at a time. Though a user can open multiple copies of the tool simultaneously, e.g., to decide which scope or step to include in which one of several processes, a multi-process extension of ViWoLZo should be easier to use. Furthermore, there is a need to combine the tool with a detailed cost model. Having accurate knowledge of cost impacts when leveling workload will help planners make work structuring decisions and compare, improve, and optimize plans.

3.5.2 Metrics and Objectives

3.5.2.1 Metrics to Meet Objectives

GCs and trades manage crews between a portfolio of projects, have different types of contracts, and perform different scopes of work and therefore would be expected to each pursue multiple objectives. In general, GCs tend to favor process location flow, whereas trades favor trade location flow, with both managing the related buffers (Frandson et al. 2015).

In a real-world situation where multiple parties work with conflicting objectives, it is essential to understand the impact of the metrics on different performance outcomes. The balance between different desired outcomes can be improved by keeping in mind their relationship to the metrics used to measure them. In Section 3.2.6.5, I demonstrated a real-work example of balancing workload using the metrics listed in Section 3.1.3.

A lower workload peak indicates the possibility of lowering the takt, and consequently lowering the process duration. By buffering for variation and keeping all workloads under the takt, the planners can make sure the process meets customer deadlines. The workload-peak-to-average ratio, measures the ratio of the workload peak to the average of workloads across all zones and steps, showed similar performance as the workload peak. This is because in the case study, the average did not change with workload re-distribution through zoning, and only changing the workload peak.

A lower variation in the workload across process steps in each zone indicates better process location flow, whereas a lower variation of workload across zones for each step (or trade) indicates better trade location flow (Tommelein et al. 2022). Lower standard deviation, and hence a lower variation, for workloads across all steps and zones, indicates reduced production variability. This also improves process location- and trade location flow.

Using unitless ratios, such as workload-peak-to-average ratio, average-of-workload-range, and coefficient of variation, can provide consistent comparisons of the level of variability in workloads and its impact on the production and flow. Although, to create a systemic use of these ratios, future work in calibrating their range of values to different classes of performance can guide users in comparing alternatives and classifying expected performance. For example, Hopp and Spearman (2008, p. 269) suggest the coefficient of variation to be classified into three variability classes, including low variability if the coefficient is less than 0.75, that it has moderate variability if it is between 0.75 and 1.33, and that it has high variability if it is greater than 1.33.

Metrics can be used to improve one or both flows as per the objective, e.g., planners can achieve constant crew size, increase worker utilization by reducing the time workers wait on work, increase space utilization by reducing the time work waits on workers, reduce workload variability for better estimation of staffing requirements, etc. Reducing workload variation (by judiciously underloading and avoiding overburdening) and keeping step cycle time below the takt (with a capacity buffer), results in (1) reduction in work (zones) waiting on workers (steps), in turn improving spatial continuity, and (2) reduction in workers waiting on work, in turn suggesting timely handoffs of zones. However, achieving both results together is difficult as one tends to counter the other.

In situations where multiple objectives conflict, multiple production design decisions must be used together. For example, planners can minimize the workload peak (reducing takt and process duration) to meet the project deadline, but in turn increase workload variability. Manifestation of this variability can increase workers waiting on work (increasing idle time) beyond the time allotted for underloading. Planners can utilize capacity buffers or have variable crew size using additional capacity to absorb this variability. Thus, sizing of each trade's capacity buffer becomes part of the workload levelling process. Other strategies available for planners to manage with excess idle time includes planning for workable backlog, skill development, improvement studies, etc.

3.5.2.2 Workload Leveling and Zoning Optimization

The work density construct can be used to optimize workload leveling problems. For example, Jabbari et al. (2020a) developed the so-called Workload Leveling and Zoning (WoLZo) algorithm that determines the zoning with the lowest possible *T(Z)*. As formulated, the WoLZo problem is NP-hard. It is solvable when the problem is small (i.e., it includes a few steps and zones) but as the problem size grows it quickly becomes computationally taxing.

Note that WoLZo is a sub-problem of the problem addressed in ViWoLZo and thus easier to solve. The objective function for WoLZo minimizes the workload peak across all the steps in a process, only by changing zoning layout. Minimizing the workload peak typically results in minimizing the process duration, barring some exceptions (Jabbari et al. 2020a, b). In contrast to WoLZo, ViWoLZo allows the user to change work structures (steps to include in a process, crew sizes, etc.) and allows zones to be discontinuous and of any shape. If additional considerations are included in a mathematical formulation, the problem size increases and becomes computationally prohibitive to solve.

Until suitable algorithms get developed, ViWoLZo provides several metrics and visual representation of the workload distribution. A ViWoLZo user can use the metrics and visuals to find the best possible workload distribution through trial-and-error. They might also apply strategies to deal with conflicting objectives. E.g., if a trade is underloaded in specific zones, then the remaining time needs to be planned for the workable backlog, skill development, improvement studies, etc. A user can thus generate alternatives and make performance trade-offs to address any number of objectives.

Follow-on research is focusing on the development of computing support systems to help make such trade-offs. Further study of multi-objective optimization is in order. This may include pareto optimization or creating an aggregate objective function by assigning weights to objectives depending on their relative importance. In the meantime, a combination of algorithms, user input, and metrics can systematically account for work structuring decisions when using the WDM to plan a project.

3.5.2.3 Need for Flow Metrics in Planning and Control

Flow is widely regarded as an important property of an efficient production system. In lean, an ideal production system exhibits continuous flow (also called one-piece flow), a type of production in which work advances through a series of process steps on a first-in-first-out basis as continuously as possible, with each step making just what is requested by the next step (Ballard and Tommelein 1999). Continuous flow is achieved by balancing work in each step and providing uninterrupted work at each step while minimizing resource idle time and WIP and maximizing the throughput of that part of the system. Like other production parameters in construction, flow is also not widely accepted or adopted as a metric and lacks standardization on the terminology.

One of the challenges in developing metrics for flow in construction is the lack of consensus on the definition of "flow" and the specific aspects of flow to consider with the context of a project-based production system (Sacks et al. 2017). To address this issue, I described several types of flows in Section 2.1.5 to establish a standard vocabulary for this research. Nonetheless, several publications mention the topic of flow and related metrics in construction project production. Bashford et al. (2003) measured workflow variability with the coefficient of variation (COV) to evaluate the impact of production strategies for completing homes. da Rocha et al. (2023) explored off-site construction from a flow viewpoint, using COV as a measure of flow. Binninger et al. (2019) analyze flow in takted projects by measuring flow efficiency (FE), reflecting the relationship between time spent creating value and the total time taken, from the trade perspective (FE_{Trade}) and from the location perspective ($FE_{Location}$). These two flow perspectives are representative of the two-dimensional nature of flows in construction identified in this research (Section 2.1.5) with trade location flow (synonymous with trade flow) and process location flow (synonymous with process flow). Haugen et al. (2020) focus on takt performance indicators, offering a set of seven metrics specifically designed for evaluating performance in takt-based construction projects. These metrics include: PPC (adopted from LPS), perfect handoff (adopted from LPS), overtime, returns, additional choices, man-hour, and staffing. Sacks et al. (2017) introduce the Construction Flow Index (CFI), a metric designed to quantify the quality of production flow in construction projects. The CFI allows measurement of flow efficiency using an equation to combine seven production parameters into one single metric.

Although the concept of measuring flow is important, clarity on what specific aspect of flow is being measured often remains ambiguous. Some existing metrics have been adapted from other planning and control methods to serve as proxies for measuring flow, such as PPC and perfect handoff, which are borrowed from the LPS (Ballard and Tommelein 2021). Kenley (2019) criticizes the CFI for its vague definition of the quality of flow, which complicates the evaluation of its usefulness. Kenley also points out a significant flaw in the CFI: its inability to measure and manage production at a sufficiently detailed level. Despite the adoption of a location-based view of production flow by Sacks et al. (2017), use of the CFI does not facilitate detailed planning for individual crews and locations. The trade- and process flow, as explored in this research, demands detailed planning of each step and zone, a level of detail that the CFI cannot provide.

This research does not incorporate metrics for measuring flow; however, the significance of such metrics has been recognized for future investigation. The integration of flow metrics, viewed from diverse perspectives and incorporating various production parameters, can contribute to enhancing efficiency, quality, and overall project success.

3.5.3 Cost Modeling for Takt Production

3.5.3.1 A Framework to Model Cost for Takt Production

The design of the framework for cost modeling accommodated the nuanced demands of location-based production approaches such as takt production. The framework signifies a departure from traditional cost modeling methods. By acknowledging the complexity of production dynamics and the inadequacy of traditional models to capture these dynamics, the research underlines the need for a framework that is both descriptive and adaptable to various project- and stakeholder characteristics.

Traditional cost modeling practices often fall short in capturing the dynamic intricacies of production systems, particularly in their ability to deal with variability and the need for flexibility in production management. These practices often abstract production processes at a high level, neglecting idle time, operational inefficiencies and buffers used, which leads to a lack of decision-making capability regarding work structuring and a misunderstanding of true production costs. They rely heavily on assumptions for contractor estimations, sidelining critical variables that significantly impact cost, thereby risking inaccuracies and potential budget overruns.

Economic-based models overlook the organizational aspects of production and its internal processes, providing an incomplete picture of project economics and failing to account for the real efficiencies or inefficiencies of production planning (Koskela and Tommelein 2009, Koskela et al. 2023). For example, the models ignore the variability in the system and thus do not account for the buffers included to absorb these variabilities and other wastes generated in the system. Additionally, estimations based on QTOs, and generic waste factors (e.g., a certain percentage for damaged wasted material) do not fully address all forms of waste, from material wastage to inefficient resource allocation. Furthermore, the expectation that contractors will surpass initial estimates (included through contractual documentation) introduces implicit fudge factors, leading to unsustainable competitive practices and complicating accurate cost modeling.

Integrating takt production with cost metrics brings numerous benefits to construction project management. It improves cost predictability by providing more accurate forecasts of project costs, enhancing the ability to anticipate financial needs and budget accordingly. This improvement is achieved by covering the shortcomings of the traditional deterministic methods by including the production view with a stochastic approach. Accuracy helps to ensure that the project team is aware of cost implications of planning and control decisions. This integration also enables enhanced cost control through real-time monitoring and management of costs, allowing for timely adjustments and mitigation of financial risks.

3.5.3.2 Considerations for Cost Modeling

Cost modeling for takt production requires consideration of certain essential production system design characteristics, including process design, resources, production rates, process variability, and support work. However, the impact on cost extends into various aspects of project management beyond these characteristics.

One such aspect is the overhead costs for GC and trades. The time trades spend on-site correlates with project overhead costs, affecting the overall budget for the project. Addressing the cost associated with supervisory staff, such as foremen and project managers, to a specific scope of work necessitates a nuanced approach—potentially employing a simple multiplier, for instance, 1.5 times the cost of a regular craft worker, to approximate these costs effectively. Other aspects include the cost of having or hiring standby capacity, cost for rework, cost implications of a delay, cost of space required for material stocking, and the cost associated with waste in the system.

The lean perspective, specifically the focus on the reduction of waste (8 types of waste described in Section 2.1.2) in the production system, increases the scope of cost modeling and estimating even further. This perspective not only seeks to accurately estimate project costs but also aims to minimize these costs through efficient production planning and control. In fact, at the highest level, lean philosophy seeks to reduce the need for resources (human labor, space, capital, and time), while improving safety and product quality as demanded by the customer (Ohno 1988). Achieving this ideal state is a continuous organizational effort made through many lean practices such as continuous improvement, just-in-time, built-in quality though jidoka, andon, and mistakeproffing (Liker 2004). Modeling cost for waste or non-value adding parts of the production system is challenging. For example, an important requirement for takt production to improve production performance is to eliminate trade stacking by not allowing multiple trades to work concurrently in the same space. Measuring the cost impact of this production decision would require innovative cost modeling, such as the use of parametric models (Hegazy and Ayed 1998) and simulation models (Elfaki et al. 2014).

These are some examples of what production system characteristics need to be considered for cost modeling. The traditional cost modelling- and estimating practices do not allow for incorporating these considerations easily, as they rely on many assumptions of what costs are considered and what generates value to the customer. However, research on takt production, lean construction, TVD, and other similar bodies of knowledge in the last two-three decades have brought many of these system characteristics considerations further than ever before.

3.5.3.3 Limitations of Cost Modeling Framework

The framework for cost modeling presented in Section 3.4 is based on several assumptions and abstractions and takes the perspective of the project or the project owner. Identifying and mapping cost modeling elements from the perspective of other stakeholders, e.g., GC and trades, would require re-assessing the elements. Many nuances to be considered also depend on factors including type of project, geography, type of contract, payment schedule, etc.

In construction cost estimating practice, the total cost of work does not include the fees for the GC and trades. Negotiated in their contract, their fees are usually fixed or a percentage of the cost of work is variable up to a Guaranteed Maximum Price (GMP). If the fees are not dependent on the production system performance, cost modeling elements need to be considered accordingly.

The pain or gain aspect of any cost is not a clear black and white, as there are always multiple implications of any decisions requiring trade-offs. For example, deciding to reduce material waste will reduce the direct cost of material consumed or purchased. However, the effort required to reduce material waste can increase time and effort required to achieve the desired result.

To overcome the limitations of the framework, many questions need to be answered at the time of cost modeling. The definition of "value" to the customer is often communicated to the project team through contracts and construction documents, including drawings and specifications. Construction design evolves over the pre-construction phase of the project, and changes must be incorporated to deal with customer demand, site conditions, sourcing and procuring material and equipment, budget constraints, etc. Hence, it is important to ask: what scope of design to consider when defining value to the customer? and at what point of time is the design considered?

The limitations and the questions surfaced here make it clear that any production decision and its impact on cost have complex and dynamic relationships, full of trade-offs. A cost model that considers and surfaces these relationships to the planners is beneficial in making decisions.

3.5.3.4 Payment Terms for Production

When studying cost modeling from the perspective of different stakeholders, it becomes evident that the success of takt production, or any other method, is intricately connected with the payment terms and subcontracting strategies employed (Vatne and Drevland 2016). Despite this connection, takt is often rolled out alongside conventional subcontracting methods, leading to a potential mismatch in trade expectations versus the on-the-ground demands of takt schedules. This mismatch can make it financially challenging for trades to comply with a takt schedule, creating different understanding of cost and benefit for the stakeholders. These expectations can be matched connecting plans at various levels of planning (Ballard and Tommelein 2021), i.e., by creating strategic takt plan in early and high-level planning (at master scheduling level) and later using it to create a more detailed operational takt (at the phase scheduling level).

TVD as a delivery method and IFOA contact are some successful examples of mechanisms that allow sharing the benefits between stakeholders to stay within, or beating, the target budget. In conventional delivery methods and contracts, other strategies can be utilized to create benefits for individual stakeholders to work towards achieving a common goal. Bonus payments and contingency distributions to incentivize stakeholders are such examples (Morris and Ballard 2024).

The differences in perception between trades and GCs regarding takt or production objectives underscore the importance of aligning payment terms with project goals. Some examples of subcontracting payment terms include:

- Salaried: Workers with a fixed salary, not directly tied to the time spent (on-site) or the quantity of work done.
- Per hour: Workers paid an hourly rate.
- Lump Sum: A fixed total payment for the completion of a project or a task, independent of time and the amount of work.
- Piece-rate: Payment based on the quantity of work performed.

The payment terms are dependent on the following variables:

- Time on-site: Amount of work time spent on the site. This variable is for payment terms that depend on the resource’s presence on the job site, regardless of the work performed.
- Time working: Amount of time spent working. This variable is for payment terms that depend on the actual time workers spend working, counted in full workdays.
- Amount of work: Quantity of work completed by a worker. This variable is for payment terms that depend on the quantity of work completed (piece-rate).

- Time and work independent: This relates to workers who are paid independent of the time or amount of work done.

To reconcile the differences and trades commitment to takt production, using incentives and other takt specific payment terms in the contract is beneficial. Implementing stage payments provides a financial incentive for trades to complete their assigned tasks in accordance with the takt schedule (Keskiniva et al. 2022). Moreover, trades need to explicitly address how idle time is accounted for and compensated, ensuring that the cost implications of any downtime are transparent and accounted for.

To make takt successful, various strategies are used to absorb uncertainty, such as use of resources. However, like slack, these strategies can be implemented by adopting measures that are planned (such as underloading steps) or that are defined in an opportunistic way (Formoso et al. 2021). These opportunistic measures can come from allowing trades to have flexibility, that can be woven into subcontract agreements. Such flexibility ensures that trades can adjust to modifications in the takt plan without suffering financial penalties, thus maintaining the flow and efficiency that takt production aims to achieve. By doing so, the payment terms directly support the production objectives, reducing other negative impacts from the trade-offs.

3.6 Conclusions

This chapter introduced the WDM and the ViWoLZo tool for location-based project production planning. The WDM is essential for computing work density, which aids in workload leveling and zoning to create effective production plans. ViWoLZo supports decision-making and what-if analyses by providing visualization and computing support.

The chapter presented ViWoLZo, a novel computing tool designed to facilitate construction process planning using the WDM. Due to the novelty of ViWoLZo, data collection from the B33 case study project team was necessary. The tool's application in the B33 case study demonstrated its effectiveness in planning and controlling project production. It provided an example of ViWoLZo's use in practice. ViWoLZo's dashboard allows users to visually identify a work space and steps within it, and then to explore alternative zoning scenarios that leverage the underlying work density data while considering metrics of the quality of the resulting process plan. These metrics, particularly those pertaining to workloads, are not commonly used in other planning methods but are highly relevant in work structuring, among other aspects. Using ViWoLZo for what-if analyses enables users to make data-driven decisions regarding the satisfaction of workloads and process plans in meeting schedule milestones. The tool, the procedure to use it, and the metrics present significant improvements and contribute new knowledge to construction process planning.

The tool's conceptualization, programming, and data entry required inventiveness in breaking away from a CPM-planning mindset. Obtaining the required data from trades and project field personnel was tedious. However, once the framework is populated with input data for a specific project, zoning the work space and creating workload histograms becomes straightforward.

Key production parameters and metrics were identified to evaluate the quality of production plans and measure performance. The chapter emphasized the importance of balancing performance for individual trades and the overall system to meet customer demand. These production parameters and metrics are implemented in the production control dashboards in Chapter 5.

ViWoLZo demonstrates that work density is a useful concept for exploring workload leveling and zoning alternatives. While initially developed to support takt planning, ViWoLZo has broader applications. It supports methodical and data-driven decision-making about construction process design, work space zoning, and workload leveling, even when takt planning itself is not the end goal. In Chapter 4, I build on the learnings from developing ViWoLZo to introduce a novel data-driven framework for production planning and control, centered on work density. This framework is implemented in a subsequent case study to develop the production control- (Chapter 5) and production planning (Chapter 6) component.

Enhancements include transitioning from a grid cell-based approach to a context-specific representation of work density, streamlining and automating the acquisition of work density data, and integrating production control with production planning to enhance practical application and incentivize collection of real-world data.

Additionally, the chapter highlighted the integration of cost modeling with production parameters to enhance decision-making. The framework developed for cost modeling connects production system design to project costs, facilitating continuous cost monitoring and control.

In summary, the chapter presented ViWoLZo as a powerful tool for location-based production planning, offering a data-driven approach to workload leveling and zoning. The findings and methodologies discussed provide valuable insights for improving production planning and execution in construction projects.

Chapter 4 Data-Driven Production Framework (DDPF) Overview

In chapter 3, I described Visual Workload Leveling and Zoning (ViWoLZo) as a data-driven approach for production design decision-making, using work density data. The collection of this data and the data analysis for ViWoLZo are predominantly manual in nature. The ViWoLZo approach, being labor-intensive and time-consuming, is susceptible to subjective bias and error arising from variability among individual people responsible for data collection. To mitigate the challenges faced in collecting and analyzing data, the current chapter introduces a novel framework, called Data-Driven Production Framework (DDPF), that incorporates an automated and objective approach to data collection and analysis.

Section 4.1 outlines the proposed data model and compares it to the model used in ViWoLZo. Section 4.2 describes a novel data schema designed with the proposed data model in mind. Following this, Section 4.3 provides an overview of DDPF, which uses a shared data model unifying production control and production planning components. This section also touches on some important characteristics of DDPF, including the use of Machine Learning (ML) and other data-driven methods to predict work density, and the need for implementing the production control component before the production planning component.

Finally, Section 4.4 provides context to the Project O case study and explains the methodology for data collection and tool development for the application of DDPF, as implemented on the case study. The subsequent chapters describe the case study-based development of the production control- (Chapter 5) and production planning (Chapter 6) components of the DDPF. They detail the procedure for data collection, analysis, storage, and reporting.

4.1 Data-Driven Model

Data-driven models are built by analyzing data and identifying patterns, despite working with limited or no assumptions about the system they are modeling. These models use ML algorithms and improve over time as more data becomes available. They work by learning from real measurements, so they can accurately represent the complexities of the real world without simplifying or making assumptions.

Figure 4.1 presents the proposed data-driven model, illustrating the process of data collection, analysis, storage, and subsequent utilization in production planning and control. This figure juxtaposes the new data-driven model with the current models of the Work Density Method (WDM), as used in the ViWoLZo, facilitating a direct comparison.

The figure follows a left-to-right flow progression of data inputs to outputs. The top segment of the figure characterized by green-colored boxes depicts the existing model used with ViWoLZo. In contrast, the bottom segment of the figure characterized by yellow-colored boxes depicts the new model designed to enable semi-automated data collection and analysis. Comparable steps between the two models are aligned vertically starting from data collection to data analysis and storage, and then merging at ViWoLZo. Although both models use ViWoLZo as the tool supporting production planning, it can be replaced by any tool based on the WDM, e.g., WoLZo (Jabbari et al. 2020a, Tommelein 2022, Singh and Tommelein 2023b).

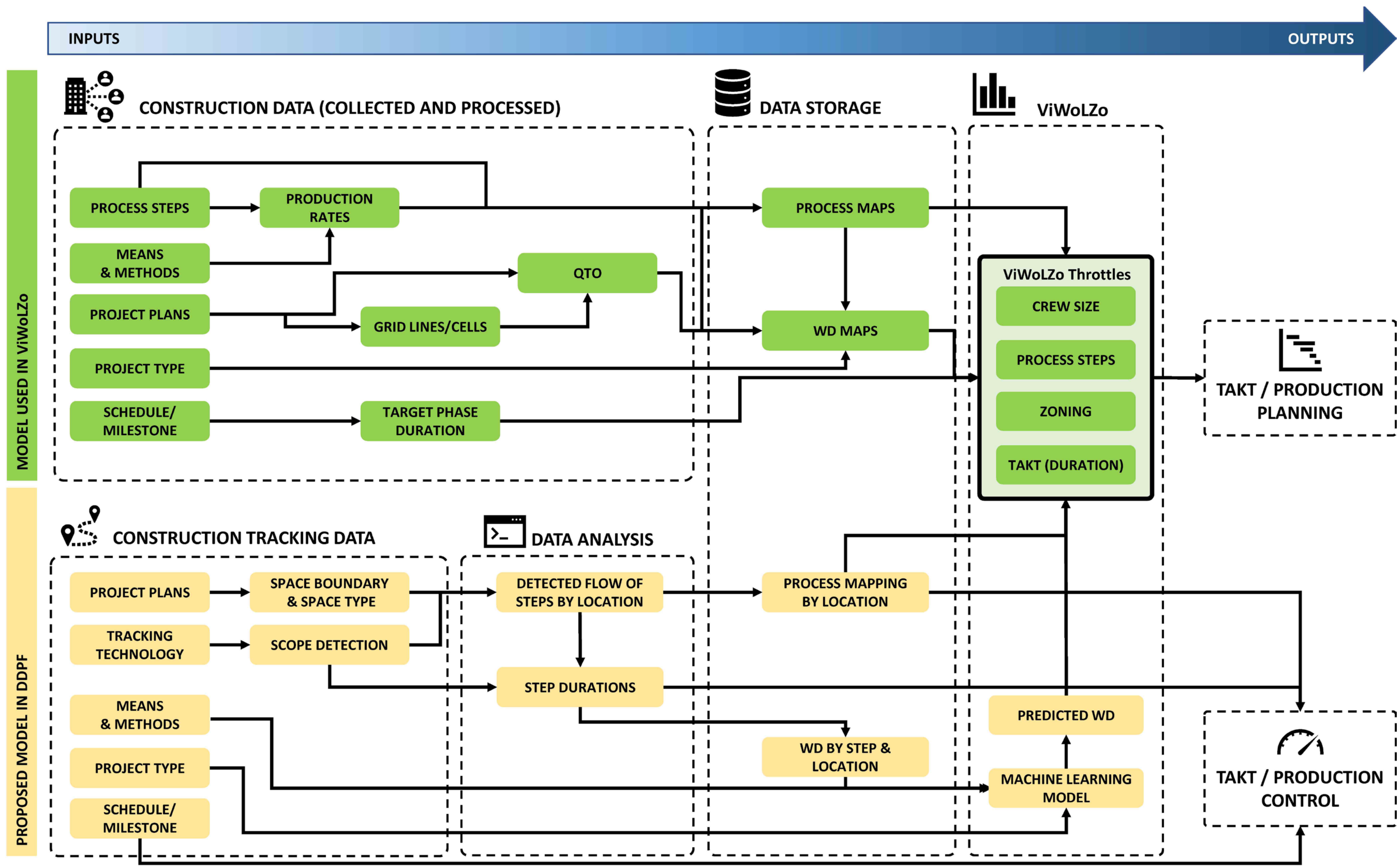


Figure 4.1: Existing and proposed data model.

The need for this new model (bottom segment in Figure 4.1) comes from various limitations of the previous model (top segment). These limitations are:

1. Limited Scope of Research: The existing body of research on the use of the WDM, including methodology described for ViWoLZo pertains to only production planning as the output. It does not explicitly include production control.
2. Manual Data Collection and Processing: Numerous steps in the data collection and processing entail manual work, contributing to inefficiencies and subjectivity.
3. Custom Configuration Requirement: Each project requires a custom configuration of the tool, involving quantity take-offs (QTOs) and process maps.
4. Data Collection from Diverse Sources: The data collection process extends to the project team, which includes trades participating in the project, amplifying complexity.
5. Challenges in Gathering Production Rates: The collection of production rates data poses challenges, as trades often consider the data to be confidential or will buffer the values when sharing such information.
6. Development of Grid-based WD: Work density is calculated and stored in cells for which a grid system is defined bespoke to a site plan, which makes it difficult, if not impossible, to use the work density maps from one site plan to another.

To overcome these limitations of the previous model, the newly proposed data model does not rely on manual collection of process maps, QTOs, grid lines, or production rates to derive work density values. Instead, it utilizes data observed from tracking technology tailored to the project's requirements, marking a shift towards a new data-driven approach. In this approach, production tracking becomes automated. However, the collection of certain contextual data related to the project and its processes, such as project plans, project type, means and methods, and location types, still requires manual effort.

The new model analyzes the collected data to compute the duration of each step and identify the sequence flow of steps, which allows the calculation of work density per step per location. In Chapter 5, I describe the implementation of this model by assuming continuous flow of work. This assumption is a limitation of the new model, discussed further in Section 5.5.3.1. Concurrently, the new model uses this data in real-time to support a production performance dashboard, which presents information to the project team for production control. Thus, the model uses a combination of tracking- and contextual data (1) as input features for a ML-based work density prediction that supports production planning, and (2) as the basis to update the production performance dashboard that supports production control, thereby completing the flow progression of data from inputs to outputs.

All the collected data stored in a dedicated database creates a repository of historical work density values along with project and process features, moving away from grid-based work density maps. This database forms the basis for training a ML model capable of predicting work density values for a given set of input features in a future project.

Despite the strengths of a data-driven model and its ability to overcome the limitations of the existing model, this approach has its own limitations:

1. It can be hard, if not impossible to understand the model's logic, as many ML models operate in a "black box" manner. For some types of ML models, the internal logic and computations

that lead to the output are not transparent, making it difficult to trace how and why specific outputs are generated.

2. Since the model learns from previous examples, it might replicate any biases present in those examples.
3. The model's success relies on the design of the data schema and the quantity and quality of collected data.

Considering these limitations, I have adopted specific strategies in this research. To address the first two limitations, I have implemented countermeasures in the data collection, analysis, and model training process, which I will describe in Section 6.4. For the third limitation, I suggest a new data schema to support the data model, which will be outlined in the following section.

However, the quantity of data used remains the most significant limitation not addressed in this research. The scope and opportunities of this research limited the creation of the data-driven framework and a proof-of-concept application of this framework to a single case study. To enhance the performance of the ML model, more data needs to be collected to make the prediction generalizable and reliable. This entails adding more projects and a greater variety of parameters to be captured in the training data. Chapters 5 and 6 go beyond a single case study proof-of-concept by exploring how data collection efforts can be improved in the future.

4.2 Database Schema

In ViWoLZo, the tool calculates work density by multiplying two data inputs: (1) production rates with (2) quantity of work (see Section 3.2.4). Work density is stored at a cell level in the form of work density maps. The process maps store the sequence of steps, and for each step, a work density map is generated as part of the planning process. Work density values in the work density map format are an estimate of time to be taken by that step to complete that step's scope in a cell (of the map). In contrast, the proposed data model (Figure 4.1) measures the work density using the actual amount of time taken to complete a scope of work, instance by instance, in a type of space, by a particular step, and other contextual information related to the project, process, and location. The resulting work density values are stored in a Process Step Library as time for a given set of parameters coming from the contextual data collection.

Similarly, in ViWoLZo, the process maps are created through manual data collection—either by participating in pull planning sessions or by extracting the information from a schedule. In contrast, the proposed data model identifies a sequence of work detected by location and generates the process map. The resulting maps are stored in a Process Library along with a given set of parameters coming from the contextual data collection.

Figure 4.2 uses an Entity Relationship Diagram (ERD) to show the Process Step Library, Process Library, and other datasets used in the data model. This ERD visually represents the data model as a relational database (Chen 1976). The data entities in the diagram exist as individual tables described by their feature type, feature name, and feature data type (three columns of the ERD tables).

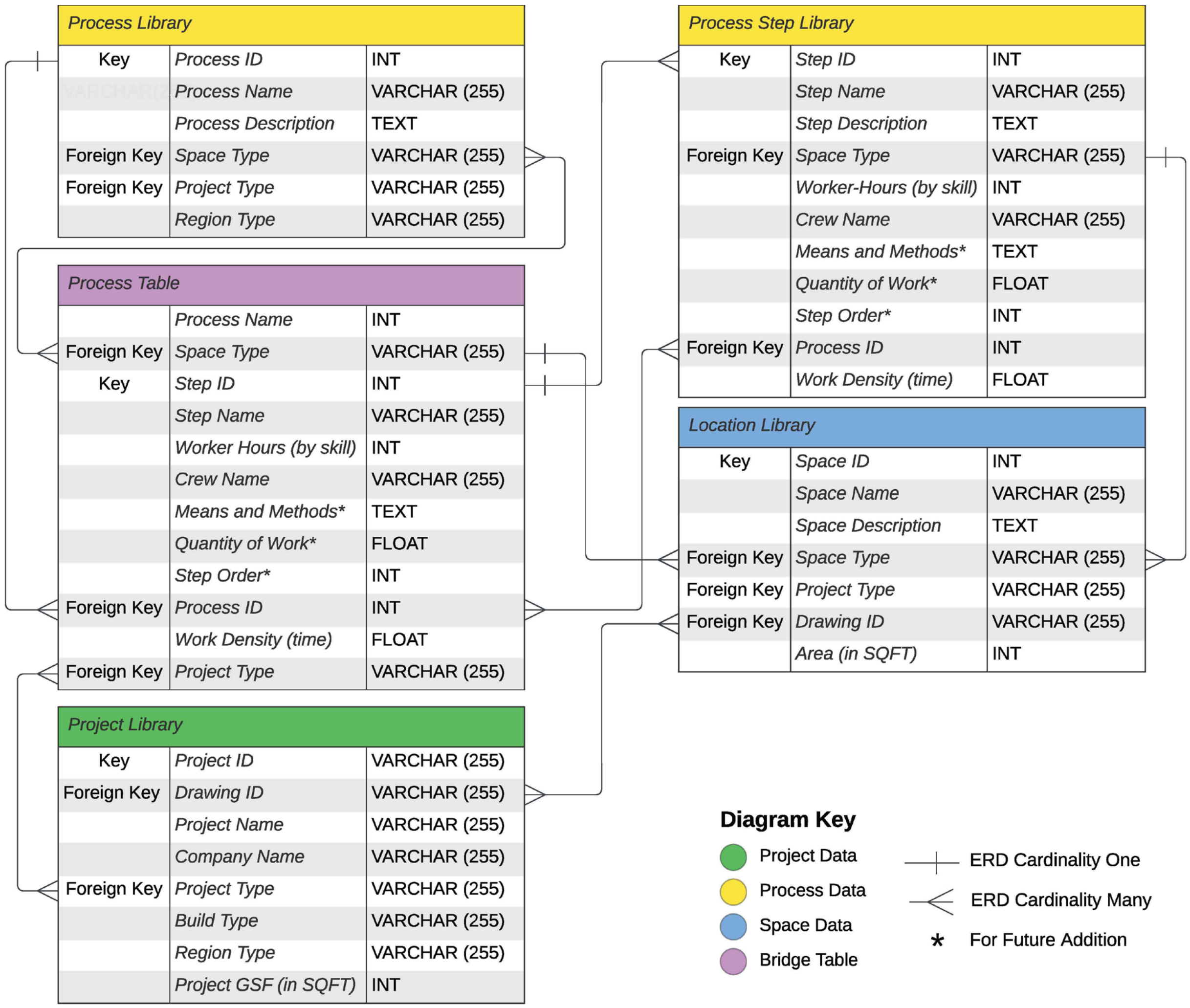


Figure 4.2: The Entity Relationship Diagram (ERD) for production database.

The entities in the data schema include:

- **Project Library** (Figure 4.2 bottom left): A project (i.e., a construction project) is the combination of all the spaces being built. Project library data provides characteristics about the type of project (e.g., hospital, multi-family residential, commercial, mixed-use), type of build (e.g., core and shell, tenant improvement, greenfield, brownfield), and type of region (e.g., urban, suburban, rural). These characteristics affect the types of spaces, processes, and process steps that exist in a project.
- **Process Library** (Figure 4.2 top left): A process is a set of steps that must be completed to achieve a desired outcome. Process library data provides the sequence of steps (linear or in parallel) for a process, grouped by types of space, project, and region.
- **Process Step Library** (Figure 4.2 top right): A process step represents a certain scope of work performed by a single trade (or possibly a crew composed of multiple trades). Process step library data includes the work density value for the step, which provides a numerical value of work density in terms of working time (calendar-hours or calendar-days), quantity of work, and the associated process, step, and space parameters. It also holds the contextual

data about the worker and crew trade skill particulars, including the crew composition (e.g., foreman, journeyman, apprentice), special means and methods (e.g., prefabrication, equipment, automation) and worker-hours by skill.

- **Location Library** (Figure 4.2 bottom right): A location library stores data related to spaces. Space is a physical area within a building or other type of structure. For example, a space might be a room, a corridor, or a stairwell. Space geometry provides the factor to normalize the work density data and space type provides the contextual reference to categorize steps and work density. A space type is a category of space, differentiated by the scope of work and the process steps associated to the type of space.
- **Process Table** (Figure 4.2 middle left): A process table is a bridge table created by joining the other four data tables. A bridge table connects two or more tables in a many-to-many relationship within a database and contains the keys from multiple tables. This bridge join facilitates the creation of a unique process for every possible pairing of space types and project types.

The ERD demonstrates the cardinality of each relationship, where cardinality signifies the potential number of entities that can associate with each other within a relationship. The diagram in Figure 4.2 uses crow's foot style to show cardinality (Everest 1976). The ERD utilizes cardinality symbols to convey the nature of these associations: the "Cardinality One" symbol indicates that relationship can associate with only one entity on that side of the relationship, whereas the "Cardinality Many" symbol indicates that relationship can associate with one or more entities on that side of the relationship. The entity relationships in the proposed schema include:

- Process-to-Process Step (one-to-many): A process can have many process steps, but a process step can belong to only one process.
- Process-to-Location (one-to-many): A process can be associated with many spaces (all the spaces of one space type), but a space can be associated with only one process.
- Process Step-to-Location (one-to-many): A process step can be associated with many spaces (all the spaces of one space type), but a space can only have one instance of a process step.
- Project-to-Location (many-to-many): A project can be associated with many spaces, and a space can also be associated with many projects (all the projects of one project type).
- Project-to-Process (many-to-many): A project can be associated with many processes, and a process can also be associated with many projects (all the projects of one project type).

The proposed data schema also introduces some fields (also called attributes in ERD terminology) for future addition. These fields are marked by an asterisk in Figure 4.2. Given the chosen research scope and implementation opportunities, this research does not include the effects of ordering or sequencing of steps, means and methods, and quantity of work. I discuss these limitations and areas of future work in Chapter 7. The design of the proposed data model and data schema support a data-driven production system. Next, I describe a framework that enables the use of this data model and schema in such a production system.

4.3 Framework for Data-Driven Takt Production

4.3.1 Framework Overview

Figure 4.3 illustrates the DDPF for data-driven production planning and control. It leverages data to drive decision-making at all levels of production management, including production planning, scheduling, and control.

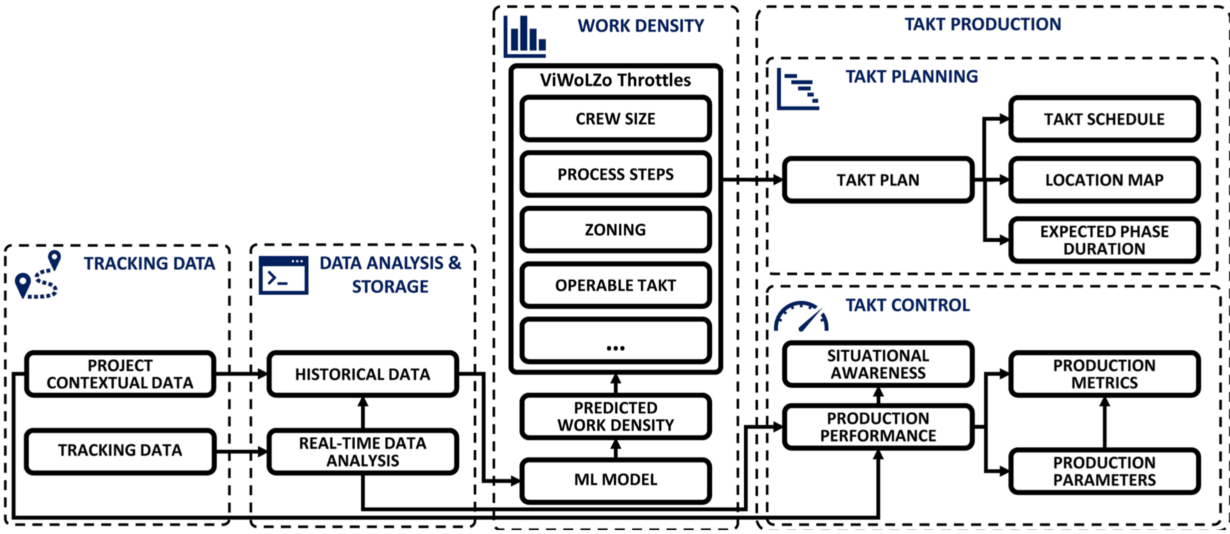


Figure 4.3: The DDPF for data-driven takt production planning and control.

DDPF has four components:

1. Tracking Data encompasses both manual and automated data collection initiatives, gathering contextual data from the project team and real-time tracking data through the use of tracking technology. The application of this component is described in Sections 5.2 and 6.2.
2. Data Analysis and Storage involves the analysis, transformation, and storage of data derived from the Tracking Data component. The application of this component is described in Sections 5.3 and 6.2.
3. Work Density includes utilization of ViWoLZo (or other tools) for the WDM to support production planning. It also includes prediction of work density using an ML model on a historical dataset. The application of this component is described in Section 6.3.
4. Takt Production (or Production Planning and Control) has two distinct sub-components:
   4.1. Takt Production Planning is for system users to determine the pace of production, based on the customer demand and the available capacity, and then to create a production plan that achieves the desired takt. The application of this sub-component is described in Section 3.2.
   4.2. Takt Production Control is for system users to monitor the production process in real time and to adjust the planned process as needed to maintain the desired takt or other production targets. The application of this sub-component is described in Section 5.4.

DDPF is described through the example of takt production. However, the framework design is generic such that it can be used for location-based production systems other than takt production (see Section 2.2.3 for non-takt location-based production).

4.3.2 Machine Learning for Work Density Prediction

ML refers to mathematical algorithms that apply statistical and computational techniques to identify patterns within a dataset. Unlike conventional rule-based methods, ML algorithms do not require explicit programming to accomplish a specific task. This is because the learning mechanism unfolds as the algorithm is exposed to the data, preferably a large set. Importantly, this approach significantly diminishes the need for domain-specific knowledge. Instead of programming the algorithm with extensive domain expertise, the focus shifts to the design and implementation of mathematical and statistical algorithms. Thus, although the intricacies of domain knowledge are not embedded directly into the system, the algorithms are adeptly crafted to analyze and learn from the data presented to them (Brunton et al. 2016).

The proposed framework does not intend to change the use of work density, as is done for example in ViWoLZo. It instead proposes a way to collect data of actual work done to measure work density by step and location. ML models are trained on the work density, and contextual data associated to the project, processes, and locations, to predict work density for future projects. This data-driven prediction-based work density is intended to be an input to ViWoLZo, or other work density-based tools, for production planning.

In this research I choose the ML model based on several criteria, specifically:

- the type of data collected—categorical data vs. numerical data
- the size of the dataset—number of data points vs. number of features
- the form of data—time-series data versus generic data

I applied common unsupervised ML techniques, including dimensionality reduction and clustering, to understand the effects of the input features on the target feature (which is work density). By identifying patterns and relationships within the data, these techniques help narrow down the significant variables from a potentially vast set of features. This focused approach allows for efficient data collection by targeting those features with a higher impact on predicting work density, thereby optimizing the data acquisition process without compromising the accuracy of future models.

The delayed prediction of work density makes planning not feasible while the data is being collected pushed the development of the production planning component after the production control component. The next section explains why.

4.3.3 Control Before Planning

The data model (Figure 4.1) and the framework (Figure 4.3) extend the application of the WDM beyond production planning by including production control. This extension prioritizes the development of the production control component before the production planning component for two reasons.

First, the work density data is generated using data collected by observing actual work on-site, as opposed to being calculated based on QTO and production rate estimates (as it is done in ViWoLZo, or other tools using the WDM described in Section 2.2.4). To encourage project teams to earnestly collect the work density data so that it can be used for production planning in future projects, it is advantageous to create a more immediate benefit. Using the collected data to support production control is one such benefit (among other benefits including managing safety, quality, logistics, etc.).

Second, the existing literature does not mention how work density might be used to support production control. To utilize work density for production control, it is important to identify and include control requirements in the data collection and storage process. Understanding these requirements is important because it ensures that the data collected is not only comprehensive but also directly relevant to the needs of production control. A plan is beneficial only when it can be effectively monitored, analyzed, and adjusted in real-time to deal with plan variations.

These two reasons make it advantageous to leverage the collected tracking data for production control. This approach is implemented during the production control of a case study. The next section provides the context of the case study project and the methodology applied in data collection and tool development.

4.4 DDPF Case Study: Project O

4.4.1 Project Context

I used production tracking data to support production control and developed a proof-of-concept tool on a case study of the construction project at 1450 Owens Street in San Francisco, California, which I will refer to henceforth as Project O. The scope of Project O encompassed the core and shell construction of a seven-story mixed-use commercial and retail tower, and a rooftop penthouse (Figure 4.4). Characterized as a warm shell construction, Project O aligns closely with the concept of a turn-key project. It includes completed bathrooms, finished drywall, and all electrical, mechanical, and plumbing installations, making the building almost ready for occupation except for cosmetic enhancements and interior finishings.

Figure 4.4: Case study project (photo taken by Vishesh Vikram Singh, 11/09/2023).

The project encompasses about 12,400 m^2 (133,000 ft^2) of laboratory space, 4,600 m^2 (50,000 ft^2) of office space, and 240 m^2 (2,600 ft^2) of ground floor retail area (Truebeck Construction 2023). The total size of the project is therefore about 17,200 m^2 (186,000 ft^2), i.e., on average about 2,460 m^2 (26,500 ft^2) per floor.

The amount and types of work to be performed on level 1 and at the penthouse (roof level) differs significantly from the rest of the building. Hence, the scheduled flow of work is different on these two levels. Levels 2 through 7 have a similar floor plan and follow a sequenced flow of work in the schedule. Figure 4.5 shows level 5 floor plan as an example for a typical floor. The plan consists of a core located in the center and surrounded by continuous open area. Figure 4.6 shows a closer view of the central core and all the rooms located inside it. The rooms are described in detail in Section 5.2.1.

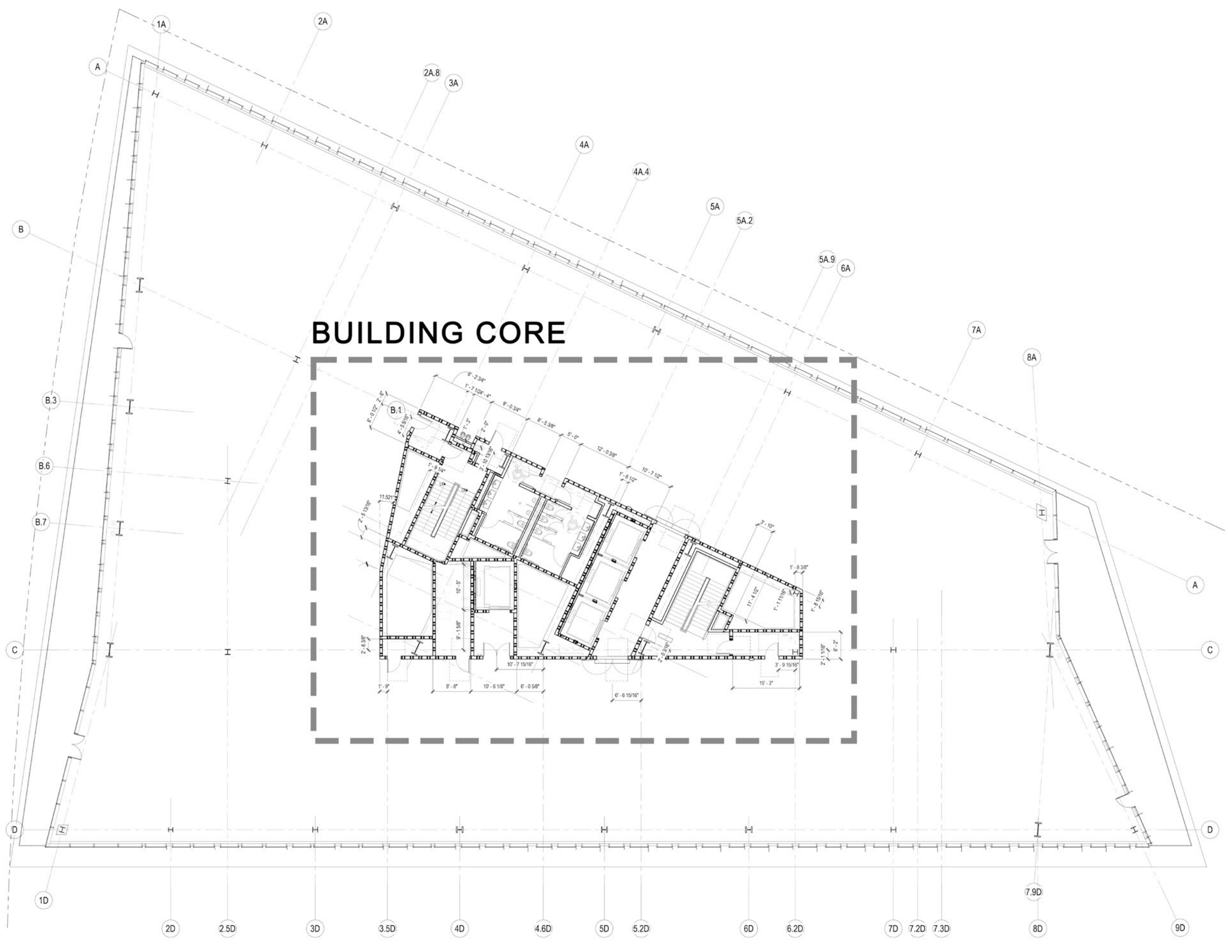


Figure 4.5: Project O typical plan with level 5 as example (used with permission by Truebeck Construction 2023).

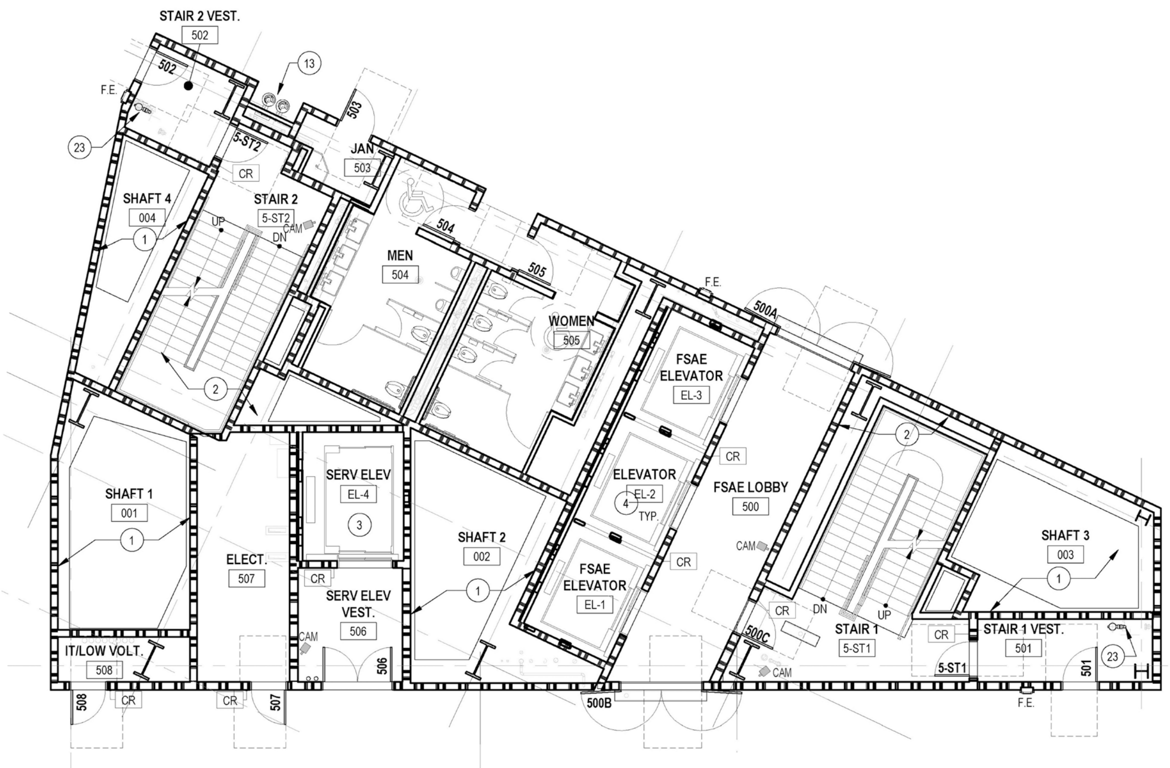


Figure 4.6: Project O typical plan of building core with level 5 as example (used with permission by Truebeck Construction 2023).

The scope of this research was limited to tracking and collecting data for levels 5, 6, and 7. These levels share identical floor plans with minor deviations around the periphery, such as the introduction of balconies on level 5 and two atriums spanning from level 5 through 7.

Chapters 5 and 6 provide more details about the project related to the control and planning applications of DDPF respectively. I developed and tested the production control component during the Project O case study. After the completion of the case study, I used the collected data from Project O to develop the production planning component. Next, I describe the methodology used to collect data and develop the tool.

4.4.2 Methodology for Data Collection and Tool Development

Construction projects are complex and often involve many stakeholders. This can make it difficult to track progress and proactively identify problems. With the ability to visualize actual performance, measure key project metrics, and identify trends, a production performance dashboard can help project managers and other stakeholders overcome this difficulty.

Figure 4.7 shows the methodology used for data collection and tool development to support DDPF. The methodology is based on an iterative process of data collection, dashboard development, reporting, and feedback from the case study's project team. Before choosing this case study, I had already decided on the tracking technology solution—360° camera-based tracking—as described in Section 2.4.2.

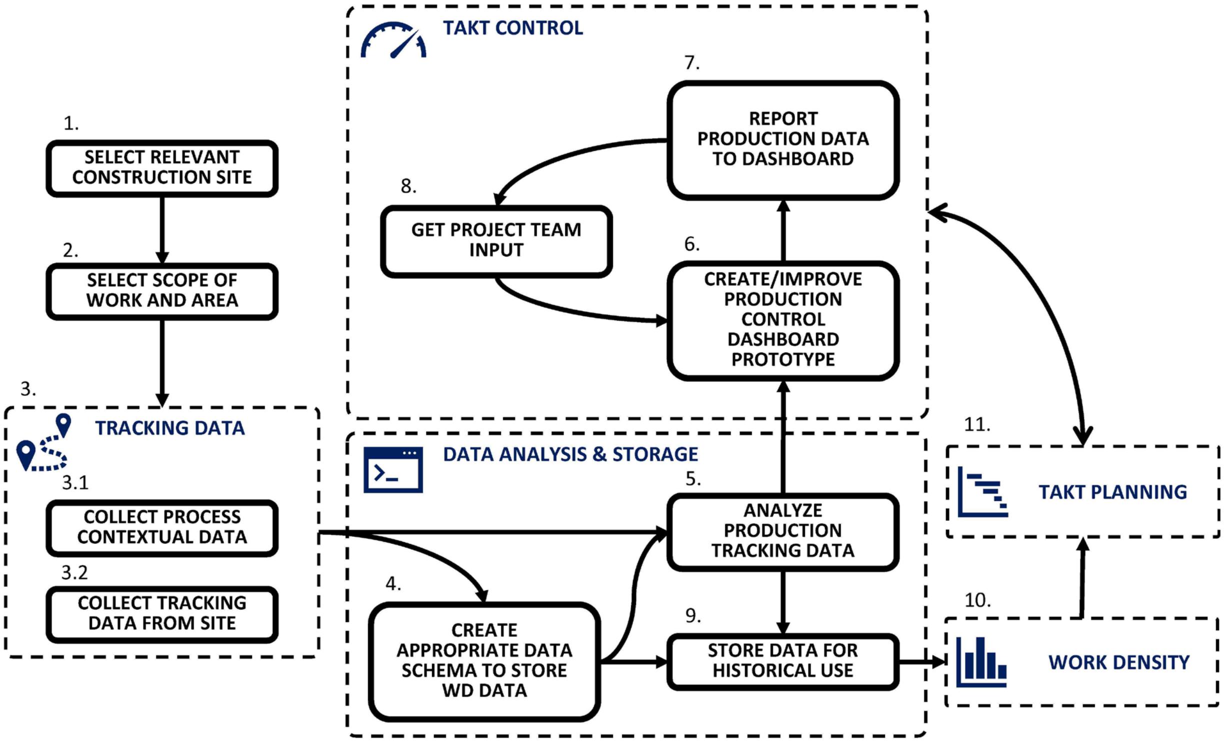


Figure 4.7: Methodology for data collection and dashboard development.

The methodology for data collection and dashboard development includes the following steps:

1. Select construction site: In selecting a suitable construction site (Project O in this case study), I took the following considerations into account: the size of the project, the phase of the project, buy-in from the project team, and access to project and tracking data. These considerations were matched to the project preference for this research, described in Section 1.6.

2. Select scope of work and area: I selected the scope of work and area to be regularly tracked and monitored through the dashboard. This step involved understanding the scope of work scheduled during the study period, the trades responsible for the work, and the expected stage of work in different locations. This understanding came from the studying of project schedule and conducting interviews with the project team. Additionally, the study of floor plans provided an understanding of the various types of locations and the work anticipated in them. I used some of the data collected in this step as contextual data and collected more in the subsequent step.

3. Data collection:

    3.1. Collect process contextual data: I collected process contextual data to include information about the individual steps in the construction processes expected to be observed. This step aimed to gather information that could not be captured or detected by the tracking technology, providing context on who was doing the work, how (the means and methods used) the work was being done, when the work was happening, and where the work was taking place. This included details such as the crew composition (including their skill levels and role) and their location of work for each step. Sections 5.2.1 and 6.2 detail this step.

3.2. Collect tracking data from site: I collected (progress) tracking data from the site for the selected work and area. Progress tracking included gathering data using a 360° camera-based tracking solution. I selected the frequency of data collection based on the selected technology solution's capture frequency limit, the physical effort required, and the cost of processing the data, as well as the objectives of the end-user (who is the dashboard user, how often do they need the information, and what is the shortest control interval). Section 5.2.2 details this step.

4. Create data schema: I created an appropriate data schema to store work density data. The schema design supports both production control and planning applications, as detailed in the data model in Section 4.1 and the proposed data schema in Section 4.2. I further refined the schema according to the specifics of the data collected from Project O and the 360° solution provider (Section 5.3.1, 5.3.2, and 6.2.5).
5. Analyze production tracking data: I analyzed the production tracking data by cleaning, transforming, and analyzing the work detection data collected from the 360° camera-based tracking and the contextual data collected from the project team. The analysis made the data suitable for the next steps: dashboarding (in step 6 for the production control application) and storage (in step 9 for the production planning application). Section 5.3 details this step.
6. Create and improve production control dashboard: I created and iteratively improved a production control dashboard prototype. The basis for the initial dashboard design rested on the dashboard's identified purpose and its documented use cases (as per Section 5.1), while also accounting for the limitations presented by the data and technology at hand. Based on feedback from the project team, I refined the dashboard. Section 5.4 details this step.
7. Reporting Production Data: I reported the analyzed production data to the project team by sharing it on a dashboard. I programmed the dashboard using a web-based data visualization tool and established a live link to work detection updates.
8. Get project team input: I collected feedback on the shared data and dashboard design from the project team. This ensures that the dashboard aligned with the information requirements of the project team and the involved stakeholders' production control efforts.
9. Store data: I stored the collected data as per a process and location-based data schema (see Section 6.2.5) upon the completion of the case study.
10. Work density: I transformed the stored data to measure work density by process step and by location, and later merged it with process and project contextual data. The complete data is prepared, through processing and feature engineering, to be trained on ML models. This is done to extract information on the effects of features on the work density and to train a model to predict work density. Chapter 6 details this step.
11. Takt Planning: I trained and tested ML models with the objective of predicting work density based on a set of input features related to the project, process, and work location. Although I implemented this step following the case study and did not apply it in creating a takt plan, I previously demonstrated the application of work density for production planning in the B33 case study through ViWoLZo, as described in Section 3.2.

In the next two chapters I will further describe these steps as well as the components of the framework. Chapter 5 details the procedure for data collection, analysis, storing, and reporting required for the control component of the framework. Following that, Chapter 6 details the procedure to transform collected data into a historical dataset, required for the planning component of the framework. This transformation allows application of advanced data-driven techniques, such as feature engineering, dimensionality reduction, and ML, to support production planning of future projects.

4.4.3 Technology Stack

During data collection and tool development, I used specific hardware and software technologies (technology stack) to facilitate data collection, data wrangling, analysis, and the implementation of ML models. This section delineates the technology stacks utilized across different steps of the research as detailed in subsequent chapters.

The technology stack for automated data collection, discussed in Section 5.2.2, utilized the StructionSite platform, now acquired by DroneDeploy. This involved the use of their 360° VideoWalk feature, which integrates time-lapse footage captured via the Insta360 One X2 camera. I extracted the data from StructionSite's database using Structured Query Language (SQL).

The technology stack for the data wrangling and analysis steps of the DDPF, discussed in Sections 5.3 and 6.2, used Python (3.9.13) programming language in the Jupyter Lab (4.0.6) environment. Key Python libraries used included Pandas (1.2.4), NumPy (1.26.4), Matplotlib (3.4.2), and Seaborn (0.11.1), facilitating comprehensive data manipulation and visualization.

The technology stack for the production performance dashboard step of the DDPF, discussed in Section 5.4, involved developing a dashboard on Google Looker Studio (henceforth referred to as "Looker Studio") using Google Chrome web browser (version 122.0.6261.131, 64-bit). Looker Studio is an online tool for converting data into customizable, informative reports and dashboards. I selected this software application as it provides a complete solution from data storage to reporting.

The technology stack for the ML implementation step of the DDPF, discussed in Section 6.3, also used Python (3.9.13) programming language in the Jupyter Lab (4.0.6) environment. Key Python libraries used included Pandas, NumPy, Matplotlib, Seaborn, along with machine learning and deep learning frameworks such as Pandas (1.2.4), NumPy (1.26.4), Matplotlib (3.4.2), Seaborn (0.11.1), Scikit-Learn (1.4.1.post1), TensorFlow and Keras (2.15.0), CatBoost (1.2.2), XGBoost (2.0.3), LightGBM (4.3.0), and Kmodes (4.3.0). These tools were integral in data preprocessing and developing predictive models to estimate work density.

I conducted the above mentioned data processing steps on a Windows 10 device (Processor: AMD Ryzen 7 4700U with Radeon Graphics 2.00 GHz, RAM: 16.0 GB, System type: 64-bit operating system, x64-based processor).

Chapter 5
Data-Driven Production Control

This chapter elaborates on the development of the production control component within the DDPF, initially introduced in Chapter 4. It details the method devised and the implementation of a proof-of-concept tool tailored for supporting production control, as demonstrated through its application in a case study Project O.

Section 5.1 outlines the data processing procedure employed in the Project O case study. The procedure is broken down into the three following sections: (1) the tracking data section (Section 5.2), (2) the data analysis and storage section (Section 5.3), and (3) the production control section (Section 5.4). The procedure is described in detail with the intent to create a method that supports data-driven production control. Finally, Section 5.5 reports the results and insights from the data processing and the case study.

5.1 Data Processing Procedure

Figure 5.1 presents an overview of the data processing procedure in three components: (1) on the left is "Tracking Data", (2) in the middle is "Data Wrangling and Analysis", and (3) on the right is "Production Control". The procedure follows the framework outlined in Figure 4.3 of Section 4.3. Each of these three components represent a component of the DDPF shown in Figure 4.3, and later illustrated in detail in Figures 5.2, 5.5, and 5.14, respectively.

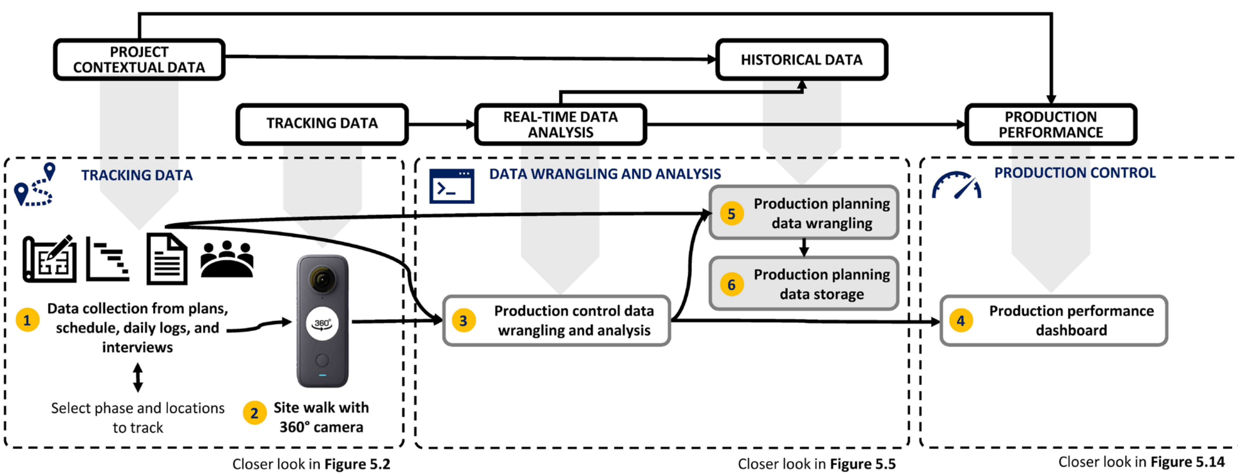


Figure 5.1: Overview of the data processing procedure for production control.

The procedural flow is depicted through arrows and the sequential steps are numbered in yellow circles, ranging from 1 to 6. The processed data after step 3 is further processed for production planning and then stored as historical data, labelled steps 5 and 6, respectively. These two steps are described later in the production planning component of DDPF (Chapter 6). The flow chart on the top of Figure 5.1 represents the associated element of the DDPF (from Figure 4.3), and the flow of data between these elements.

Next, I take a closer look at each of three sections and the steps, explaining the data structuring decisions made, processing actions taken, and outputs generated.

5.2 Data Collection

Figure 5.2 provides a closer look into the data collection component of Figure 5.1 (left), detailing the steps involved and the output generated at each step. Figure 5.2 is divided in two halves: (1) at the top is "Data Processing Steps" and (2) at the bottom is "Output example" corresponding to each step of the data processing procedure. The component is called "Tracking Data" because the data being collected tracks production on-site. To support the analysis of the tracking data, some contextual data was also collected.

Since the DDPF is a proof-of-concept, the required input data and the methodology for data collection were not readily available. The Project O case study allowed for an iterative development of this methodology while collecting the data. This included understanding the current state of data collection and the possibilities of a future state. The methodology is described in Section 4.4.2.

Through an iterative process of data collection and research scope definition, I familiarized myself with the project to answer questions such as: What contextual data is needed? What data is available? What tracking data should be collected? And when and where should it be collected? Answers to these questions came from talking to the GC's project team including the superintendents, foremen, and field engineer, as well as participating in the weekly field coordination meeting (GC staff only), and weekly trade partner foremen meeting including the GC and the trades. These answers were organized in the form of:

- A WBS to show the scope of work relevant to the time period of the study
- A LBS and types of spaces used in the schedule and for weekly planning and control
- Planned flow(s) of processes through different types of spaces
- Planning and control methods and tools used
- The project team's production control data needs

By aligning the project team's needs with the research objectives, I collected the data using the following steps (Figure 5.2):

1. Data collection from plans, schedule, daily logs, and interviews. This was done iteratively with the selection of a phase and locations to track.
2. Site walk with 360° Camera

Steps 1 and 2 are expanded in Sections 5.2.1 and 5.2.2, respectively.

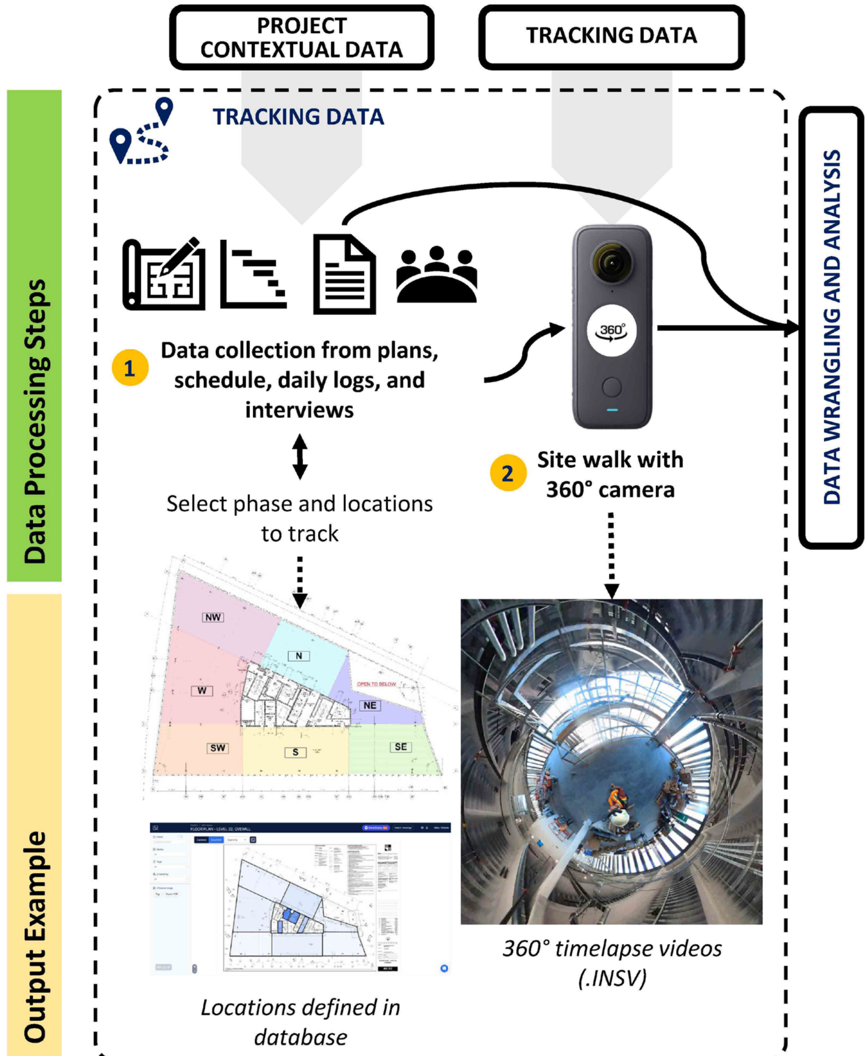


Figure 5.2: Tracking data component of the data processing procedure for production control.

5.2.1 Manual Data Collection

Following the establishment of scope for the case study in terms of spaces on the site and a timeframe, an iterative approach (as per Section 4.4.2) to manual data collection was adopted. This is step 1 in the data processing procedure (Figure 5.1 and 5.2). The step includes collecting contextual data to identify the scopes of work and locations for production tracking. The sources for the contextual data were:

1. Location Data: was collected to identify the characteristics of different spaces within the project structure, including their name, numbering convention, type of space, and any instances of multiple spaces with similar work. By matching the schedule to the timeframe of data collection, building floor levels 5, 6, and 7 were selected. These three levels included rooms and vertical shafts in the central core of the building, and a continuous open area around the periphery of the building (Figures 4.5 and 4.6). Table 5.1 provides an overview of the selected location data, including the names of locations, their types, location number ID system used to identify similar rooms across floors, and their average

area (in ft^2). Table 5.1 provides the average area of each location name across the three levels, but the actual area of each room slightly varied across levels.

2. Six-week Lookahead Schedule: was updated by the project superintendent, primarily on Fridays and then revised on Mondays in preparation for the weekly foremen meetings on Tuesday. The schedule served as a crucial tool for outlining the scope of work and assigning responsibilities to the various trades involved in the project. The schedule's primary purpose is to ensure that all parties are aware of their duties and the locations where the work needs to be executed. This is ensured primarily by discussing updates from the last week of work and the schedule for the next six weeks and discussing in detail the work scheduled in the upcoming week.
3. Daily Logs: capture day-to-day activities by scope of work, trade, and location. Commonly known as timesheets, daily logs offer detailed insights into the trade's daily operations, including scope of work performed, location of the activities, number of workers present, individual and total hours worked, and distribution of workers by their role: foremen, journeymen, and apprentices. Beyond the traditional timesheets, the daily logs are also used to document weather conditions from a weather station installed on the job site, and any delays caused due to weather conditions.

The open area was segmented into seven distinct zones, as depicted in Figure 5.3. The three levels had identical floor plans except for an atrium on the North East corner of the building, that started at level 5's slab and ended at level 7's ceiling. The atrium part of the floor plan is open to below for level 6 and 7.

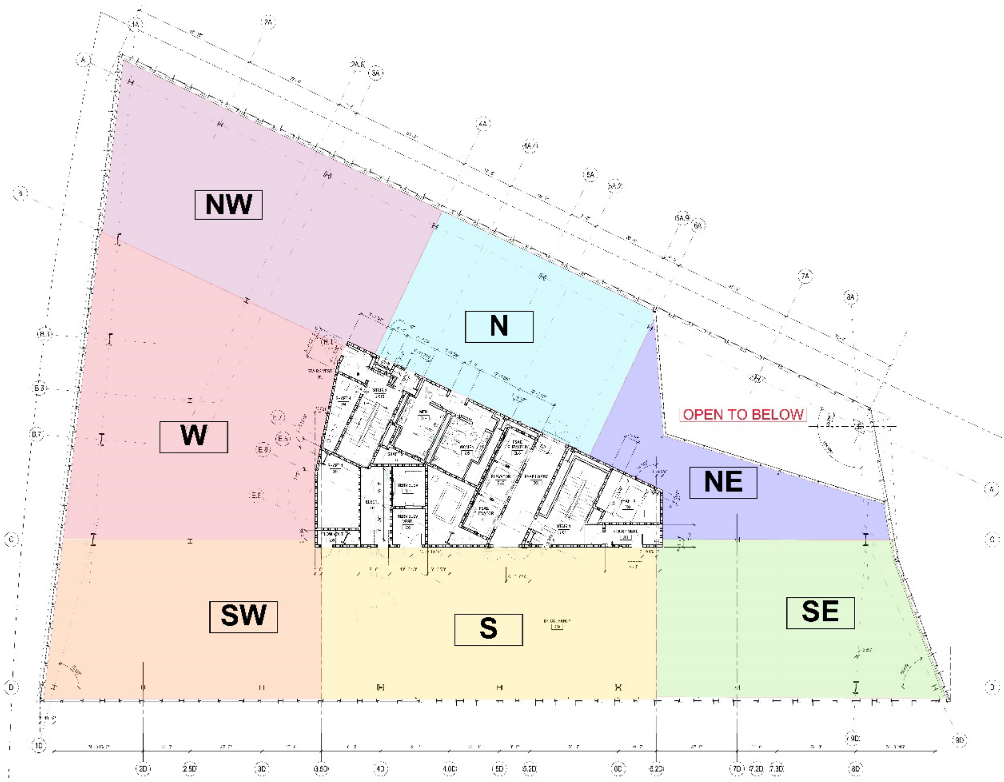


Figure 5.3: Open area zoning map for a typical floor (level 7 example here) on Project O.

Table 5.1: Location data overview for distinct location names.

Location name	Location type	Location number	Average area (ft^2)
Fire Service Access Elevator (FSAE) Lobby	Lobby/Corridor	x00 (e.g., 500, 600, 700)	259
Stair 1 Vestibule	Room	x01	81
Stair 2 Vestibule	Room	x02	65
Janitor's Closet (JAN)	Room	x03	41
Men's Bathroom	Bathroom	x04	195
Women's Bathroom	Bathroom	x05	281
Service Elevator Vestibule	Room	x06	89
Electrical Room	Room	x07	171
Information Technology and Low Voltage Room (IT/LOW VOLT.)	Room	x08	44
North East (NE) Zone	Open Area	x81	2,810
South East (SE) Zone	Open Area	x82	3,070
South (S) Zone	Open Area	x83	3,863
South West (SW) Zone	Open Area	x84	2691
West (W) Zone	Open Area	x85	4,449
North West (NW) Zone	Open Area	x86	4,096
North (N) Zone	Open Area	x87	2,898
Staircase 1	Staircase	x-ST1	372
Staircase 2	Staircase	x-ST2	236

An understanding of the contextual data gathered from these three sources provided information about the locations and the processes to track, which is covered next in step 2

5.2.2 Automated Data Collection

The production tracking part of the data collection was automated using the chosen tracking technology solution—360° camera-based tracking (described in Section 2.4.2). The data was collected using the StructionSite (owned by DroneDeploy) 360° VideoWalk platform (StructionSite 2022b). VideoWalk is a form of reality capture that uses a single 360° image, or a series of images extracted from a time-lapse video. In this research, all the VideoWalks are extracted from a time lapse shot on Insta360 One X2, at a frequency of 0.5 second, and image resolutions of 5760 pixels × 2880 pixels.

Figure 5.4 shows a screenshot of 360° VideoWalks from Project O on the StructionSite application. The center of the application shows a level 5 floor plan with locations marked as per the convention described in Table 5.1. In the selected location of West (W) Zone, the orange dots represent individual 360° image frames from the time-lapse video mapped to the plan using VSLAM. On the right of the application, an image gallery shows the 360° image, one per dot.

Figure 5.4: Screenshot of StructionSite 360° VideoWalks from Project O case study level 5 (taken from https://app.structionsite.com/, visited 02/21/2024).

Step 2 in the data processing procedure (Figures 5.1 and 5.2) included taking a time-lapse video while walking around the site. Some considerations taken while collecting the data include:

- Plan a walking route so that the walk passes through all the locations to be tracked
- Walk the site at a consistent frequency, at least as frequent as the weekly foremen meeting, when production control and planning decisions are made
- Match location and time of data capture to schedule and flow of activities observed
- Make sure the view of the camera is not obstructed

The automated data collection on Project O took place between 07/06/2023 to 11/14/2023, with 26 individual days of data capture. For each day of data capture, time-lapse videos of the walk for each level were uploaded to the StructionSite application for processing. The application processing includes stitching together the image to create the 360° images, correcting images for alignment and vertical orientation, localizing the coordinates of each frame on the floor plan and thus identifying the location bounding the coordinates, and running Computer Vision (CV)-based work detection for scopes of construction work. However, due to errors identified during image processing, data captured on 07/17/2023, 09/12/2023, and 09/19/2023 were discarded, leaving 23 dates of captured data. This error was caused due to connectivity issue between the StructionSite mobile application and the 360°camera hardware, causing incorrect localization of the frames on the floor plan.

The data processing by StructionSite, including VideoWalk and CV-based work detection, and the other data processing steps are part of step 3 of the data wrangling and analysis, described next.

5.3 Data Wrangling and Analysis

Figure 5.5 provides a closer look into the data wrangling and analysis component of the data processing procedure, the second one of the three components shown in Figure 5.1 (middle). Data wrangling includes cleaning and unifying messy and complex raw datasets. It involves dealing with missing values, correcting inconsistencies, and reshaping data formats to make them suitable for analysis. Data analysis refers to inspecting this newly formatted data with the goal of discovering useful information, thereby informing conclusions, and supporting decision-making.

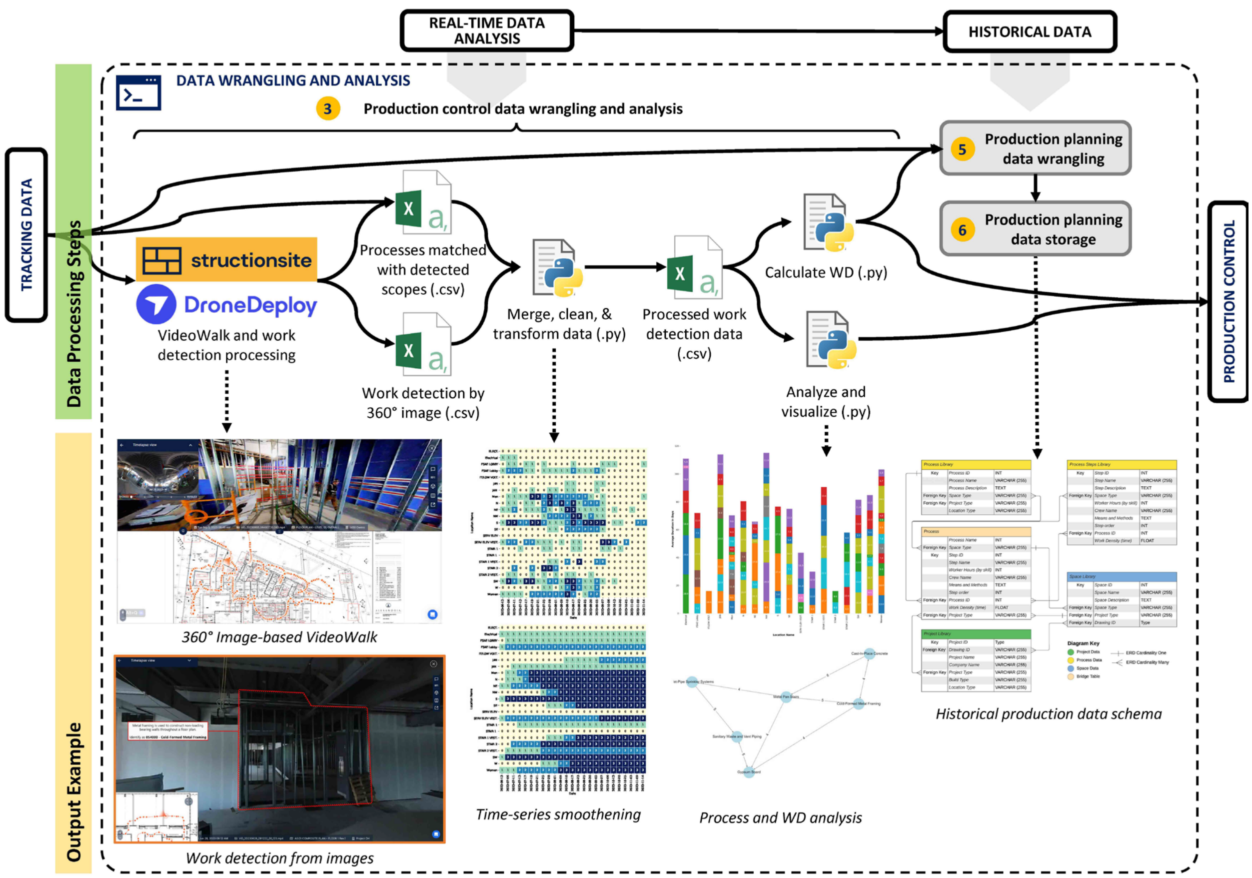


Figure 5.5: Data wrangling and analysis component of the data processing procedure for production control.

Figure 5.5 provides a closer look into the steps involved and the output generated at each step of this component. Step 3 includes data wrangling and analysis required for the production control component of the framework. Section 4.4.3 delineates the technology stack used for this step. The data generated at the end of step 3 undergoes further refinement for production planning purposes before being stored as historical data, as delineated in Steps 5 and 6, respectively. These two steps are expanded on in the production planning component of DDPF in Chapter 6.

Section 5.3.1 describes the VideoWalk data processing to detect work, as implemented by StructionSite. Section 5.3.2 details merging of work detection and other sources of data. Section 5.3.3 describes how the merged data is cleaned and transformed to ensure the feasibility and reliability of data analysis. The concluding Section 5.3.4 describes the analysis and post-data wrangling.

5.3.1 VideoWalk and Work Detection Processing

I captured the VideoWalk data at Project O and uploaded it to the StructionSite application after every walk. Depending on the duration of the walk and user traffic on the application, StructionSite took anywhere from 2 to 8 hours to process the images from upload to completion. Variability in walk duration stemmed from site-specific conditions such as progress in construction activities, obstructions due to material storage, and restricted areas owing to ongoing work or safety measures. User activity on the application exhibited daily, weekly, and seasonal patterns, typically peaking at the end of the workday and on Fridays. This timing aligns with the amount of activity on-site as data capture was usually planned when there is a smaller number of workers on the site so that there is minimal interference with data collection. Summer months saw heightened activity, attributed to the presence of interns tasked with data capture. Consequently, higher user traffic, coupled with finite computational resources, occasionally resulted in delayed processing times due to the accumulation of VideoWalks in the queue.

The image processing included stitching, correction, localization, and work detection. After completing the processing for a day's capture, I extracted the processed tracking data from the StructionSite database. Figure 5.6 illustrates the Entity Relationship Diagram (ERD) for the datasets I used for extraction. I performed the extraction using Structured Query Language (SQL), creating a query table named WorkDetection Query (purple table) by joining fields from entities in the StructionSite data (orange tables). The entities in the ERD include:

- **Project dataset** (Figure 5.6 top left) contains details about the construction project and is input by the project team. This entity contains details such as the project ID, gross square footage (GSF), project name, company name, and various types such as project-, build-, and location type, and number of levels.
- **Drawings dataset** (Figure 5.6 middle left) contains the list of drawings or floor plans, usually containing one for each level. Drawings are connected to projects and contain a drawing ID and drawing name.
- **Location dataset** (Figure 5.6 bottom left) contains information about specific spaces within a project. It is created by setting up locations on each drawing and assigning them a location ID, name, number, and type. The values used on StructionSite were consistent with the values in Table 5.1. It also references the project it is associated with and includes the drawing ID as a foreign key.

- **VideoWalk dataset** (Figure 5.6 top right) contains the 360° image frames and their project-, drawing-, and pin ID to connect the images in the frame to the project, location and detected work. It also contains the frame detection date.
- **Work Detection dataset** (Figure 5.6 bottom right) contains data about detected work by individual VideoWalk frame, identified by a Pin ID. The work detection catalogs construction specifications with fields for the Construction Specifications Institute (CSI) MasterFormat section number and title.

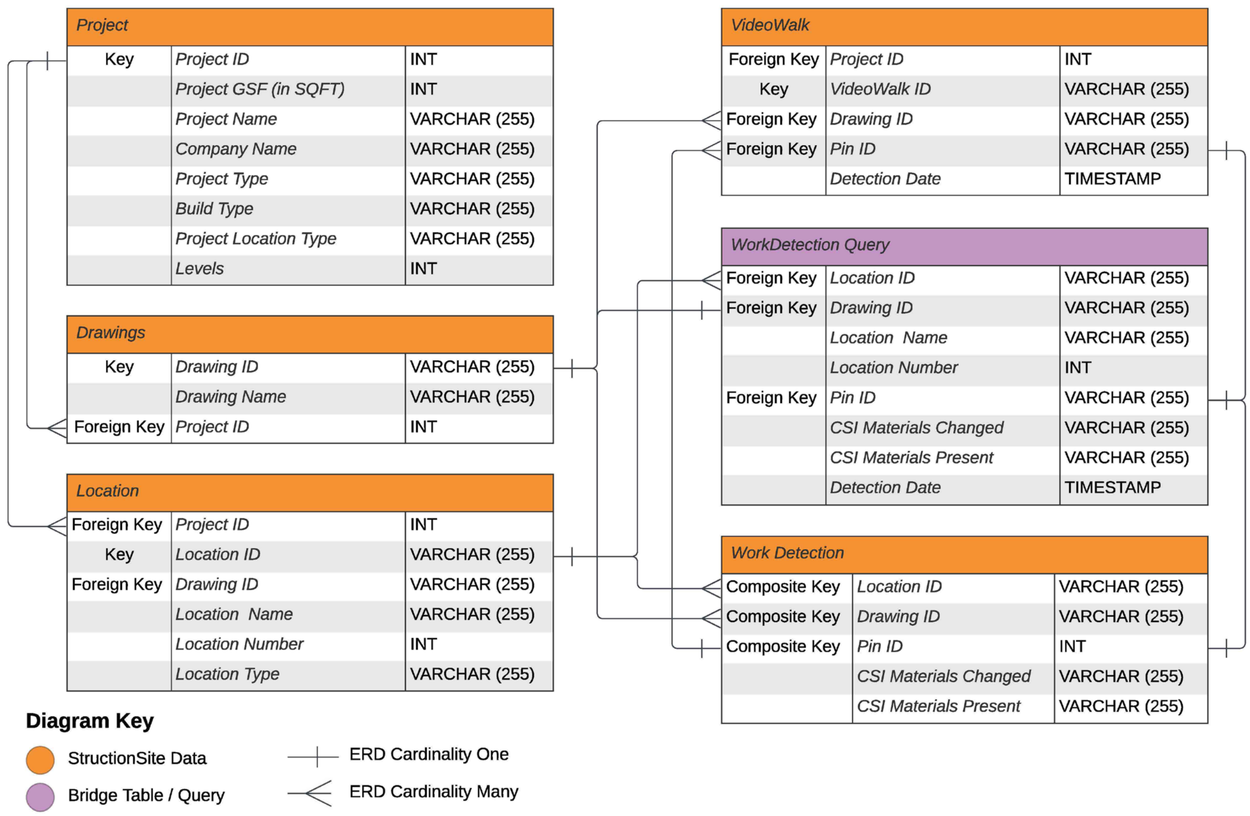


Figure 5.6: The Entity Relationship Diagram (ERD) for StructionSite 360° imaging-based tracking data.

StructionSite processes the VideoWalk captures using their proprietary algorithm. This algorithm samples one frame per location, transforms the image into a non-distorted projection, and finally runs an object detection CV model to detect scopes of work that are associated with the CSI MasterFormat classification structure.

I queried all these datasets and joined them into a single table that links the detected work to its location. Figure 5.7 shows the number of detections by their day of capture, and Figure 5.8 shows the cumulative number of detections over time. Both figures highlight a significant increase in detections between September 5 and 27, 2023. This surge resulted from the loss of captures in mid-September due to the processing error, leading to an accumulation of detections during that period.

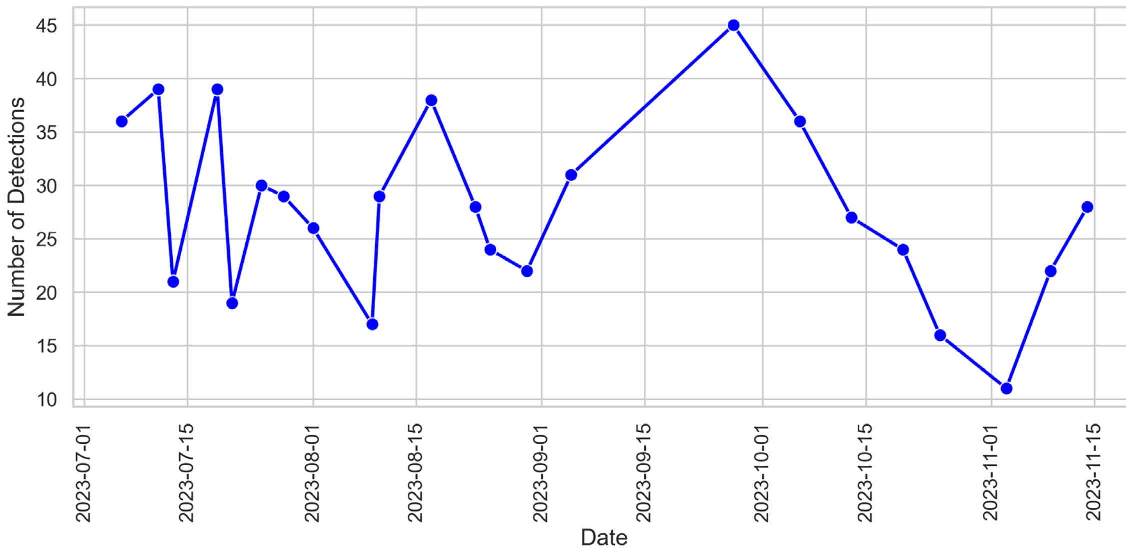


Figure 5.7: Number of work detections by date of detection.

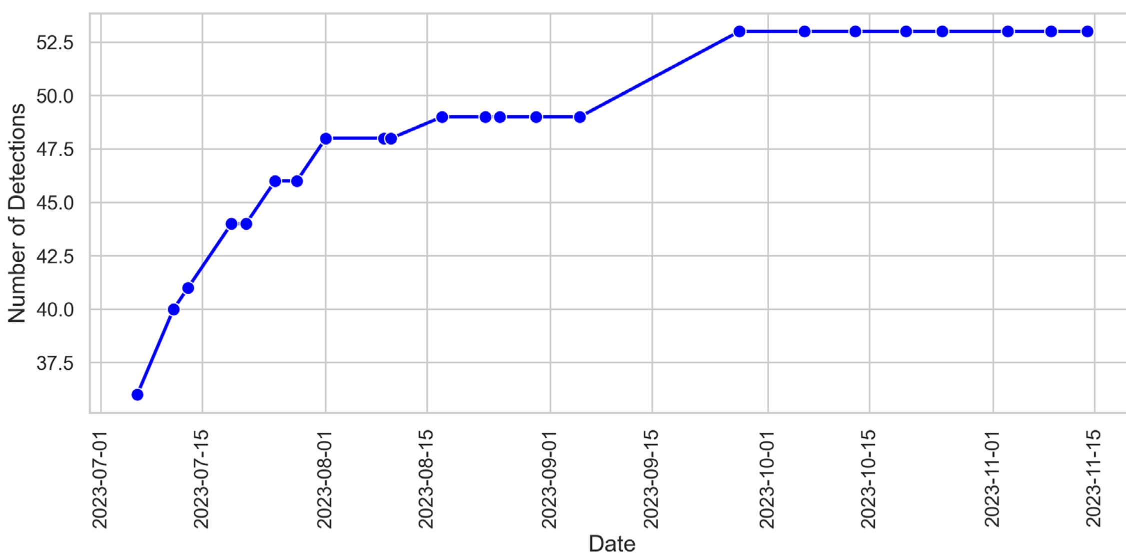


Figure 5.8: Cumulative number of work detections by date of detection.

I used the data queried from StructionSite to generate two sets of information. The first set comprises the scopes of work detected, categorized by their location and time of detection. The second set matches these scopes of work with the process steps anticipated for Project O, as identified in Section 5.2.1. Following this, I merged, cleaned, and transformed these two sets for further analysis.

5.3.2 Merge, Clean, and Transform Data

I merged processed work detection data and other queried data into a single source of information regarding the locations-, steps-, trades-, and detected work data. I also cleaned and transformed this data for use in production control.

My primary focus in data transformations and manipulations was on preparing and integrating the data for analysis. Before processing the data, I conducted a preliminary data exploration to inspect the datasets. This exploration helped me to verify data integrity, understand dataset structures, and identify any anomalies or patterns that warranted further investigation. The insights from this preliminary exploration guided me in the following steps:

1. Merging Data: I merged multiple work detection datasets, each related to individual drawings (one for each floor plan), into a single dataset. I then joined this merged data with a list of 59 CSI codes and their corresponding process step names (listed in Appendix C). Project O's process step library matched with detected work for 50 of these 59 CSI codes. Since all the three floors included in the case study included similar floor plans, I assumed the scope of work in each location on all floors to be the same. Figure 5.9 illustrates by means of an ERD how the CSI and process steps library data are related. These merged datasets provided a comprehensive view of the data, facilitating comparisons, aggregations, and trend analyses across different levels.
2. Preliminary Data Cleaning and Formatting: I took several steps to clean the data to maintain consistency. This was especially important in matching or comparing data across different datasets and within subsequent analyses. This included ensuring that CSI codes were in the correct and standard format, confirming all data fields were in correct data type and format, and ensuring location data was consistent with the location library created for the project.
3. Data Transformation: The transformation process involved converting work detection changes by date into a one-hot encoded dataset—where each distinct work detection CSI code is encoded in a unique column with binary values indicating presence (1) or absence (0) of a process step in a location—and pruning columns and rows to retain only the essential data. Other data transformations included correcting anomalies and discrepancies in the data collection or the work detection processing steps. This effort made the time-series data continuous and smooth across all locations by improving the readiness of the data for error detection and efficient computation

To merge the StructionSite data with Project O case study in step 1, I used the ERD illustrated in Figure 5.9. The actual data collected on Project O is described in Appendix C.

The entities in the ERD (Figure 5.9) include:

- **Work Detection CSI MasterFormat dataset** (Figure 5.9 top left) stores the CSI MasterFormat classification system's number and title for all possible scopes of work that can be detected by StructionSite. It is a trimmed version of the work detection dataset (Figure 5.6) described in Section 5.3.1.
- **Location dataset** (Figure 5.9 top middle left) is the same as the project dataset (Figure 5.6) described in Section 5.3.1.
- **Drawings dataset** (Figure 5.9 bottom middle left) is the same as the project dataset (Figure 5.6) described in Section 5.3.1.
- **Project dataset** (Figure 5.9 bottom left) represents the construction project. It is the same as the project dataset (Figure 5.6) described in Section 5.3.1.

- **Process Steps Library** (Figure 5.9 top right) is the same as the process step library (Figure 4.2) described in Section 4.2. It is part of the suggested production database and thus connects to other entities in the production database. It also connects to the CSI work detection CSI MasterFormat dataset.
- **Location Library** (Figure 5.9 middle right) is the same as the location step library (Figure 4.2) described in Section 4.2.
- **Process Library** (Figure 5.9 bottom right) is the same as the process library (Figure 4.2) described in Section 4.2.

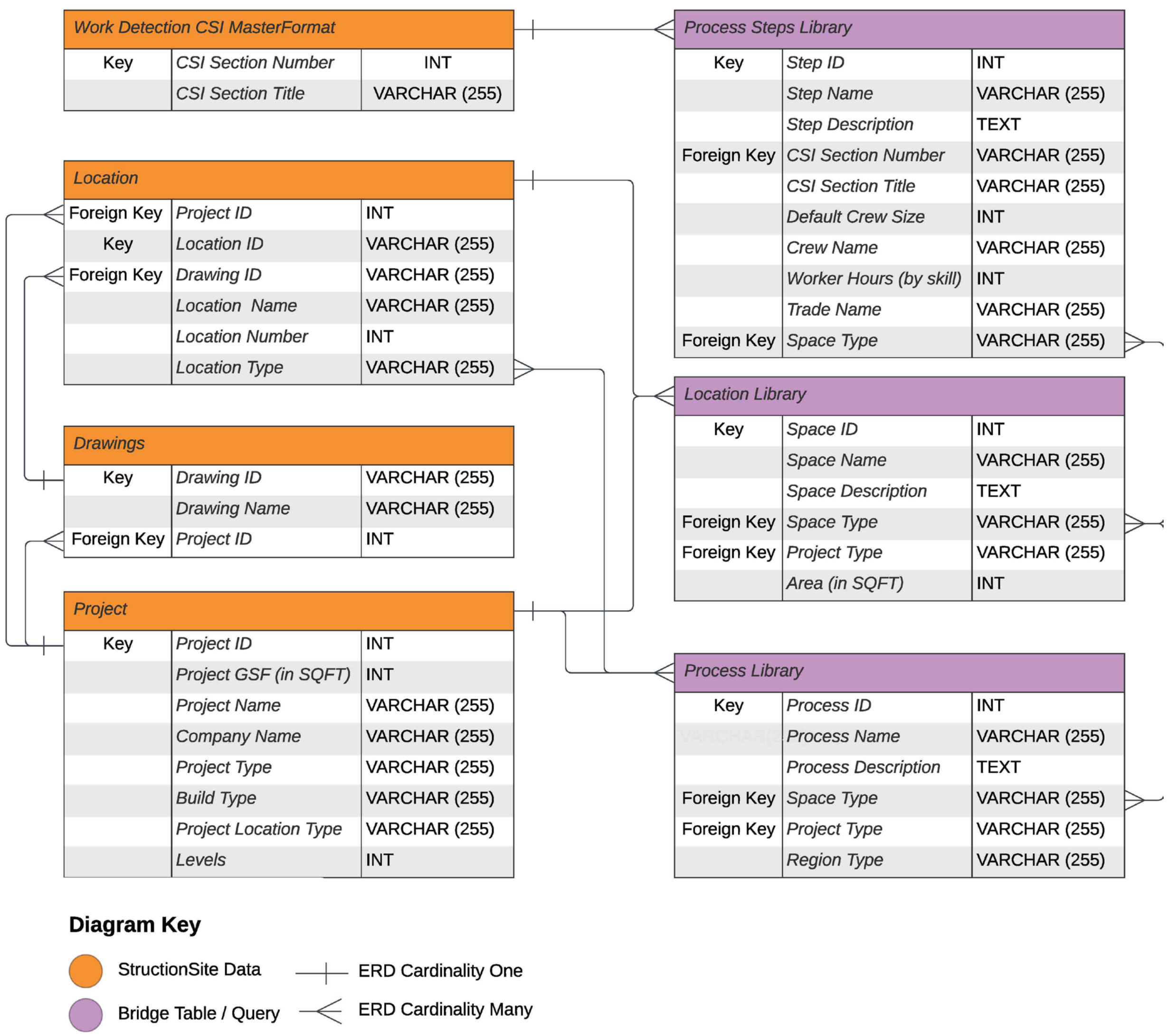


Figure 5.9: The Entity Relationship Diagram (ERD) for merging StructionSite data with Project O case study data.

During preliminary exploration of the data, I uncovered some discrepancies that stemmed from issues in data collection or the work detection processing. A notable example of this involved locations where work was detected initially but failed to be detected on one or several subsequent dates. Upon investigating these discrepancies, I deduced that they could be attributed to an improper walking path or obstructions from objects and newly installed work, which obscured the view of previously detected in-place work. Consequently, work that was visible and detected at an earlier date might not be detectable later.

This issue is inherent in tracking the progress of construction projects, where various scopes of work can become concealed as the project advances. For instance, framing and in-wall utilities are eventually covered by drywall, rendering them invisible to visual detection methods thereafter. Therefore, one crucial data transformation needed to address and correct this type of discrepancy before utilizing the data for further analysis.

The discrepancy with missing work detections was corrected by smoothing time-series data. Data for each location and each scope of work was checked, and if a work was detected, then all future entries for that work at that location were set to detected. This implies that once work for a step is present or changed in a location, it remains so in all subsequent records for that location.

Another crucial data transformation needed for smoothing time-series data was related to making sure the detection dates are consistent across the locations. This happened when VideoWalk was not captured in a location, or it did not detect any new work. Detection dates across all locations were identified and for those missing any dates, they were created by filling in the detections that were already completed for an earlier date in that location.

Figures 5.10, 5.11, and 5.12 show how these data transformations work by using the example of missing work detection discrepancy for thermal insulation installation step (referred as CSI 072100 in CSI MasterFormat). Since thermal insulation gets hidden under other materials, it might be detected for a few days and then remain un-detected. These figures display detection of thermal insulation by locations (location number, type, or level on vertical axis) over time (detection dates on horizontal axis). The numbers in the cells represent the frequency of detections, comparing the data before and after the smoothing transformation.

In Figure 5.10, each cell represents a day for an individual location number (room or zone) across all three levels, with values being either 0 (undetected) or 1 (detected). In Figure 5.11, each cell represents a day for a location name. Since each location name has three instances of similar location numbers (one for each level 5, 6, and 7), the possible values range from 0 (no detection) to 3 (detection on all levels). In Figure 5.12, each cell represents a day for a level. Since each level has a total of seventeen locations, the possible values range from 0 (no detection) to 17 (detection at all locations on the level). However, since most steps do not involve work in all 17 locations, the maximum value for each step varies.

The data after smoothing in Figures 5.11 and 5.12 reveal a more aggregated view of detections. Figure 5.10 shows the most detailed information, displaying work detection by individual location numbers. Figure 5.11 provides a slightly less detailed view, with detections aggregated by location names, while Figure 5.12 offers the least detailed information, with detections aggregated by levels. This aggregation causes discrepancies between the number of detections before and after smoothing. For example, in Figure 5.11, for the location name “Men” (men’s bathroom), the visual before data smoothing (top) shows the first “3” for detection on three levels on 08/17/2023. However, the visual after data smoothing (bottom) shows the first “3” on an earlier date, 08/09/2023. This can be understood by examining Figure 5.10 after smoothing (right), where location numbers 504, 604, and 704 (Men’s bathrooms on levels 5, 6, and 7) have their first detections on 07/19/2023, 07/25/2023, and 08/09/2023, respectively. This means that between the dates 07/25/2023 and 08/09/2023, Figure 5.11 is showing “2” detections at a time, but for three different location numbers.

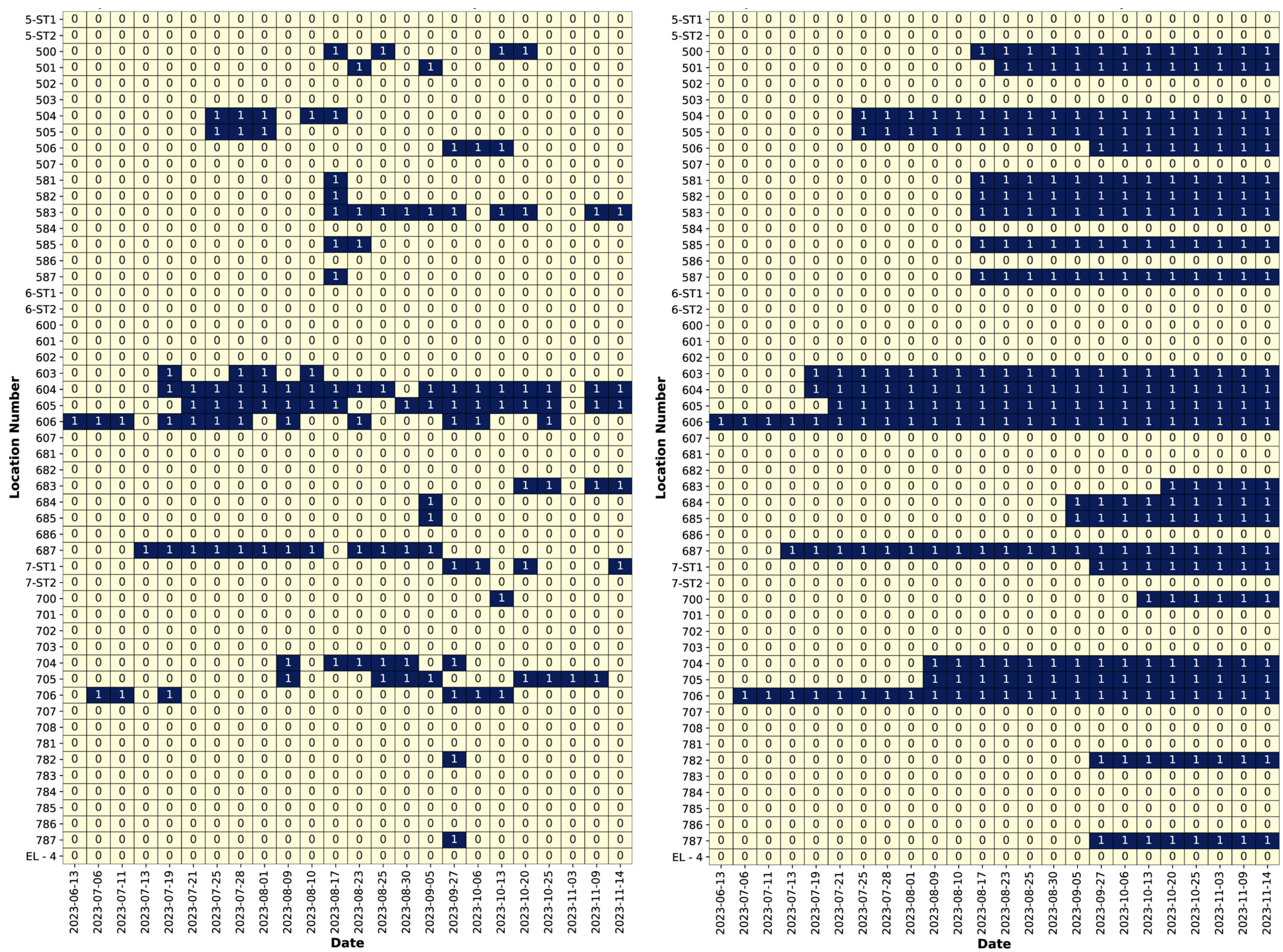
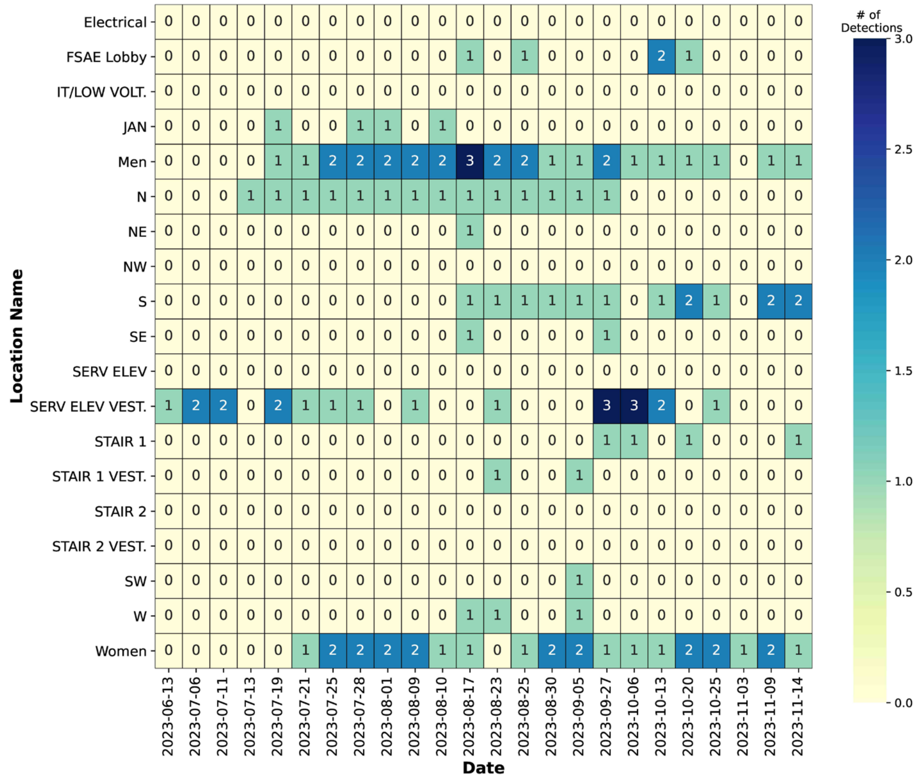


Figure 5.10: Updates of status for thermal insulation process step by location numbers for each of the three levels (shown on vertical axis) over time (shown on horizontal axis), before and after data smoothing (left and right respectively).



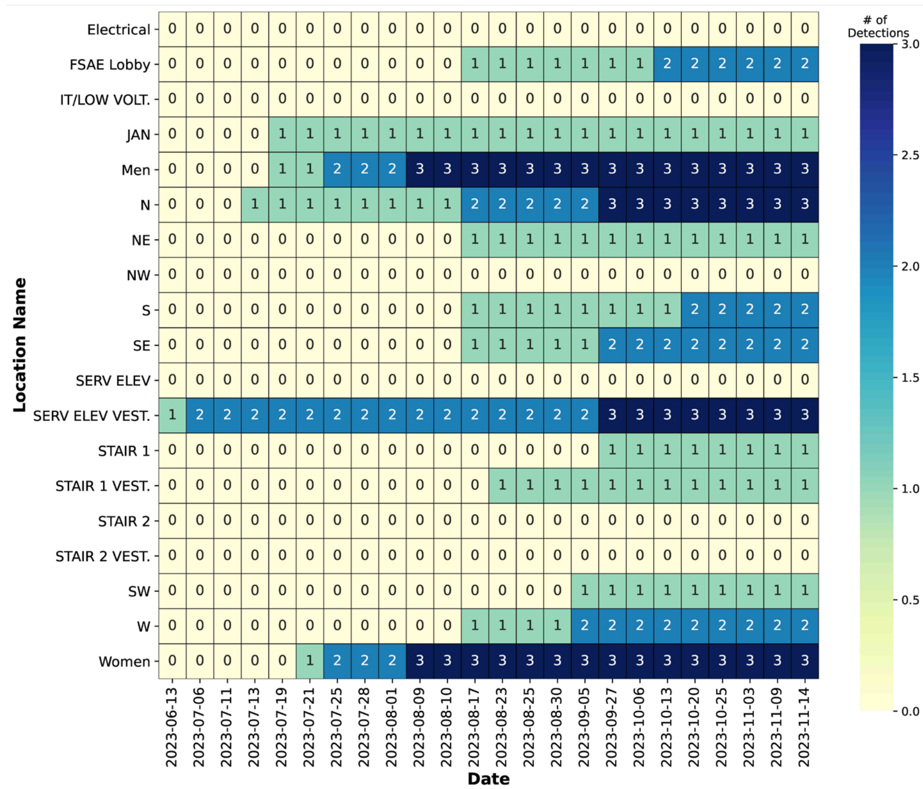
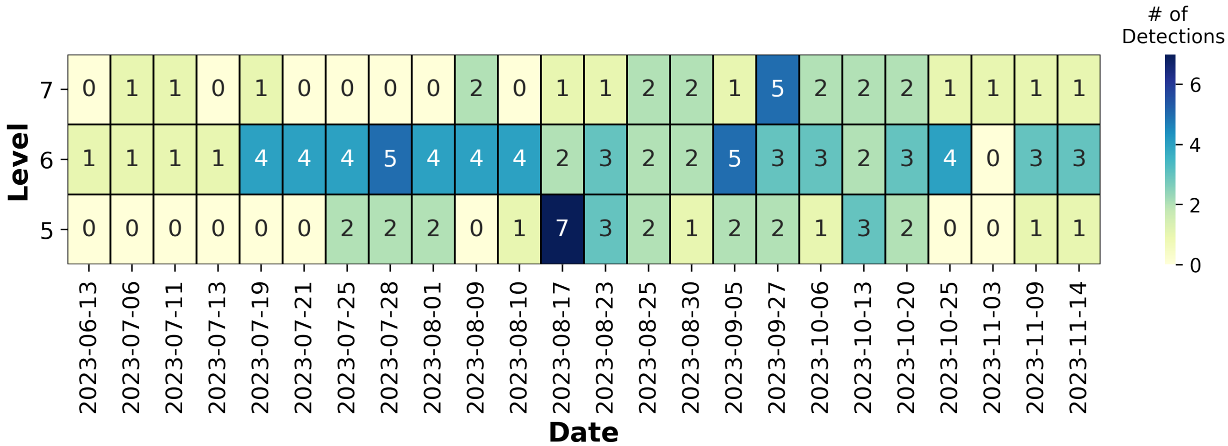


Figure 5.11: Updates of status for thermal insulation process step aggregated by location name (combining data from the three levels) (shown on vertical axis) over time (shown on horizontal axis), before and after data smoothing (top and bottom respectively).



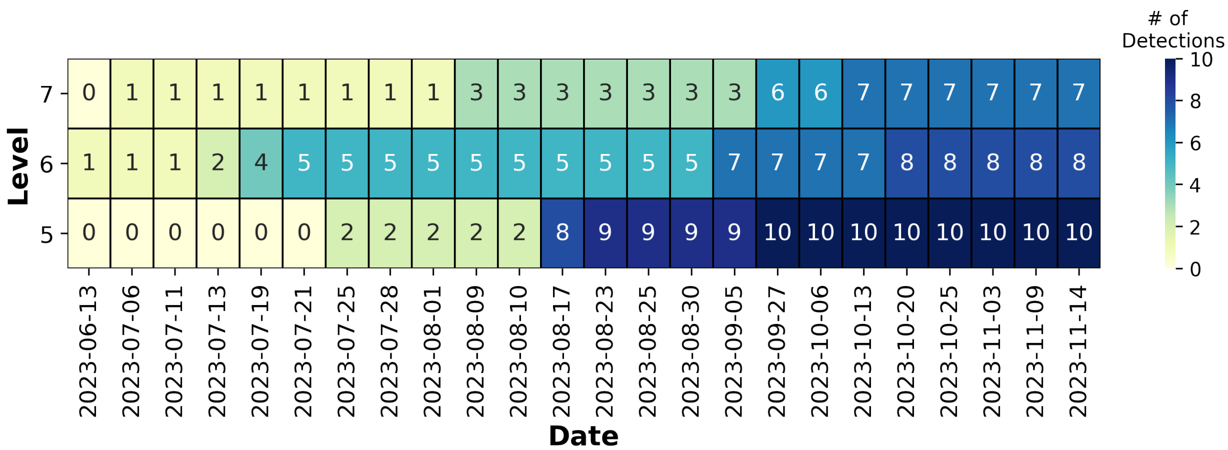


Figure 5.12: Updates of status for thermal insulation process step aggregated by level (combining data from all location numbers on a given level) (shown on vertical axis) over time (shown on horizontal axis), before and after data smoothing (top and bottom respectively).

This step in the data wrangling and analysis is essential for ensuring the data is processed to a suitable format for analysis and reporting, supporting the integrity and validity of any insights derived from the dataset. The output is a single processed dataset of all work detection related data for the project and is called “Processed Work Detection Data” in Figure 5.5.

5.3.3 Work Detection to Work Density Calculation

At this stage, the processed work detection data is ready to be used for analysis to support production control and planning. An important contribution of the DDPF to the body of knowledge of data-driven production systems is a new approach to calculating work density using work detection data. The departure from the existing approach as discussed in Section 3.1.1 and then applied using ViWoLZo in Section 3.2.4, omits the quantity of work and production rates as input, and the need for work density maps to store the work density. This makes work density independent of the unit of quantity (and production rates) for a scope of work. This is helpful as the same final output can be measured in different units, e.g., drywall can be measured in linear feet for a fixed height of wall versus square feet area of the wall. This also makes work density independent of the architectural design of the project as it is no longer attached to the cells of a work density map. This is helpful as it reduces the manual work of creating bespoke work density maps for each floor plan.

Instead, this new approach to calculate the work density for a specific process step is tied to a location (identified by its location number representing a room or a zone). To calculate it, I analyzed the processed work detection data using the following data transformation algorithm:

1. Transform the dataset from a multi-measurement column format into a structure where each row represents an observed value (also known as data melting). This adjustment is applied to the "Location" column (indicating the Location Number), all step columns (with each step allocated its own column), and the "Date" column (marking the capture date).
2. Remove rows with no work detection.
3. Determine the initial detection date across all rows (each row symbolizing a step within a location) by selecting the minimal "Date" value for every combination of step and location. This identified date is then assigned as the "Start Date" for the respective row.
4. Sort the data by "Location" column and then by the "Start Date" column.
5. Introduce a "Finish Date" column, with value equal to the nearest succeeding "Start Date" for each specific location number. In instances where a succeeding date for that location number is absent, the "Finish Date" remains unassigned.
6. Add a "Work Density" column, illustrating the day count differential between the "Finish Date" and the "Start Date". Should a "Finish Date" be missing, the corresponding "Work Density" value remains unassigned.
7. Exclude rows featuring unassigned (Null) or Zero values in the "Work Density" column.

This transformation provides a list of steps and locations, along with the start and finish date of work, and their work density, i.e., the time it takes to complete a step in a given location and quantified in calendar days. Tommelein (2017) defines work density as: "Given a certain work area, work density describes the time a given trade will require to do their work in that area, based on the product design and the scope of work done by that trade for a given task in the schedule (thus depending on work already in place and work that will follow), the means and methods the trade will use to do their work while accounting for their crews' capabilities and crew size". Hence, to convey the complete definition of work density, it is necessary to connect the calculated work density values for a given set of input features related to the product (e.g., features of the work's locations and the project) and the process (e.g., features of the process steps, involved crew, and applied means and methods). The relational data schema designated for the storage and linkage of work density metrics with other feature datasets will be discussed in Section 6.2.4.

It is important to highlight that the algorithm assumes the duration of a step (time between start and finish) to be the work density, although if not measured accurately, this duration might have slack built into it to make sure the work is completed in time (Formoso et al. 2021, Saurin et al. 2021). Figure 5.13 shows a sample of steps by location calculated on Project O, in a Gantt chart representation. The bars represent the start- and finish date of each step, and the length of the bar is equal to the work density for the step.

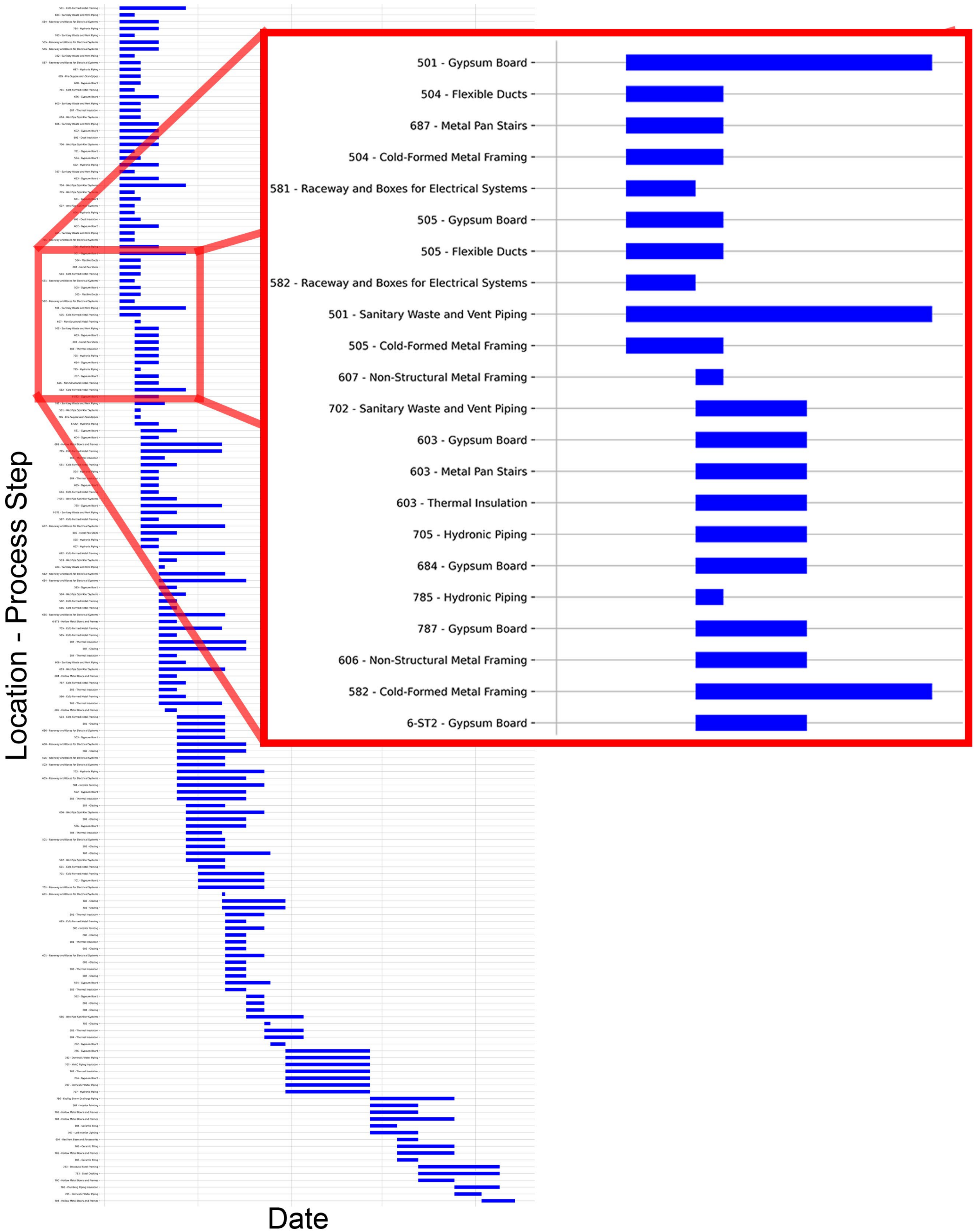


Figure 5.13: Sample data of work density calculation by step and location on Project O in Gantt chart representation.

5.3.4 Data Analysis and Visualization

Other than work density calculation, the processed work detection data was analyzed and visualized to understand work patterns and support production control efforts. Different approaches were adopted to dissect and interpret the data, including:

- Time-based analysis: Focusing on the frequency and patterns of work detection across various timeframes, trends over time were studied to identify changes in work on a weekly and monthly basis.
- Location-based analysis: Grouping the data based on location (location number and location type) allowed for analysis of changes across different locations. This location-based grouping facilitated examination of progress data and flow of process through the locations.
- Process step-based analysis: Grouping the data based on steps allowed for analysis of step sequence through locations, and the time required at each location. This step-based grouping facilitated an understanding of situational awareness and flow through locations for a step.

Some of the analysis required filtering the data with specific properties. The research used a range of decision variables, including the selection of specific steps, determination of timeframes for analysis, and the choice of locations or location types. This flexibility in filtering and sorting the data empowered me to conduct customized analyses based on the specific interests and the requirements of the project and the research.

Visualization played a key role in this analysis, with the application of line graphs, heatmaps, bar charts, Grant charts, etc. providing a visual representation of work detections over time. These visualizations revealed fluctuations in construction activity and offered a preliminary look at potential patterns or trends.

Analysis and visualization included in the research, such as those performed by process step, location, location type, and level, were added to the production performance and control dashboard, enabling the project team to glean actionable insights and make informed decisions based on the observed patterns and trends in the data. The results from this analysis are discussed in Section 5.5.1. The design of this dashboard and implementation of the data analysis is described next.

5.4 Production Performance Dashboard for Production Control

The data processed in step 3 comes into the production control component of the data processing procedure, the last of the three components shown in Figure 5.1 (right). Figure 5.14 provides a closer look into the steps involved and the output generated in this component. Step 4 takes the data produced from the data wrangling and analysis—encompassing time-, location-, and process step-based analysis—and shares it into a dashboard for reporting and decision-making purposes.

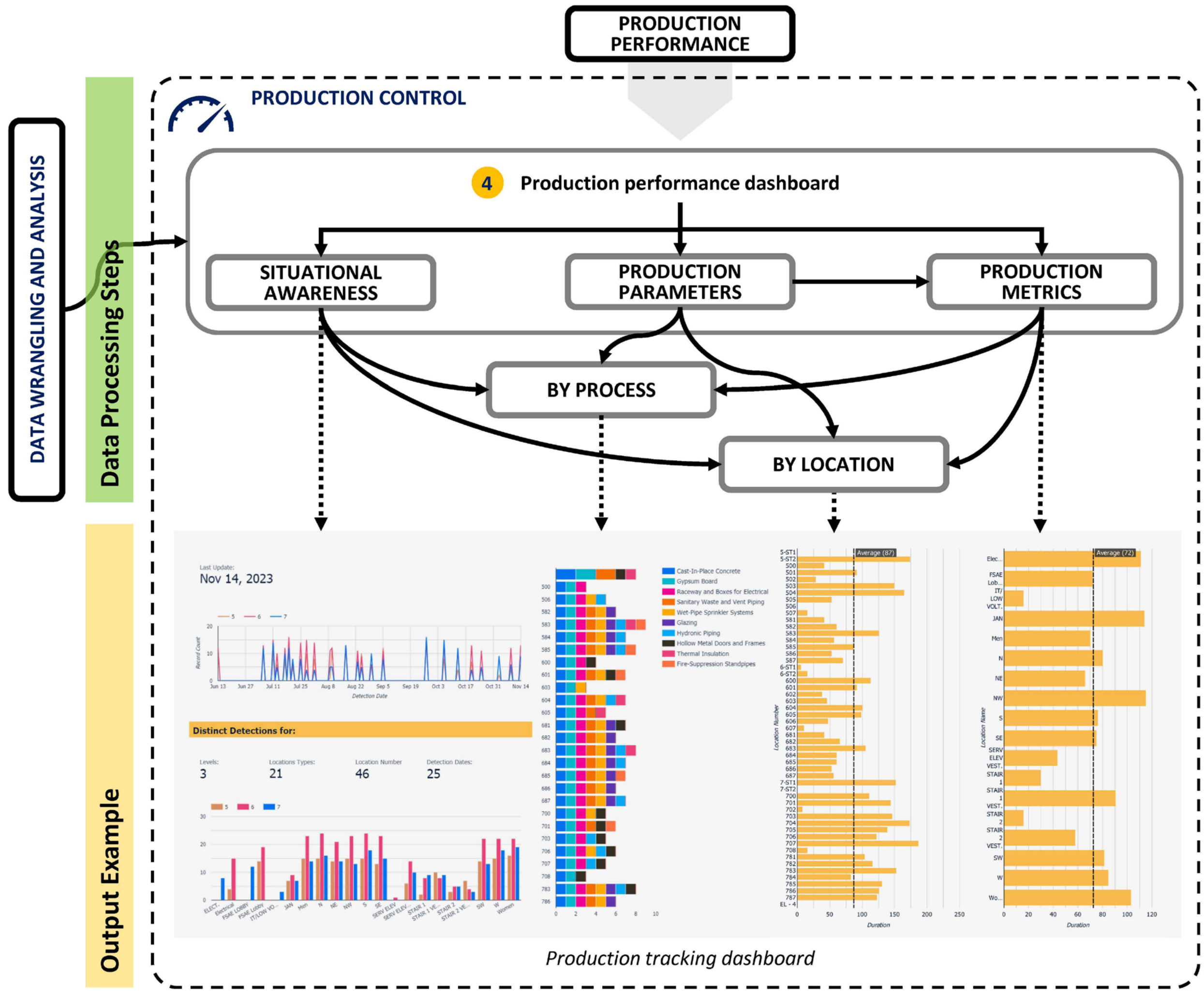


Figure 5.14: Production control component of the data processing procedure for production control.

Dashboards function as tools for reporting information by showcasing data through a visual interface. They utilize visual aids including charts and maps, along with textual descriptions, to condense and display complex data in a format that is straightforward and easy to understand. A user can consume this data to get updates or to make decisions related to the data. In this implementation, I developed a production performance dashboard aimed at reporting to the project team the performance of the production system in order to support their production control and decision-making efforts. Section 5.4.1 describes the development process of the dashboard, detailing its purpose, target users, use cases, functional requirements, and visual design principles. Section 5.4.2 details the practical implementation of the dashboard and the steps involved in the context of Project O. Section 4.4.3 delineates the technology stack used for dashboard implementation.

5.4.1 Dashboard Development

This section describes various aspects considered in the development of the production performance dashboard. Section 4.4.2 described the methodology used for the development in Project O case study

5.4.1.1 Purpose of the Dashboard

The purpose of the production performance dashboard, as identified in this research, is to support the project team's project control efforts. To achieve this purpose, the dashboard provides near-real-time updates on production performance, utilizing tracking data. These updates assist the team in keeping proactive "control" of the project by making sure work is happening as planned or steering the production system towards the intended plan.

The dashboard supports production control by offering insights into three sub-components (Figure 5.14 step 4):

1. **Situational awareness** provides transparency to management and the project team in knowing what work is happening where, finding anomalies, and doing root cause analysis to make sure work is happening as planned. In the industry, the prevalent methods of communication for such tasks are person-to-person communication or group meetings. These methods allow for communication of what work is happening where, but it is time-consuming and often incomplete and prone to errors. Any-time access to the latest situation in any part of the site makes project control decisions quicker and more reliable.
2. **Production parameters** are variables that describe aspects of the production system. Section 3.3.1 describes the production parameters identified for this research. By measuring these parameters on the actual worksite, planners can evaluate the implementation of the production system and identify any deviations from expected performance. This evaluation enables planners to determine whether the production system can meet established customer demands or adjust to updated demands, thereby facilitating appropriate adjustments to the production system design.
3. **Production metrics** include indicators used to assess the efficiency and effectiveness of the production system and support production control efforts. Section 3.3.2 describes the production metrics identified for this research. These metrics assess various aspects of production, including the continuity and punctuality of work and work space handoffs, work density, the amount of work conducted out of sequence, and comparisons of steps and locations within the production process. Moreover, these metrics offer a basis for comparing performance across different production decisions within a project or across projects, enhancing the understanding of production system decisions and areas for improvement.

These three sub-components of the dashboard communicate production performance to support the user in making production control decisions. These control decisions include adjusting the parameters initially set during production planning, as discussed in Chapter 3, enabling the user to steer the production towards the desired outcome. Each of the three sub-components are grouped by process step and by location (Figure 5.14), allowing planners to adjust by targeting specific steps or locations.

On Project O, the project team executed production control efforts once a week. However, for more granular control, this effort can be more frequent, e.g., once every day.

5.4.1.2 Users and Use Case

This research places emphasis on understanding the user and the use cases. User research provided an understanding of who the user is, their familiarity with the subject matter, and their specific use cases in engaging with the data. I addressed questions including "Who is the user?", "Why are they invested in this data?", "What do they already know?", and "What more do they want to know?".

The primary users I identified are project superintendents, foremen, and project managers. They can use the dashboard to monitor and manage production performance, identify potential issues, and make data-driven decisions to steer production. The dashboard can be used during their:

- Daily check-in meetings to update the current day or week's commitments or progress on the commitments to the Last Planner® System.
- Weekly coordination meetings with the trade partners to discuss next week's weekly work plan and the lookahead plan.
- Owner-Architect-Contractor (OAC) meeting to discuss current progress with project leaders and the owner.

If needed, access to the dashboard can be shared with people outside the primary users or made public to the project. In that case the purpose of the dashboard expands to provide transparency and communication of who is working where whenever an update is required on an as-need basis.

I validated the dashboard's functionality by conducting user testing sessions with the project superintendent, foremen, and field engineers. Feedback from these testing sessions ensured the dashboard meets the user needs and facilitates efficient project production control.

5.4.1.3 Functionality Requirements

The dashboard's functionality places importance on ease of use and comprehension. This involved the creation of a visually intuitive interface using Looker Studio. Looker Studio's cloud-based infrastructure enabled dynamic data connections, continuous synchronization, and real-time updates. This made prototyping and gathering user feedback quicker and allowed for sharing of the latest information across all users.

To enhance the user's comprehension of the dashboard, I incorporated a diverse array of visualizations, including charts, graphs, and tables. Furthermore, I layered the data in various hierarchies to make the visuals simpler without losing the details. Using the capabilities of drilling down, and filtering the data, based on specific details (e.g., date, trade, process, process step, location, space type, etc.), users accessed specific and detailed information from the presented layered data.

Following the iterative development of the dashboard, its function expanded to include the generation of customized reports for users. Such reports are routinely used to disseminate information during weekly coordination meetings.

5.4.1.4 Principles of Visual Design in Dashboard Development

To help users with decision-making, it is important to consider how the dashboard displays information (such as data points, metrics, and visualizations) and encourages user action. To drive ease-of-use and efficient user action, I incorporated principles of visual design in the dashboard development process. The principles stress the importance of designing visualizations and reports to meet user needs and purposes.

The principles of visual design used in dashboard development incorporate the guidelines presented by the National Academies of Sciences, Engineering, and Medicine (2017) and Google Analytics Academy (2023). These principles include:

1. **Keep it Simple:** Visualizations should convey only the essential elements of the concept, keep text to a minimum, and be easily understood. Complexity should be avoided in favor of clarity and simplicity.
2. **Make it Clear:** To guide the viewer's eye, establish anchors in the visual. This includes using easily readable fonts, choosing a readable font size, and increasing font size for key statements to make them stand out. Overlays can be used to create emphasis through differentiation of format (e.g., position, color, shape, and size).
3. **Titles and Text:** Titles are key elements of a dashboard, and they are often the most memorable part of a visualization. Effective captions and labels placed next to data, as opposed to below the axis, can enhance understanding.
4. **Human Recognizable Objects:** Visual cues, such as pictograms or images, can enhance the effectiveness of a dashboard. Instead of relying solely on text-based labels, designers should consider using visual cues or pictures to improve retention. This extends to making data components resemble related objects, enhancing comprehension.
5. **Redundancy:** Repeating elements such as titles, captions, labels, and pictograms as much as possible and appropriate among related visualizations improves comprehension. Redundancy helps reinforce key information and makes it more accessible to the viewer.
6. **Begin with High Level:** Dashboards should start with an overview that allows viewers to quickly grasp the big picture. This approach avoids overwhelming the user with excessive details on the initial dashboard page. Instead, viewers can access more detailed information as needed through filter controls, additional report pages, or hyperlinks. This principle encourages a user-centric approach, ensuring that the dashboard caters to the specific information needs of the users.
7. **Similar and Different Style:** Visual elements that are similar in shape, size, and color are perceived to be more closely related. Conversely, different elements should visually contrast. Applying this principle to dashboard development involves using similar style (color scheme, fonts, etc.), making it easier for viewers to understand the relationships within the data. Consistency helps the audience know what to expect and prevents distractions caused by changes in the dashboard's visual appearance. Distinguishing different items through contrasting visual elements enhances data comprehension.
8. **Use of the Right Chart:** The choice of the appropriate chart type is essential to convey information effectively. It is vital to select a chart that aligns with the viewer's goals and the nature of the data.

9. **Use of Color:** Color is a powerful tool for guiding viewers through a dashboard. The principles of color use in dashboard development include:
    a. Brand Your Report: Incorporating the organization's branding by using specific color palettes ensures visual consistency and reinforces the brand identity.
    b. Use Transparency for Visual Hierarchy: Adjusting component color transparency helps create a visual hierarchy, emphasizing certain data points or components over others.
    c. Use Saturation to Draw Attention: Intense colors can draw the eye to important metrics or critical charts, making it easier for viewers to identify key insights.
    d. Don't Rely Solely on Color: Although color is a useful tool, it should not be the sole means of conveying information, as not all viewers may discern color differences. Therefore, important data points should be highlighted effectively through other means.

The next section details the implementation of the proof-of-concept dashboard that incorporates these principles, functionality requirements, use cases, and purpose, as identified in this section.

5.4.2 Dashboard Implementation

The implementation of the production performance dashboard (Figure 5.14 step 4) is divided into three sub-components: (1) situational awareness, (2) production parameters, and (3) production metrics. This section describes the implementation of these sub-components of the dashboard in the context of Project O.

5.4.2.1 Implementation Steps

Dashboard implementation on Looker Studio involved the following steps:

1. Connect Data: Connect the Looker Studio platform to processed datasets (step 3 of Figures 5.1 and 5.5) stored on a cloud-based database, defining the data sources and data features (features are called dimensions in Looker Studio) for the dashboard. This included creating a live data source for Process Step Library using an Extract, Transform, and Load (ETL) data pipeline. This also included creating a static data source instance for datasets such as Process- and Location Libraries, which are constant for the project or the phase of planning. The ETL pipeline extracts the latest data from the static datasets and a database hosted by StructionSite, transforms the data as per the steps described in Section 5.3, and loads the data into Looker Studio.
2. Transform Data: To enhance or modify the data, I employed various techniques such as creating calculated new features, altering data aggregation methods, and joining different datasets. This allowed for a comprehensive dataset that supported nuanced visualizations and analyses.
3. Generate Parameters, Metrics and Plot Visualizations: To calculate parameters and metrics, I applied aggregations and custom functions to the data. To visualize the data, I added dashboard components including charts, tables, maps, and graphs.

4. Update and Refine Dashboard: I designed the dashboard to stay “live” with a pre-defined one-hour data refresh rate, facilitating a shared and near real-time source of truth for all project stakeholders. I programmed the dashboard to cache dashboard data to enhance performance, however a user can update the cache by refreshing data on-demand.
5. Share with Users: I shared the dashboard with users including the superintendent, foremen, and field engineer on Project O. This was controlled through permissions, determining who could view or edit the reports. I provided editing permission to users providing feedback.
6. Explore Data to Find Insights: Conditioning features, such as drill down, filter, and sort, enabled deeper exploration into the data presented in individual charts and metrics. This exploration provided additional context and detailed information about specific data points, uncovering new layers of insight. The use of feature conditioning is described with examples in the next three sections. The ability to adjust the date range also played a crucial role in tailoring the analysis to specific timeframes.

Following these steps, I implemented the three sub-components of the dashboard, each described in the next three sections.

5.4.2.2 Situational Awareness

The first sub-component of the dashboard contains high level updates related to project and production tracking, providing situational awareness. The situational awareness sub-component is intended to provide near real-time access to the situation on the site and create transparency. It aims to enable management- and project teams to know what work is detected where, finding anomalies, making sure work is happening as planned, and doing root cause analysis for deviations.

In the construction industry, the prevalent source of information for situational awareness is person-to-person communication or group meetings. These methods allow for communicating what work is happening where, but come at the cost of being time-consuming, delayed, often incomplete, and prone to errors, with no single point of truth. In contrast, ubiquitous and constant access to the situation on the project site makes project control decisions quicker and more reliable. To enable this, the dashboard design incorporates several metrics and graphs that together give a near real-time status of the tracking data collection efforts and the project’s progress.

Figure 5.15 shows a screenshot of the “Project Overview” dashboard page. The page reports an overview of the work detection across the project, giving the status for tracking data collection. A line graph (top left) communicates the status of the detected work. The labeled numbers 5, 6, and 7 represent the different floor levels of the project being tracked, visualizing the number of detections on each floor on the days of capture over the 5-month span of data capture. A bar graph (bottom left) displays the breakdown of the number of detections by location type. As shown, this data is grouped by the location types, with three bars per group for the three levels. This visualizes the distribution of detections across different location types within the project, across different levels for a location type, and across location types within a level.

Figure 5.15 also shows key metrics about the data capture and work detection, including number of unique levels, location types, location numbers, and detection dates. These metrics provide a quick overview of the work detection situation across the project.

The sidebar at the right of every dashboard page, delineated by a vertical divider in Figure 5.15, contains data conditioning filters and quick links. These filters allow the user to refine the displayed data by date range, floor level, location name, and location number. At the bottom of the sidebar, a button labeled "View 360" opens the latest 360° VideoWalks of the project on StructionSite's website.

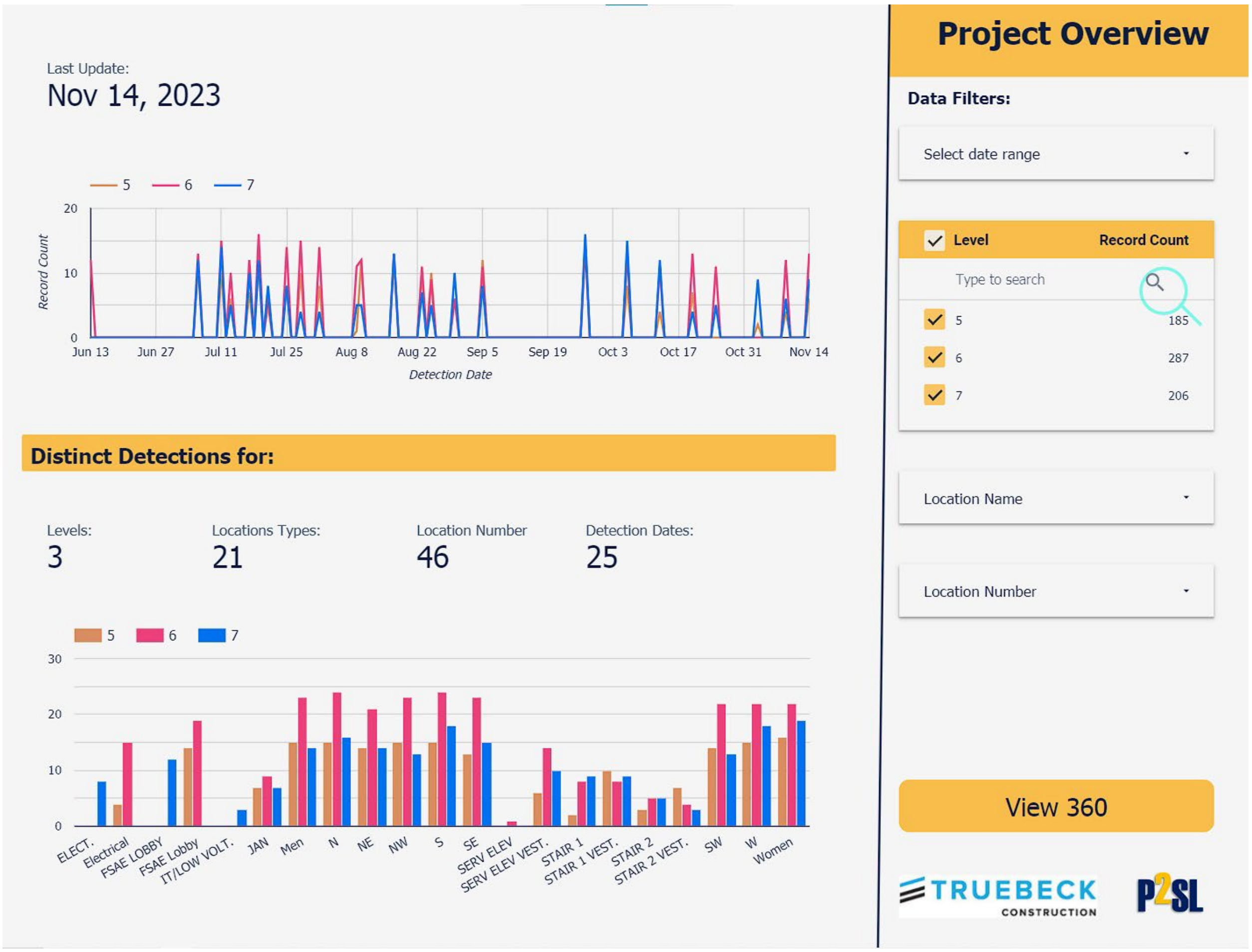


Figure 5.15: Project O dashboard: work detection project overview.

Figure 5.16 shows a screenshot of the "Work Detection Status" dashboard page. The page reports the status for work detection across the project locations in the format of a pivot table. The rows of the table correspond to the scopes of work detected, representing steps (e.g., "Domestic Water Piping", "Fire-Suppression Standpipes", "Hollow Metal Doors and Frames"). The table includes columns for the counts of these steps in each location numbers (e.g., 583, 701, 703) grouped by location name (e.g., "JAN", "Women", "Electrical"). Table 5.1 provides a list of location names and numbers for Project O. The illustrated example uses data filters (right side of Figure 5.16) to show data with date of detection between 11/01/2023 and 11/17/2023. A user can choose to use other filters, including step, location name, or location number to see the status of the work detected on a specific date, date range, or current date.

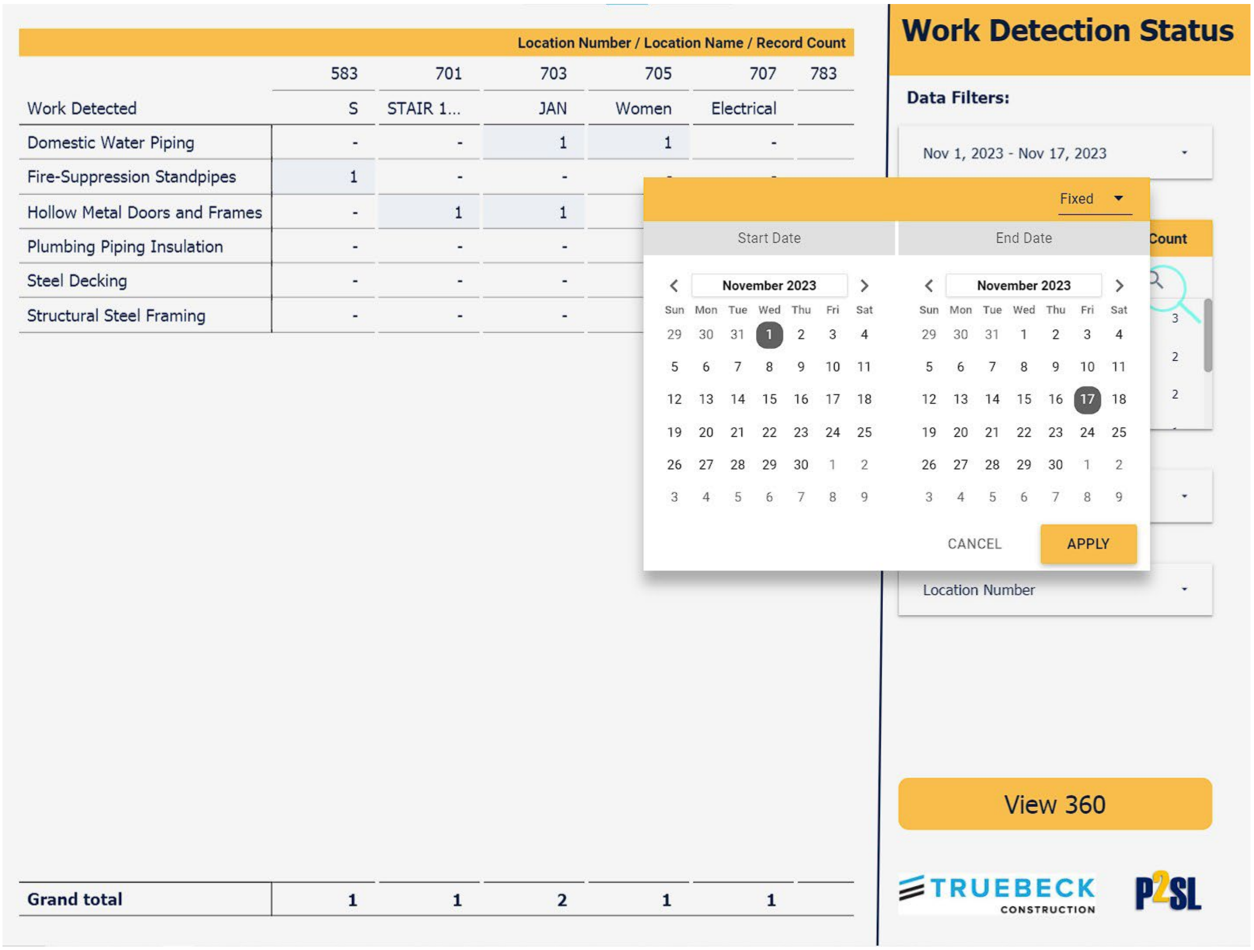


Figure 5.16: Project O dashboard: work detection status with data of detection filtered between 11/01/2023 and 11/17/2023.

5.4.2.3 Production Parameters

The second sub-component of the dashboard contains information on production parameters—variables that measure and describe the production system design. The production parameters sub-component is intended to support the project team in evaluating the implementation of the production system and determining whether the system can meet the established customer demand or adjust to newly updated demand. The project team can implement production control by adjusting production parameters, such as reconfiguration of processes or zoning.

Production parameters shared on the dashboard are the same as those used in Visual Workload Leveling and Zoning (ViWoLZo) tool (Sections 3.1.1 and 3.3.2). The parameters include the number of steps in a process (S), number of zones (Z), cumulative work density (referred to as workload or step cycle time) (W), and workload peak or operable takt ($T(Z)$). Since Project O's management team did not use takt to plan the project, the dashboard did not calculate some of the production parameters used in ViWoLZo, including the customer or demand takt (T_c), the process duration or lead time (D), and planned takt (T).

The dashboard systematically depicts the steps associated with discrete locations within the project. Figures 5.17 and 5.18 show screenshots of the "Steps by Location" dashboard page. The left side of the page reports a tabular compilation of data segregated into three primary columns:

"Location Number", "Location Name", and "Steps". This table quantifies the number of steps detected in each location, thus measuring the steps in a process (S) production parameter. Adjacent to this table is a Sankey diagram (shown in the middle), which graphically represents the workflow and procedural linkage. The width of the connectors in a Sankey diagram represents the frequency of the connection. Here, the frequency of detecting a step in a "Location Number" can only be zero or one. The data filters interface (shown at the right) allows the user to apply filters based on date range, process step, location name, and location number, to drill down the presented data to understand the workflow.

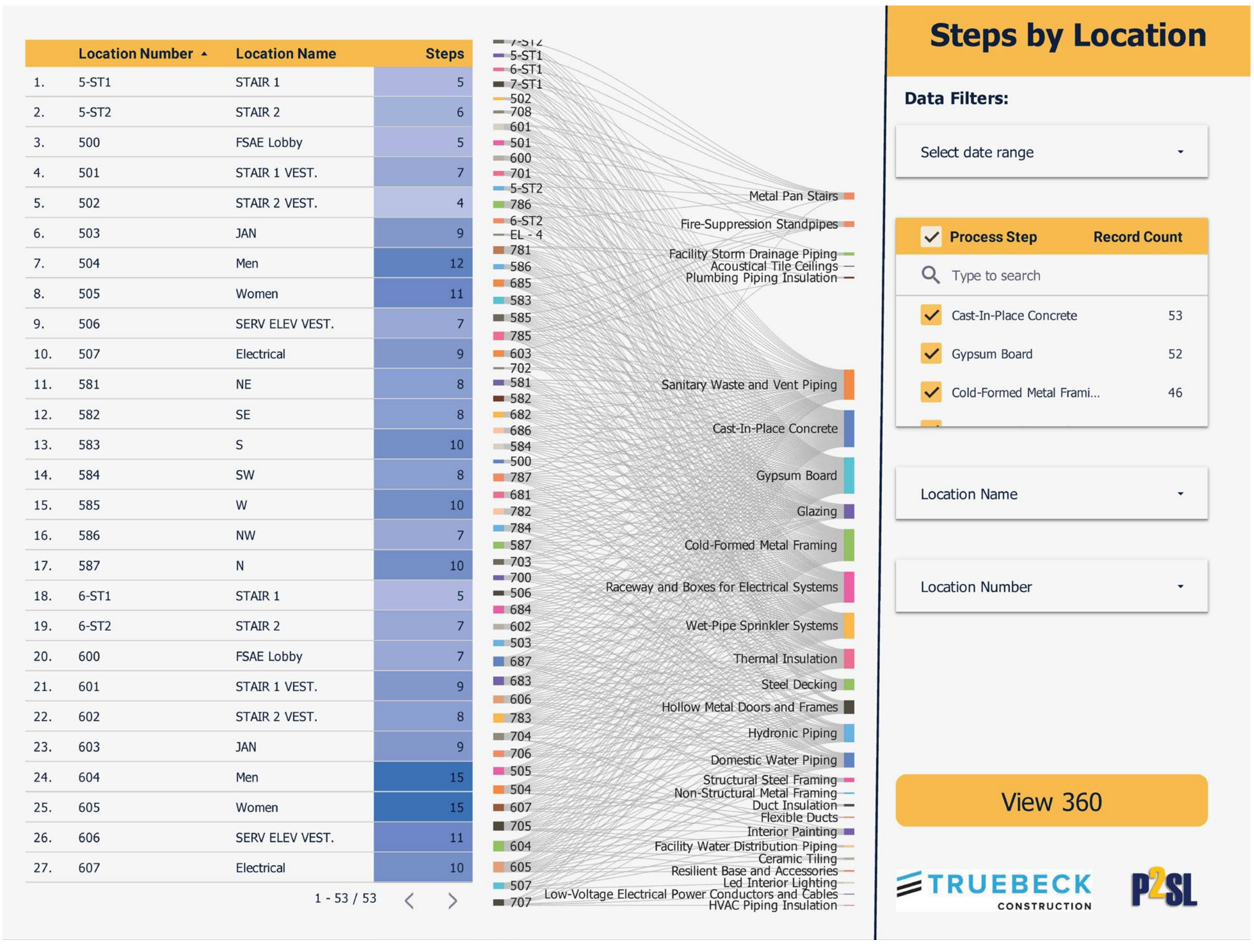


Figure 5.17: Project O dashboard: steps by location number and name.

Figure 5.18 shows the application of one such data filter, isolating the steps pertinent to location number "505", which is a women's bathroom. The application of the filter brings up the process steps for this specific location within the Sankey diagram. The magenta stripe on the left side of the Sankey demarcates the filtered location, connected to the step whose work has been detected in the location.

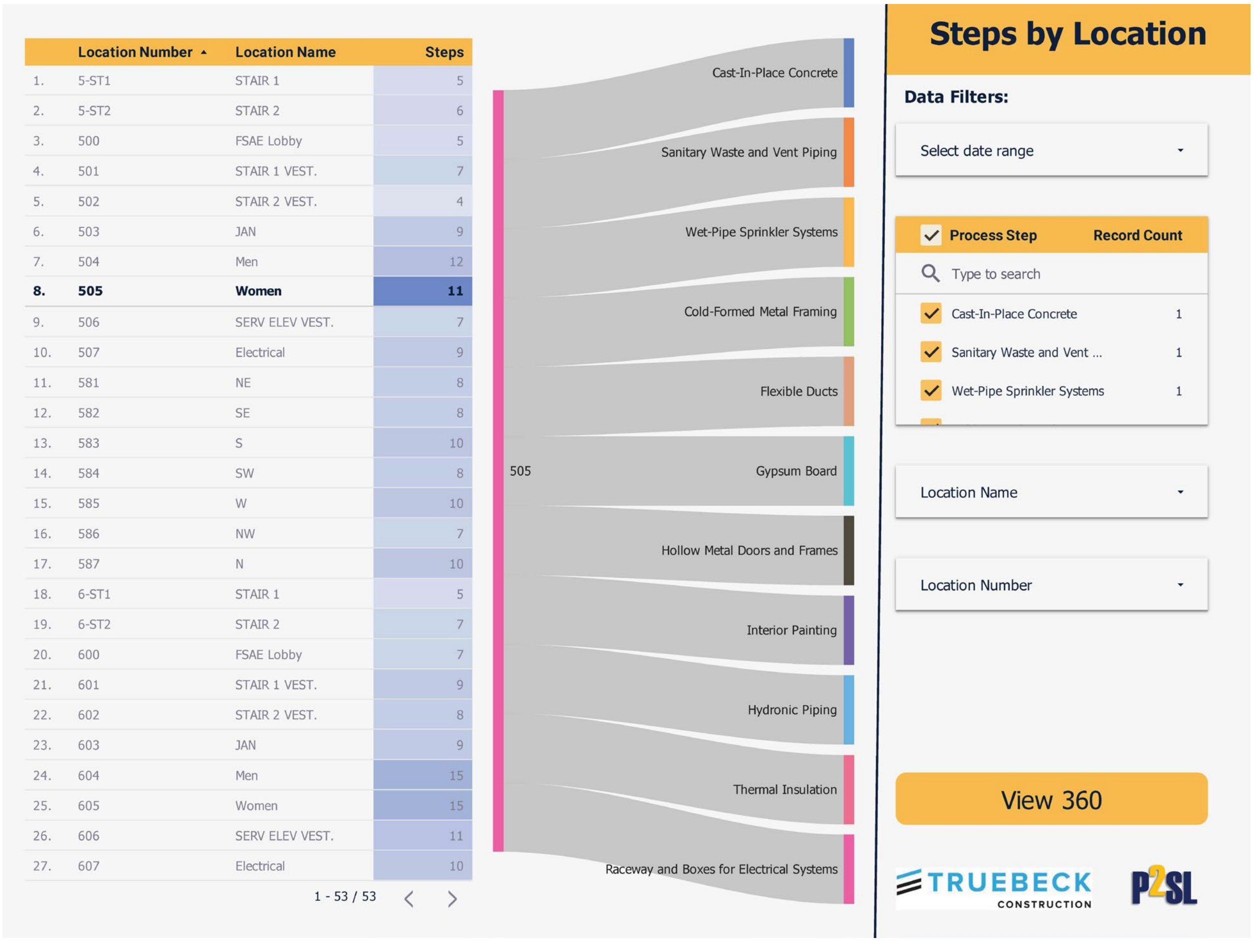


Figure 5.18: Project O dashboard: steps by location number and name with example location number "505" selected.

Figures 5.19 and 5.20 show screenshots of the "Cycle Time by Location" dashboard page. The page reports horizontal histograms visualizing the step cycle times averaged across locations of the project, representing the cumulative work density or workload or step cycle time (W) production parameter in days. The left histogram groups the step cycle time by location number and the right histogram groups the step cycle time by location name. The data point for each bar in each histogram takes the average of all selected steps and locations with that name.

The histograms contain two types of lines illustrating statistical parameters. The dotted black line, with notations such as "Average (21)", illustrates the mean step cycle time for the plotted data, which here is 21 days. The dotted red lines, with notations such as "Min to Max (2 to 40)", illustrate the range between minimum and maximum recorded step cycle times for the plotted data. The maximum value represents the workload peak or operable takt ($T(Z)$) production parameter. The histograms provide a visual representation of the duration of steps across various locations, allowing the project team to quickly assess which areas are consuming more time than others and how they compare to the average. This data can help to identify bottlenecks or inefficiencies within the process.

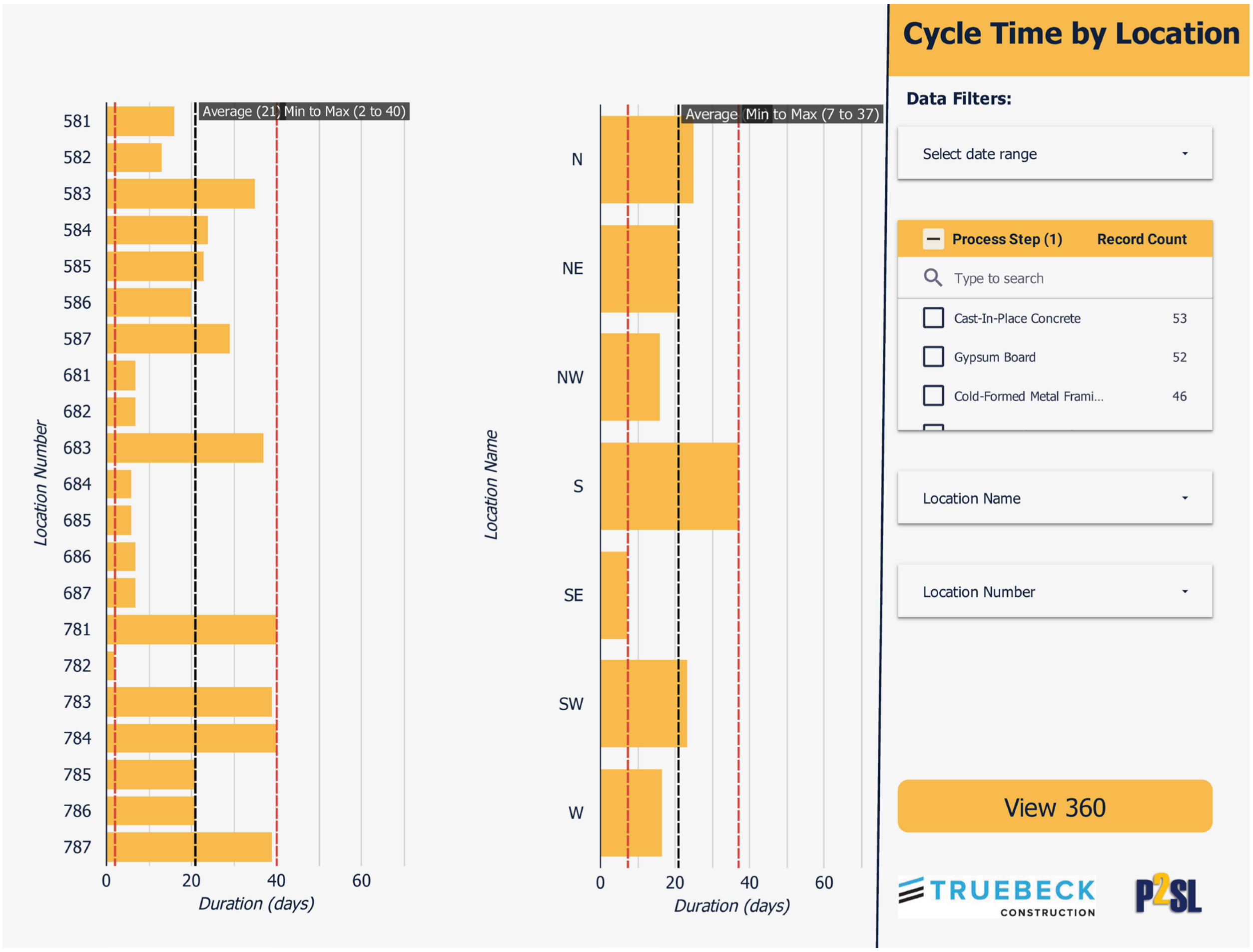


Figure 5.19: Project O dashboard: average step cycle time by location number (on left) and by location name (on right), filtered with "Glazing" process step.

In Figure 5.19, the data is filtered to show only the "Glazing" process step, thus the histograms show only locations that are on the periphery of the building. Although not visible in the figure, the "Process Step" filter (shown on the right side) has only the "Glazing" step selected. In the histogram on the left, each bar represents the cycle time of one step in one location (e.g., 581, 582). In the histogram on the right, each bar represents the cycle time of one step averaged for all three location numbers with the same location name (e.g., value for "NE" is the average of 581, 681, and 781).

Figure 5.20 presents an even more focused analysis by applying an additional filter to the "NE" location name, representing the North East zone. The histograms now display cycle times exclusive to this zone, facilitating a targeted assessment of performance for the "Glazing" process step in the three instances of the zone on levels 5, 6, and 7. The distribution in the left histogram shows that the time for enclosing the North East portion of the 7th floor took disproportionately longer than the other two floors. This refined view enables the project team to isolate and evaluate specific segments of the construction process, potentially informing decision-making, and resource allocation to improve cycle times. This data can be used both retrospectively (e.g., by looking at the performance data to confirm with ground reality, find anomalies, and issues) and in real-time (e.g., by measuring ongoing cycle time performance to past performance in similar locations).

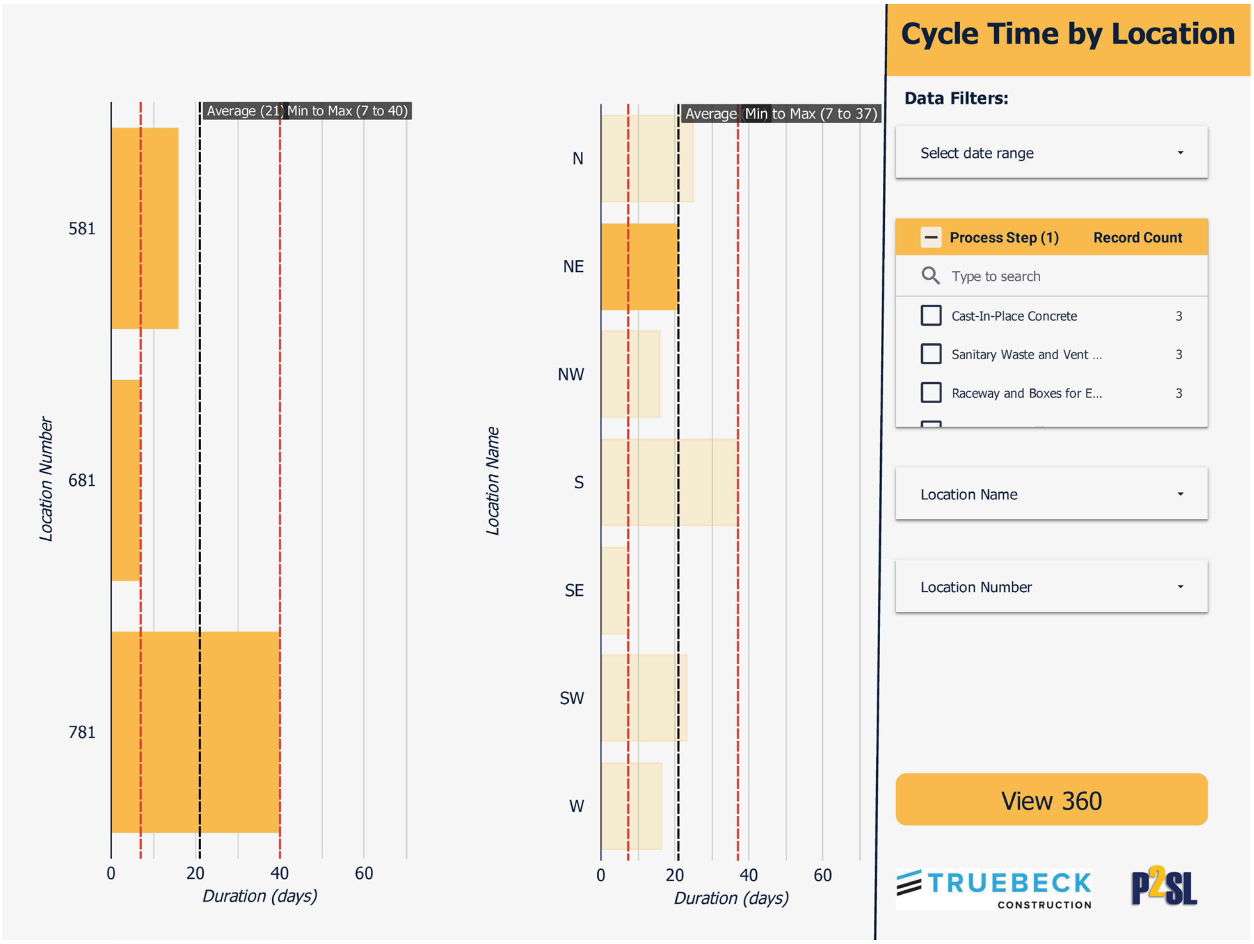


Figure 5.20: Project O dashboard: average step cycle time by location number (on left) and by location name (on right), filtered with "Glazing" process step and "NE" (North East zone) location name.

5.4.2.4 Production Metrics

The second sub-component of the dashboard contains information on production metrics—measurable values used to evaluate the performance or success of a production system. These metrics guide the project team in their production control efforts. Additionally, these metrics facilitate the comparison of performance across various production decisions within a project or between projects, thereby improving the understanding of production system decisions and identifying potential areas for improvement.

Production metrics shared on the dashboard are the same as those used in ViWoLZo (Sections 3.1.3 and 3.3.1). These metrics include the workload (W) by step and zone, the workload peak ($T(Z)$) of a process, the duration of a process (D), the average and standard deviation of workloads of all steps for all zones in a process, and the number of workers. The Project O implementation did not include some metrics, including handoff and returns. However, identification of process location flow (the sequence of process steps in a location) and trade location flow (the sequence of locations for a process step) provides a qualitative proxy for these missing metrics. These flows indicate if continuous and on-time handoffs of work and work space are happening as planned, and if trades are returning to the same location to complete unfinished or incorrect work.

Figure 5.21 shows a screenshot of the as-done Gantt chart on the dashboard. Gantt charts are commonly used for tracking the progress of activites on the project schedule. The Gantt chart in the snaphshot is structured with “Location Number - Process Step” on the vertical axis, and time on the horizontal axis. Each row represents a specific location number followed by the process step executed in that location. The horizontal bars across the chart represent the as-done workload and timeframe for each step at the specified locations, as measured using the work detection data. Different colors correspond to different steps, as indicated in the legend on the right side of the chart. The length and placement of these bars provide a visual representation of when each step starts, its duration, and when it is was finished. For instance, “785 - Cold-Formed Metal Framing” indicates that at location 785, the step of cold-formed metal framing was executed during the length of the bar, starting on July 13, 2023 and finishing on August 9, 2023 with 20 working days. When summed across multiple rows for the same location, the total length of the combined bars would represent the duration of a process.

I developed the Gantt chart to be an interactive tool where the user can organize data by grouping, slicing, and ordering the bars by their process step, location, and start- or finish dates. In the example screenshot shown in Figure 5.21, the data is grouped by process steps, enabling the user to understand the trade location flow and the project’s overall workflow. For example, the cascading sequence of the blue bars represents flow for the “Cold-Formed Metal Framing” step. The screenshot shows how a user might slice the data by selecting a frame (shown in the top portion of Figure 5.21) and the zoomed-in view of the chart after the selection (shown in the bottom portion of Figure 5.21). Users can receive additional information about the steps by hovering over the bars, as shown for the “785 - Cold-Formed Metal Framing” row, in the zoomed-in view.

Figure 5.22 shows another example from the dashboard catering to production system performance evaluation by visualizing flow. This screenshot shows a pair of horizontal stacked bar charts visualizing the sequence of steps detected across locations of the project, representing process location flow. Each bar is a stack of different colors, with each color corresponding to a different step, such as “Cast-In-Place Concrete” “Gypsum Board”, and so on, as indicated in the legend. The length of the bars does not indicate any magnitude in duration.

For the bar chart on the left, the vertical axis represents the location numbers (e.g., 500, 506) and the horizontal axis represents sequence of process steps detected in each location. The set of bars for each location shows steps already completed in each location, communicating the process by location. The bar chart on the right shows a similar stacked bar chart. However, this chart uses location names (e.g., “Women”, “Men”) on the vertical axis. Since location names have multiple location instances on floors 5, 6, and 7, the bars are added for the completion of a step in any of the instances for that location name.

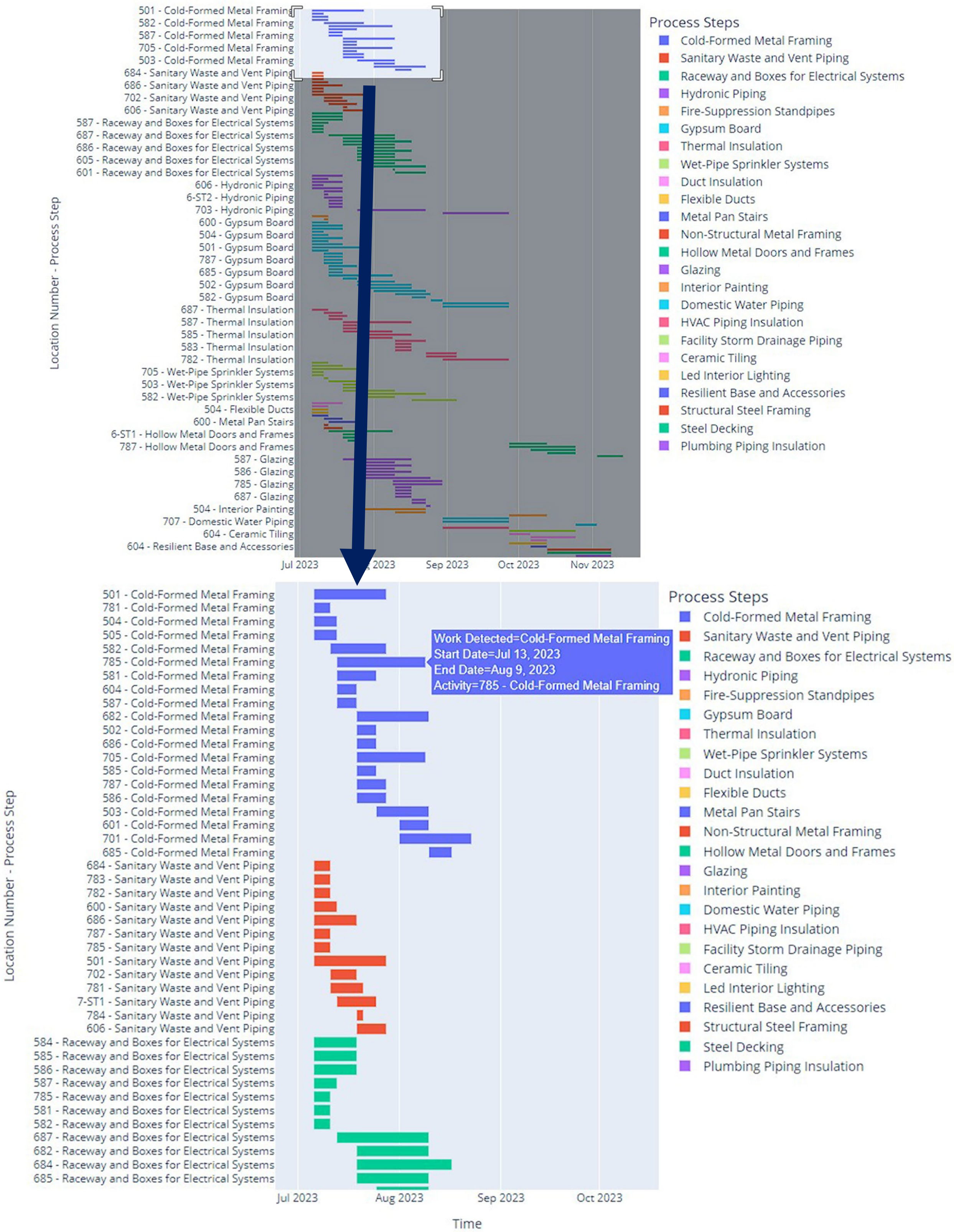


Figure 5.21: Project O dashboard: as-done Gantt chart grouped by process steps (top) and zoomed-in view of selected frame (bottom).

Figure 5.22 is a simple visual to understand the flow of steps in a location, it does not communicate the workloads for the steps. The workloads are shown by means of bar heights in the vertical stacked bar on the dashboard in Figure 5.23 overcomes this issue. Each bar is again a stack of different colors, with each color corresponding to a different step, as indicated in the legend. However, this time the height of the bars indicates the workload in days per step per location.

For the top bar chart, the vertical axis represents the workload per location number and the horizontal axis represents location numbers (e.g., 501, 502). The bottom bar chart is similar, but it represents the average workload per location name on the vertical axis and the location names (e.g., "Electrical", "FSAE Lobby") on the horizontal axis.

These bar charts are helpful for comparing the total workload across locations as well as the proportional duration of each type of step and understanding the composition of workloads at each location.

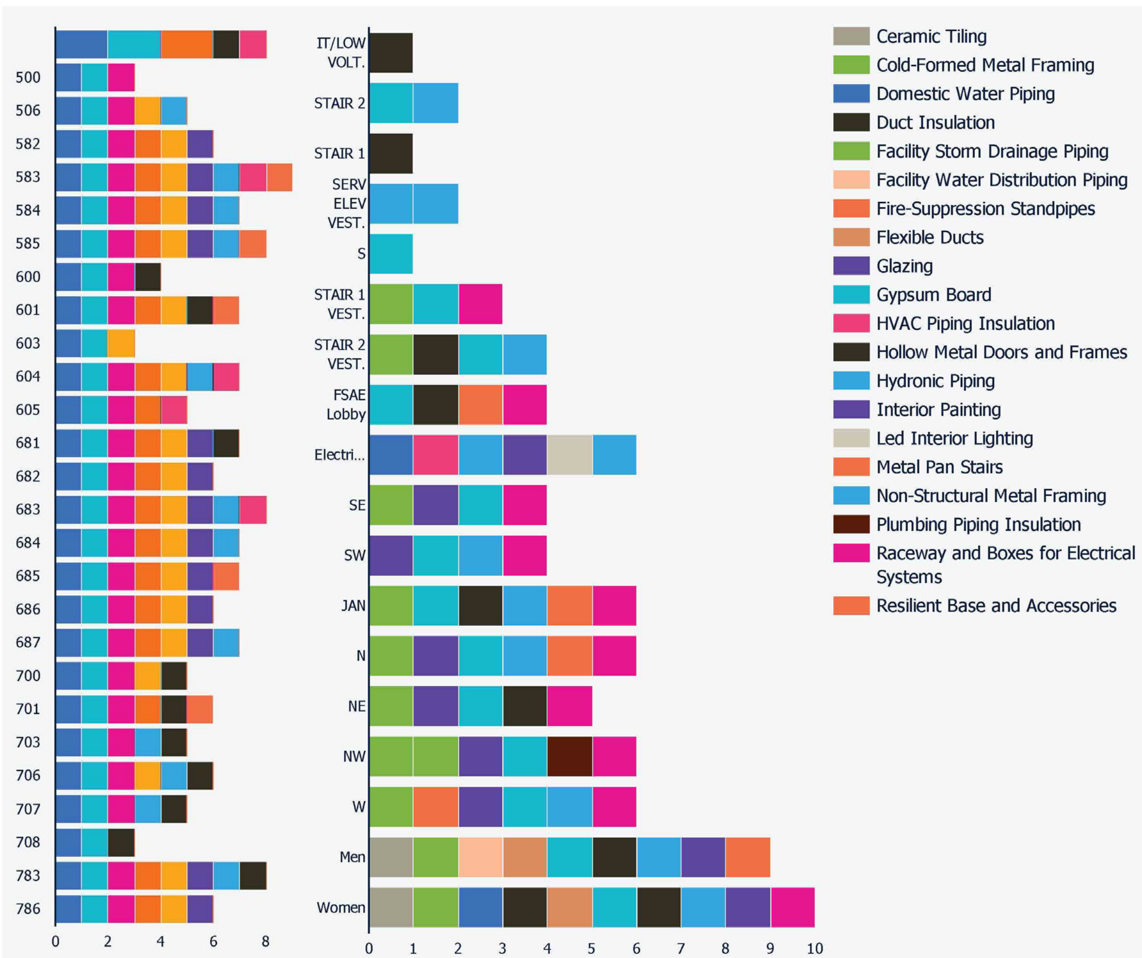


Figure 5.22: Project O dashboard: Process steps and flow by location number (left) and location name (right).

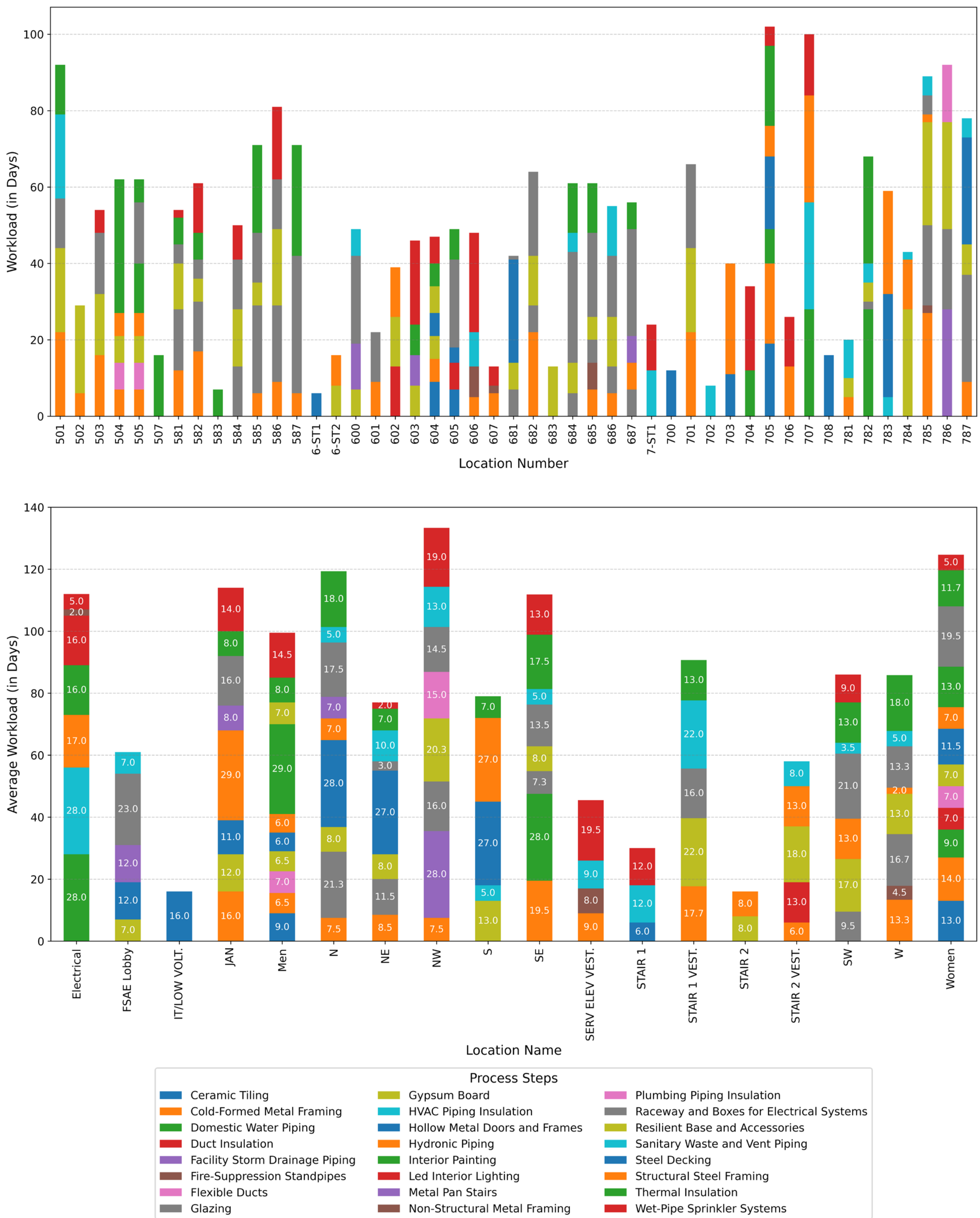


Figure 5.23: Stacked process step bar chart for workload by location number (top) and average workload by location name (bottom).

5.5 Results and Discussion

5.5.1 Data Analysis Results

Before using the processed data for the production control of Project O, I conducted an analysis during the data wrangling and analysis phase. This analysis entailed both exploratory and descriptive investigations from various perspectives, including time-based, location-based, process step-based, and work density analyses.

5.5.1.1 Time-based Analysis

Time-based visualization of work detection offered insights into the relationship between the number of work detections with the frequency- and the length of data collection.

Figure 5.24 consists of six plots representing time-series line plots with number of work detections by date of detection. The top plot duplicates the previously shown line plot in Figure 5.7 and the bottom five plots break-out the top plot by months, from July to November of 2023. The plot shows fluctuations across the study period, which may reflect differing levels of construction activity and capture frequency. Assuming a steady pace of starting new work, thus no big variations in site activities, the relationship between the number of work detection and capture frequency becomes apparent. Notably, weeks with more frequent data collection (more than once a week) resulted in fewer detections per capture compared to less frequent captures, underscoring the importance of maintaining a consistent data collection frequency to ensure smooth and reliable work detection data. This frequency also impacts the resolution of work density calculation as it is constrained to the time span between individual work detections.

In the case of the tracking technology used, the 360° VideoWalk platform (StructionSite 2022b), walking speed significantly impacts the detection results. For successful data capture, the maximum walking speed is constrained by the time-lapse frequency. The camera operates at a constant rate of one image per 0.5 seconds, which works satisfactorily for a slow to paced walking speed in lit locations. In low-light conditions, the maximum acceptable walking speed decreases, as images can become unusable due to motion blur. On the lower end, StructionSite's video processing- and vSLAM algorithms identify and remove frames where the camera's location remains unchanged between subsequent images, thereby reducing the number of frames per location.

Future work can look at synchronizing data capture with the schedule to measure work that is expected in locations as planned. Analyzing data over a longer timeframe or incorporating additional seasonal context is necessary to identify clear seasonal patterns and trends.

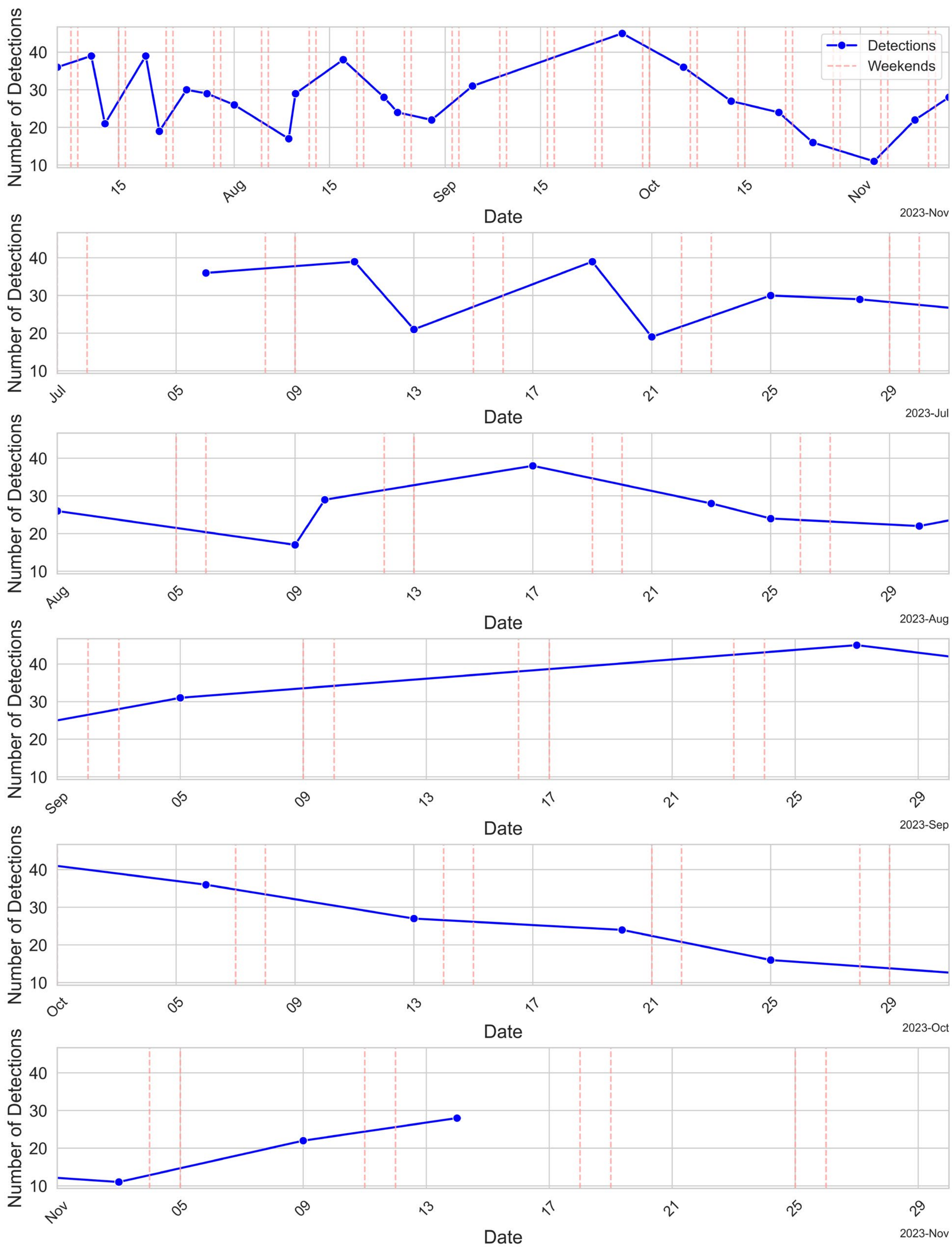


Figure 5.24: Number of work detections by date of detection (top plot, showing the same data as

in Figure 5.7) and monthly break-out (bottom 5 plots).

5.5.1.2 Location-based Analysis

Location-based visualization of work detection offered insights into the trade location flow and the duration of time spent at each location. The unit locations analyzed include the floor level, location name, and location number.

Figures 5.25 and 5.26 display the number of detections aggregated by floor level for the "Glazing" and "Domestic Water Piping" process steps, respectively. The color gradient (darker represents a greater number of detections) and the numbers in the cells indicate the number of detections. This enables a quick visual assessment of where and in what sequence steps were detected and allows for a general estimation of time spent at each location (floor levels in Figures 5.25 and 5.26) by observing how sparse the detections are distributed.

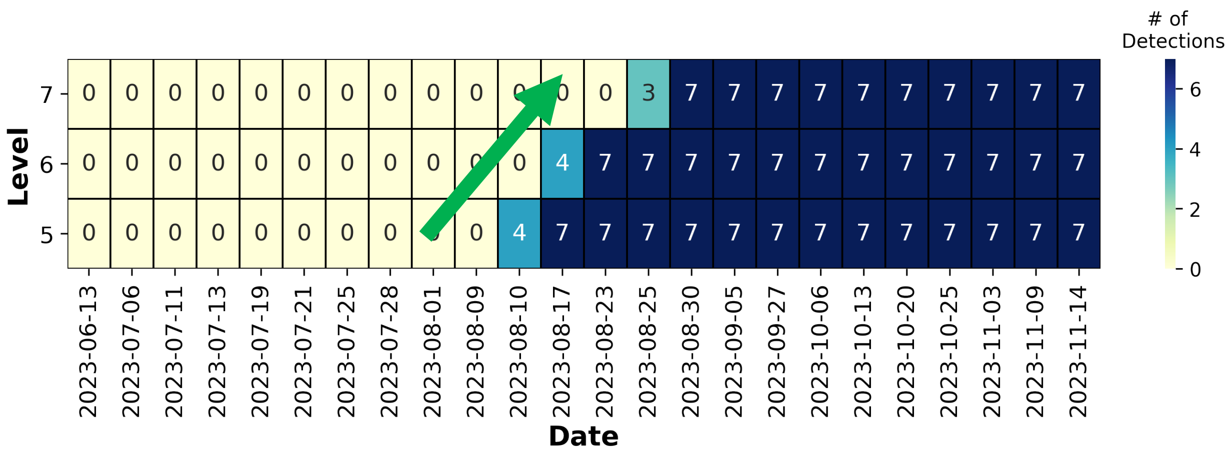


Figure 5.25: Number of detections for "Glazing" process step aggregated by level (combining data from all location numbers on a given level) (shown on vertical axis) over time (shown on horizontal axis).

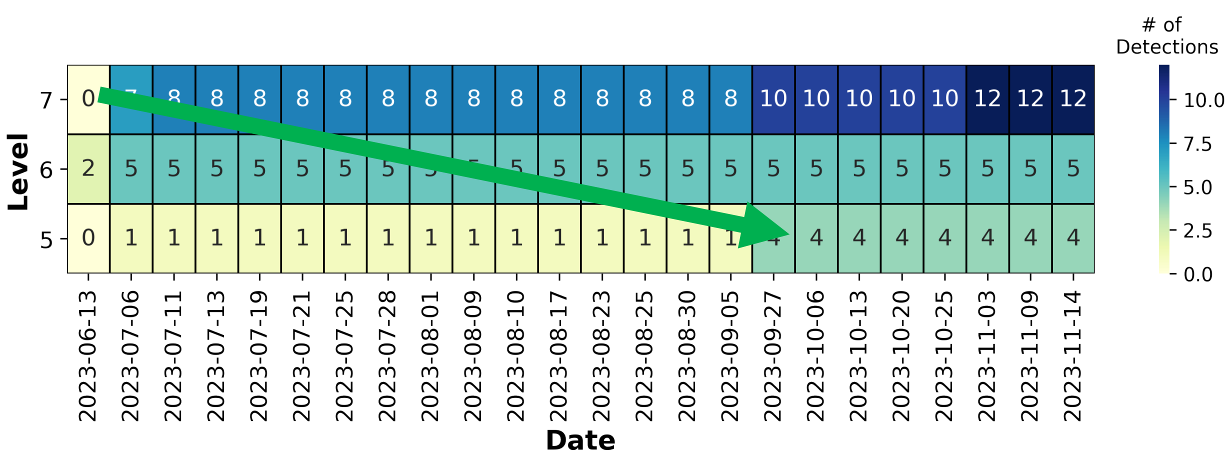


Figure 5.26: Number of detections for "Domestic Water Piping" process step aggregated by level (combining data from all location numbers on a given level) (shown on vertical axis) over time (shown on horizontal axis).

In Figure 5.25, the "Glazing" trade appears to move from bottom to top, with work sequenced from level 5 to level 7, as indicated by a green arrow. The interval between levels is approximately one week. Conversely, Figure 5.26 shows that the "Domestic Water Piping" trade moves from top to bottom, from level 7 to level 5, with work spanning multiple weeks and occurring simultaneously on several floors. Work progress on the same level seems to be stretched out over multiple weeks, possibly suggesting the trade was working on multiple floors at the same time.

Figure 5.27 further elaborates on the "Glazing" process step by examining the number of detections by location number. It is evident that "Glazing" occurs primarily in peripheral zones of the building, such as the "NE" (North East) zone on level 5, indicated by location number 581. The work progresses through approximately 3-4 zones per week and advances one floor every two weeks.

The glazing trade's location flow was clockwise on level 5 and counterclockwise on levels 6 and 7. Figure 5.27 includes annotations showing the flow using green arrows on the floorplans, with deviations marked in red boxes. Location number 781 ("NE" zone on level 7) took a week longer than other similar locations and disrupted the flow due to a more difficult access compared to similar location on other floors. The glazing panels in Location number 781 were part of a two-floor high atrium, thus requiring special equipment and extra safety measures, slowing the production and taking longer installation time compared to panels with regular access, pushing it off the trade's regular flow.

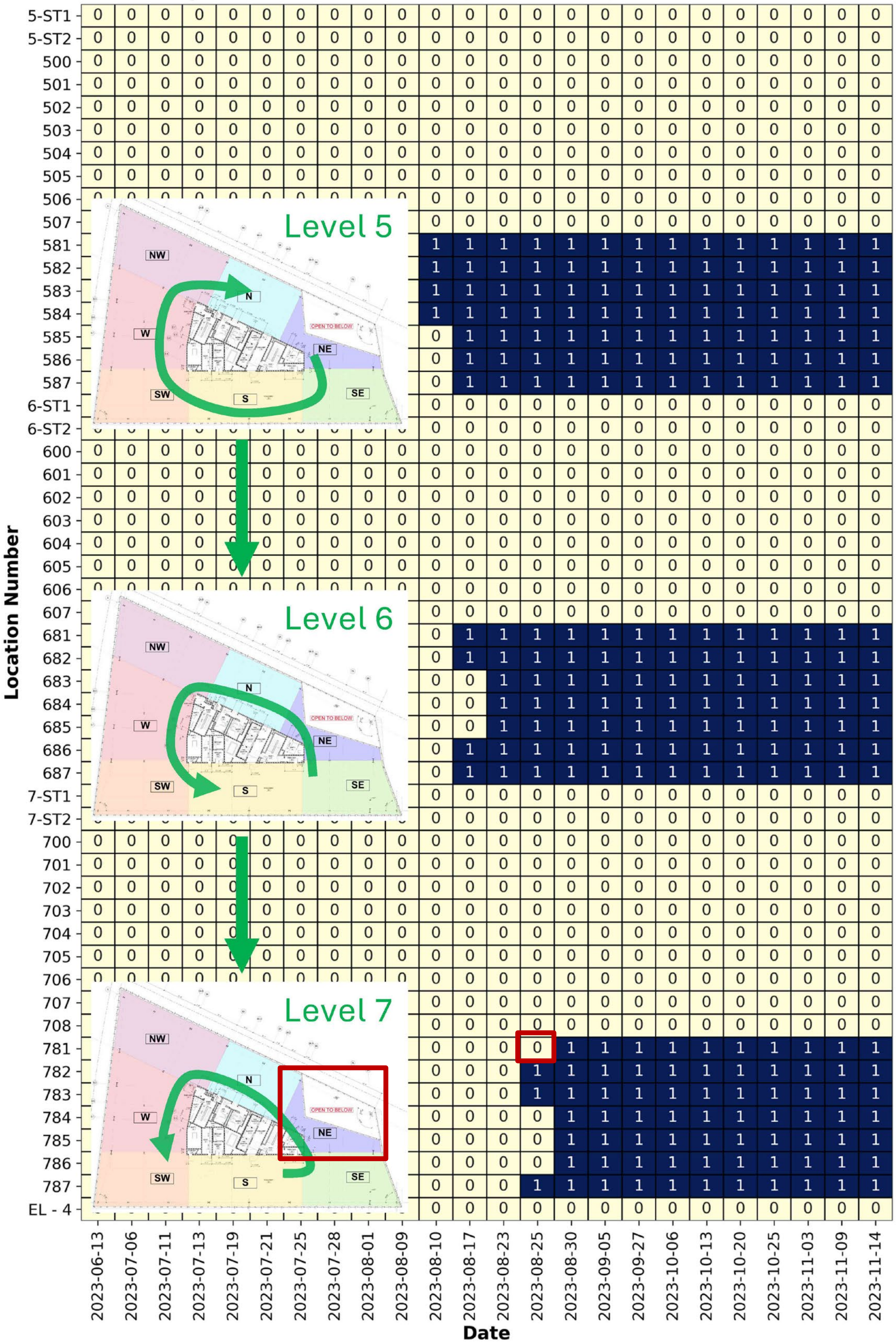


Figure 5.27: Number of detections for “Glazing” process step by location number over time.

Figure 5.28 displays a screenshot from the StructionSite 360° VideoWalk for the level 7 North East zone during the "Glazing" work. The screenshot includes frames from two dates, August 17 (on left) and August 23, 2023 (on right), allowing for a comparison of the progress over time. The bottom left corner of the screenshot shows a floor plan with pins indicating the locations of the captured 360° images, with a selected pin in location number 781. In the left frame, glazing work has not started in location number 781 but is completed on the lower levels visible (location numbers 581 and 681), as also detected in Figure 5.27. In the right frame, glazing work is ongoing in location number 781, with a worker suspended on a harness, highlighting the difficulty of installing the panels in the atrium.

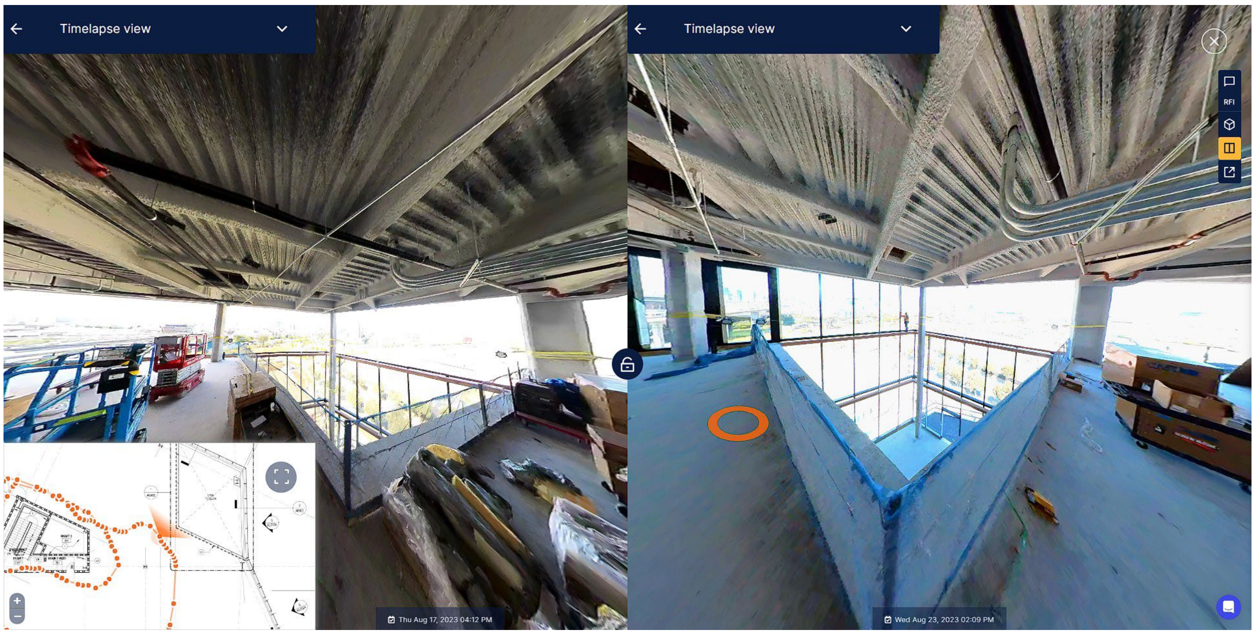


Figure 5.28: Screenshot of StructionSite 360° VideoWalks from Project O case study level 7 North East zone glazing work in atrium, comparing August 17, 2023 (left frame) and August 23, 2023 (right frame) with the captured image pins on a floor plan (bottom left) (taken from https://app.structionsite.com/, visited 02/21/2024).

The location-based analysis presented how a project team might study flow, find deviations, and then confirm it with site conditions and real work on-site. Sections 5.4.2.3 and 5.4.2.4 illustrate how other visualizations, including histograms, bar charts, stacked bar charts, and Gantt charts, can enhance location-based analysis. Different groupings in the same chart can reveal various patterns. For example, Figure 5.29 uses a Gantt chart to analyze and compare the flow and duration of work across different location names. It shows similar workflows for facilities labeled "Men" and "Women", highlighting expected similarities in construction sequences for these comparable areas on each floor and across floors.

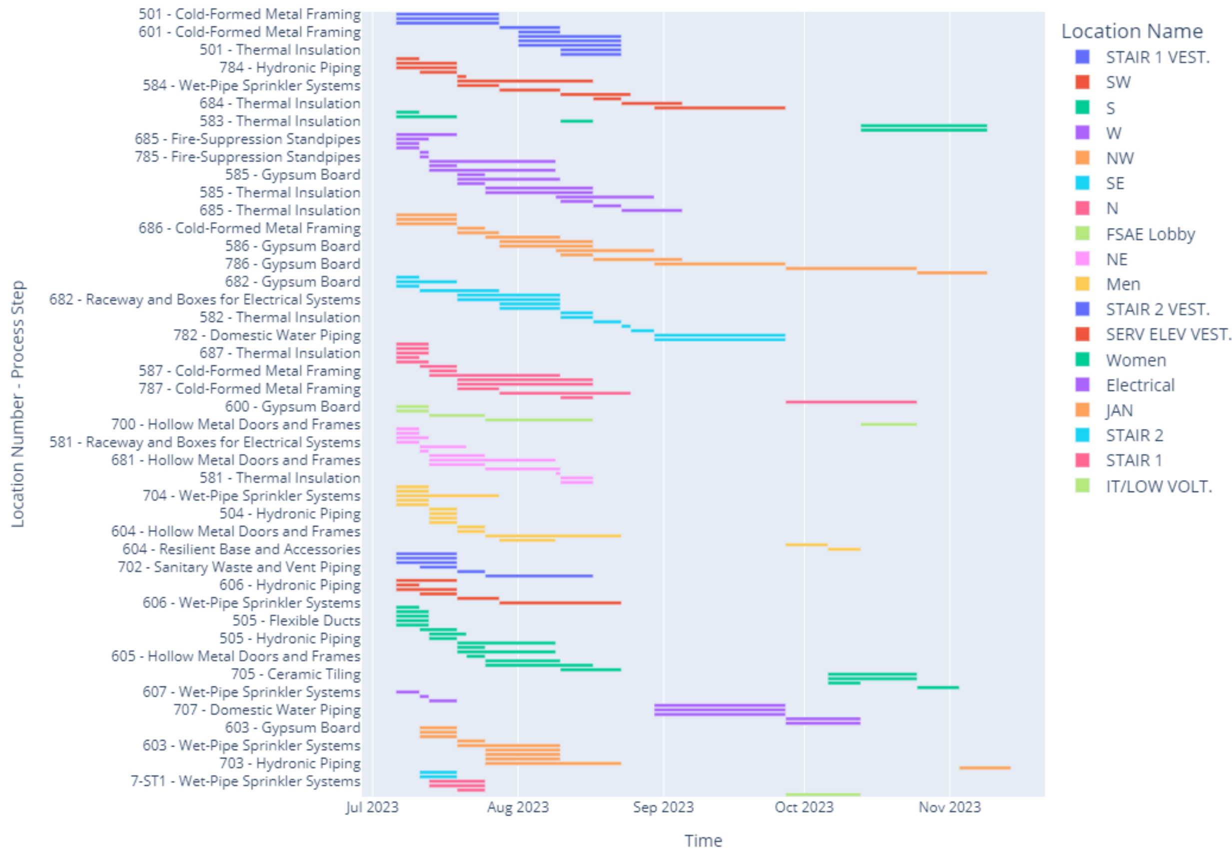


Figure 5.29: Gantt chart grouped by location name.

5.5.1.3 Process Step-based Analysis

Process step-based analysis examines production data from the perspective of individual steps. Since each step is associated with a specific scope of work carried out by one trade—or potentially a collaboration of multiple trades—this method also offers indirect insights into the workflow of trades, with some responsible for performing multiple steps in a process.

Data grouped by process steps enables an analysis of the trade location flow and the duration of work at each location. Figure 5.30 segments the time series line plot in Figures 5.7 by grouping the number of work detections by process steps. This graph illustrates short-term variations and intermittent spikes in detections. However, the complexity of interpreting this data due to the multitude of steps led me to conduct a two-tiered process step-based analysis: (1) at the level of individual locations, and (2) at the level of specific steps.

In the first tier of analysis—I filtered the data to display line plots for individual locations. Figure 5.31 demonstrates this with a cumulative number of detections by process step for a women's bathroom (location number 506). Additionally, for zones—which in a takt plan could represent multiple rooms but in Project O denote sub-divided open areas—I analyzed detections by zone. Figures 5.32 and 5.33 depict the cumulative detections by process step for the South East zone (location 582) and the North West zone (location 586), respectively. In these plots, each line, differentiated by color and labeling, corresponds to a distinct process step.

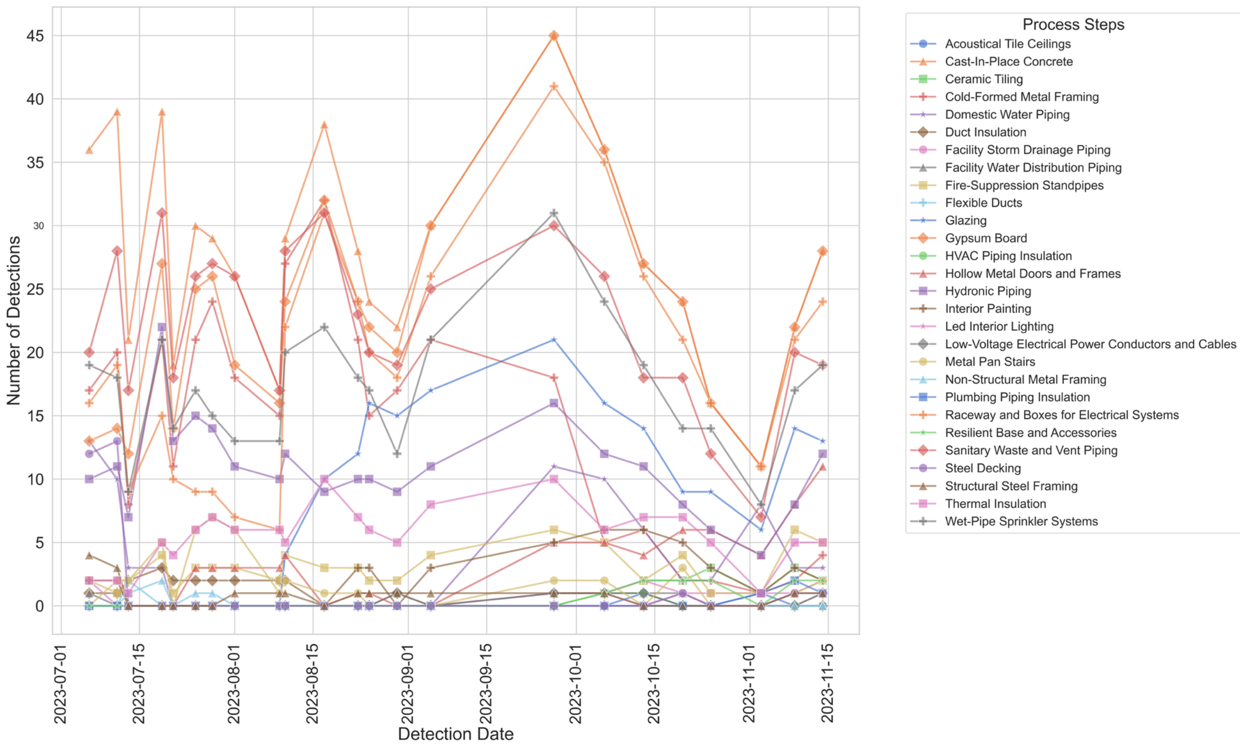


Figure 5.30: Number of work detections by date of detection grouped by process step.

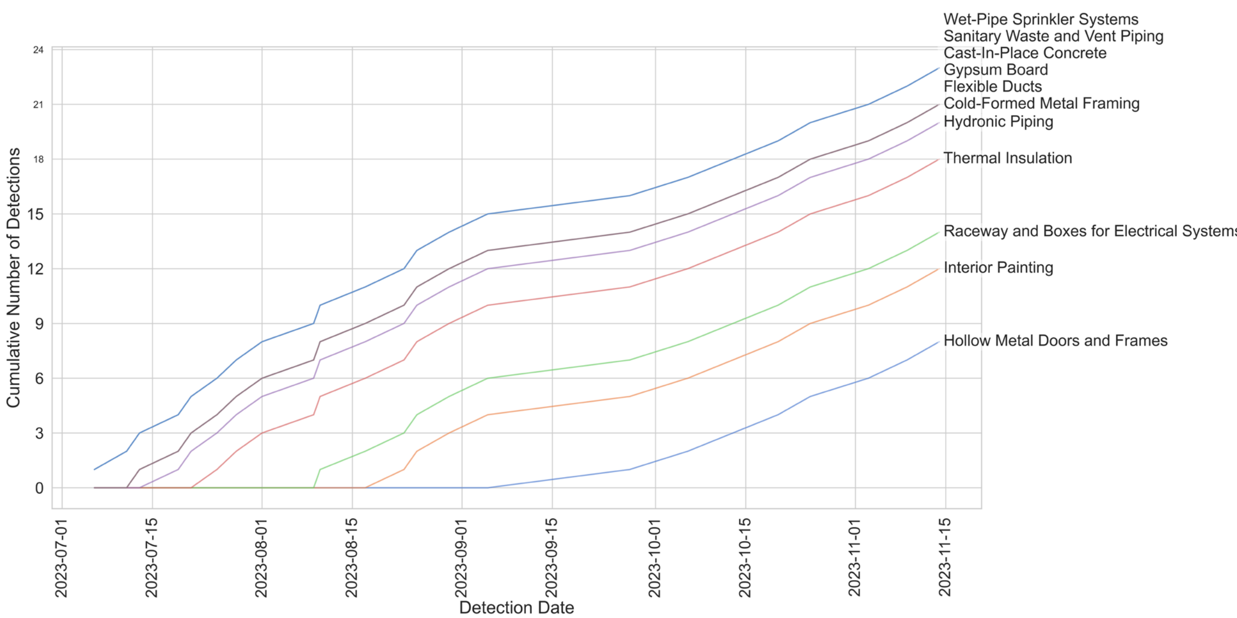


Figure 5.31: Cumulative number of detections by process step for location number 506 (women's bathroom).

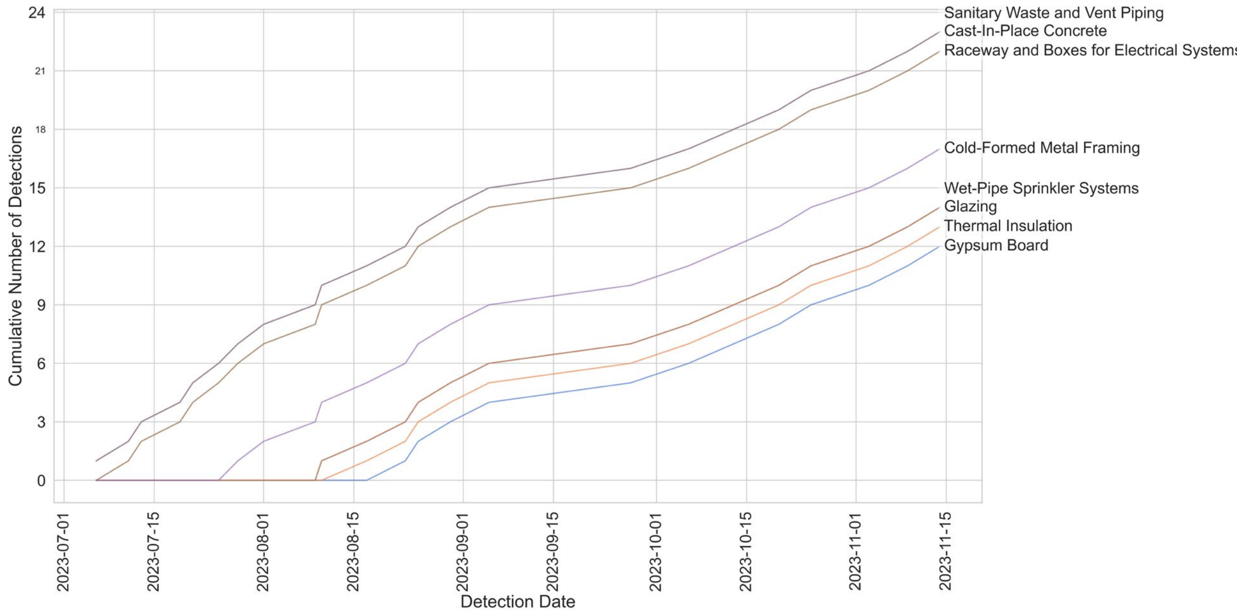


Figure 5.32: Cumulative number of detections by process step for location number 582 (South East zone).

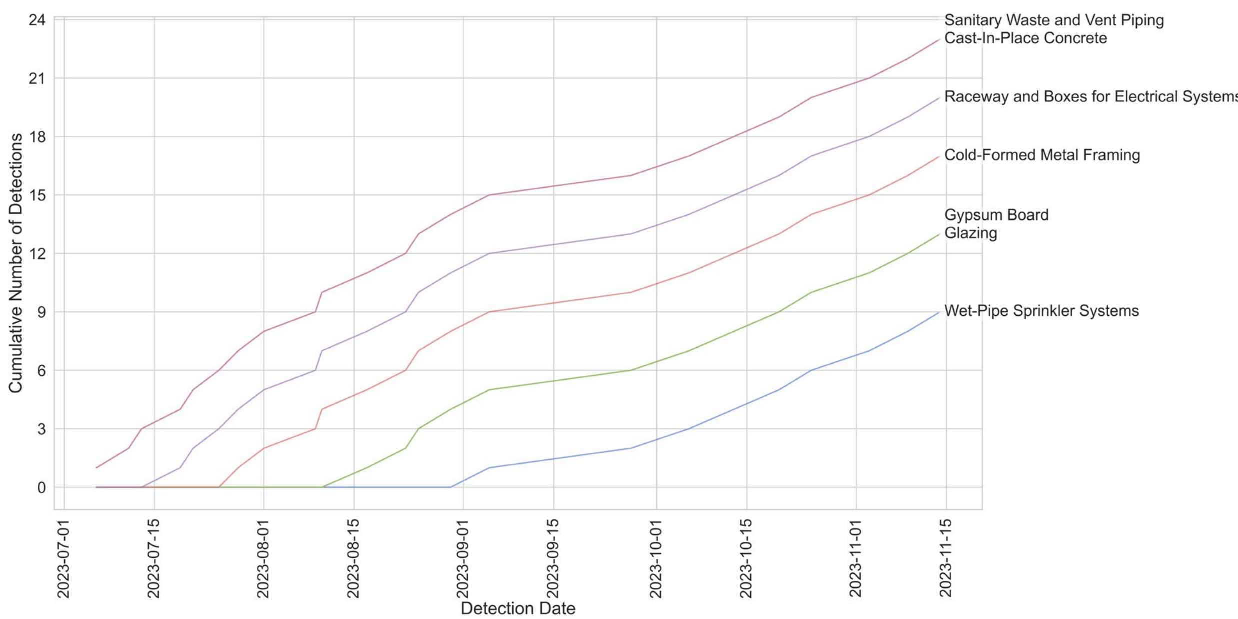


Figure 5.33: Cumulative number of detections by process step for location number 586 (North West zone).

These visualizations are helpful in discerning the sequence of steps within a location, which can shed light on the progression of work through different areas. For instance, some scopes of work had commenced before data capture began, as evidenced by the consistent upward trajectory from the first capture date, suggesting ongoing and consistent work detections for that step. For example, in Figure 5.31 the lines for “Wet-Pipe Sprinkler Systems”, “Sanitary Waste and Vent Piping”, etc. start the first date of capture (2023-07-06) with one detection each, and then continue to increase by one every time they are detected again. In contrast, steps that appear later, such as

"Thermal Insulation", "Raceway and Boxes for Electrical Systems", "Interior Painting", etc., show fewer detections, with their lines beginning to appear around mid-August or later. The horizontal gaps between lines provide a quantitative measure of the time lags between steps, indirectly indicating their durations. A detailed discussion on duration-based analysis is presented in the work density analysis section (Section 5.5.1.4).

From these charts, one can infer that the initial construction work, such as concrete casting, commenced first, followed by the mechanical installations such as ducts and piping. The finishing processes, such as painting, and door installations occur later in the timeline. This order of operations describes both the sequence of process steps and their flow through the locations.

These line plots also facilitate a comparison of work progress and the sequencing of steps across various locations. Figures 5.32 and 5.33 display data from zones that are of comparable size and located on the same floor, revealing subtle variances in the initiation of steps and their subsequent temporal lags. For example, for the step "Raceway and Boxes for Electrical Systems", the first detection in the South East zone happened on 2023-07-11, whereas in the North West zone it happened on 2023-07-17. Such nuances illustrate how a step, and its associated crew is moving on a floor and gives an insight into the time required to complete a floor.

In the second tier of analysis—focusing on individual steps—Gantt charts clarify the flow of trades by isolating specific steps. Figures 5.34, 5.35, and 5.36 each display a Gantt chart for "Cold-Formed Metal Framing", "Thermal Insulation", and "Hollow Metal Doors and Frames" process steps respectively. These charts delineate the start- and end dates of each step within locations, with the bar length representing cumulative work density (workload). The charts are arranged chronologically by the start date of each step.

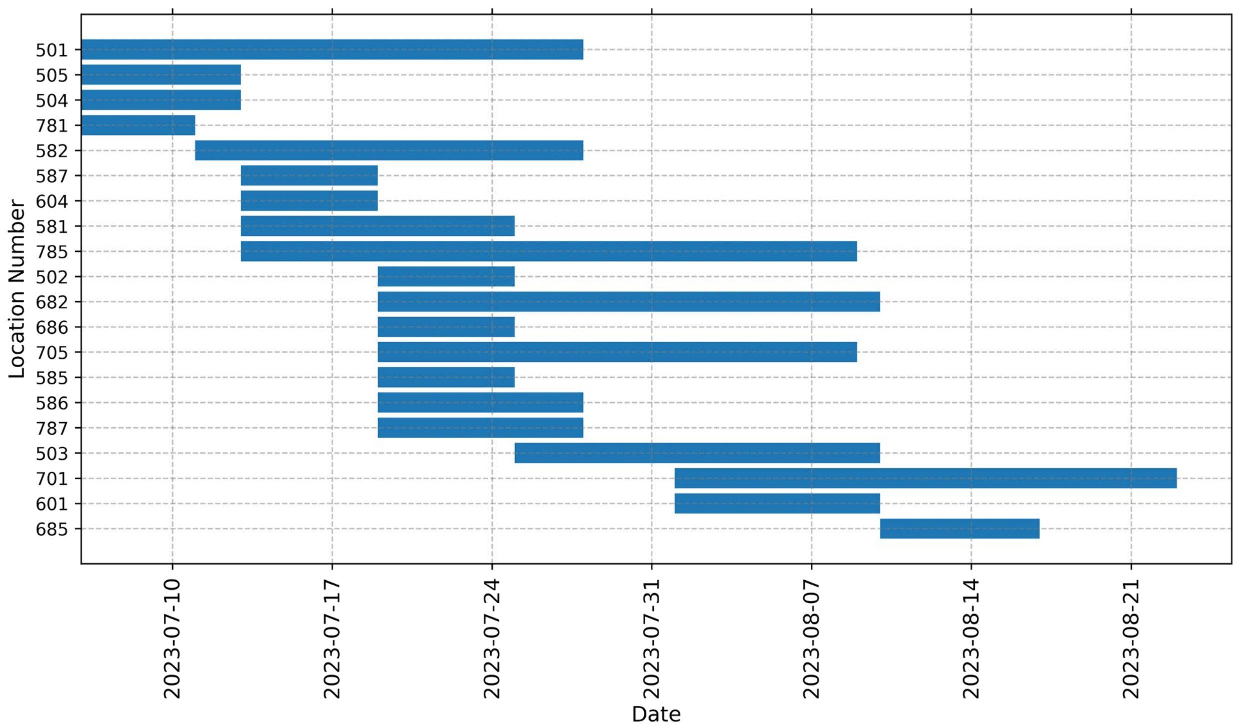


Figure 5.34: Gantt chart for "Cold-Formed Metal Framing" process step.

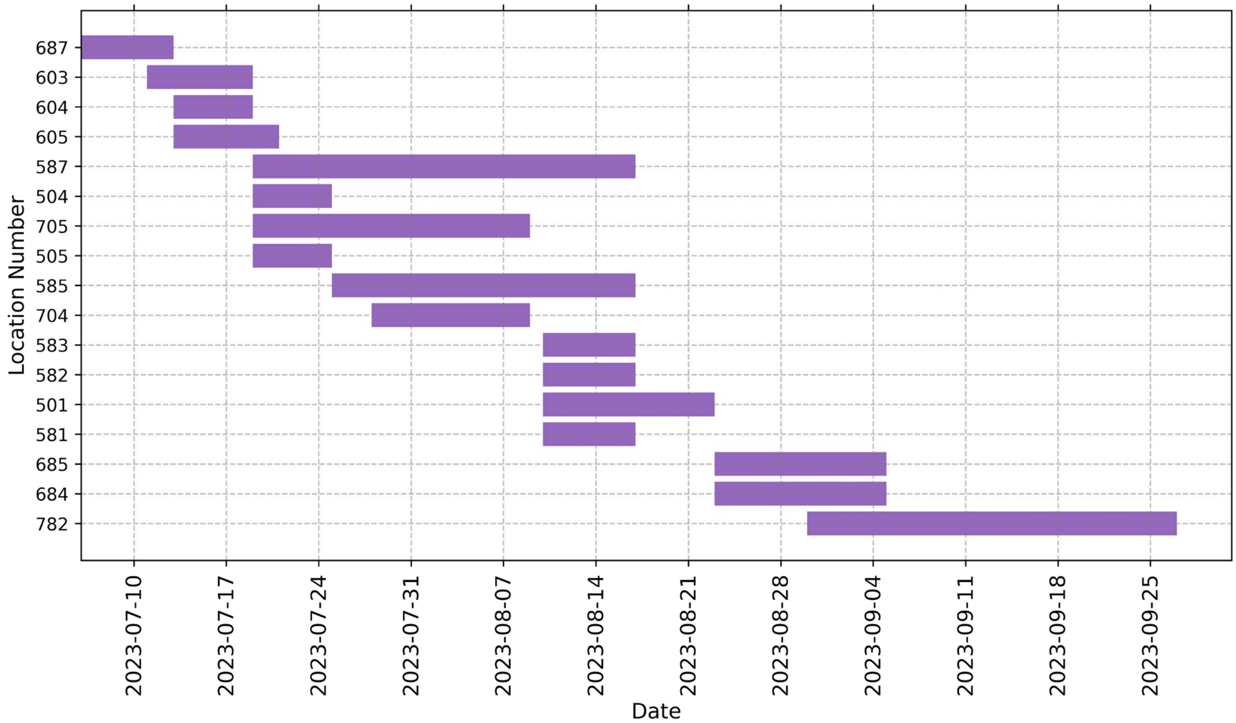


Figure 5.35: Gantt chart for “Thermal Insulation” process step.

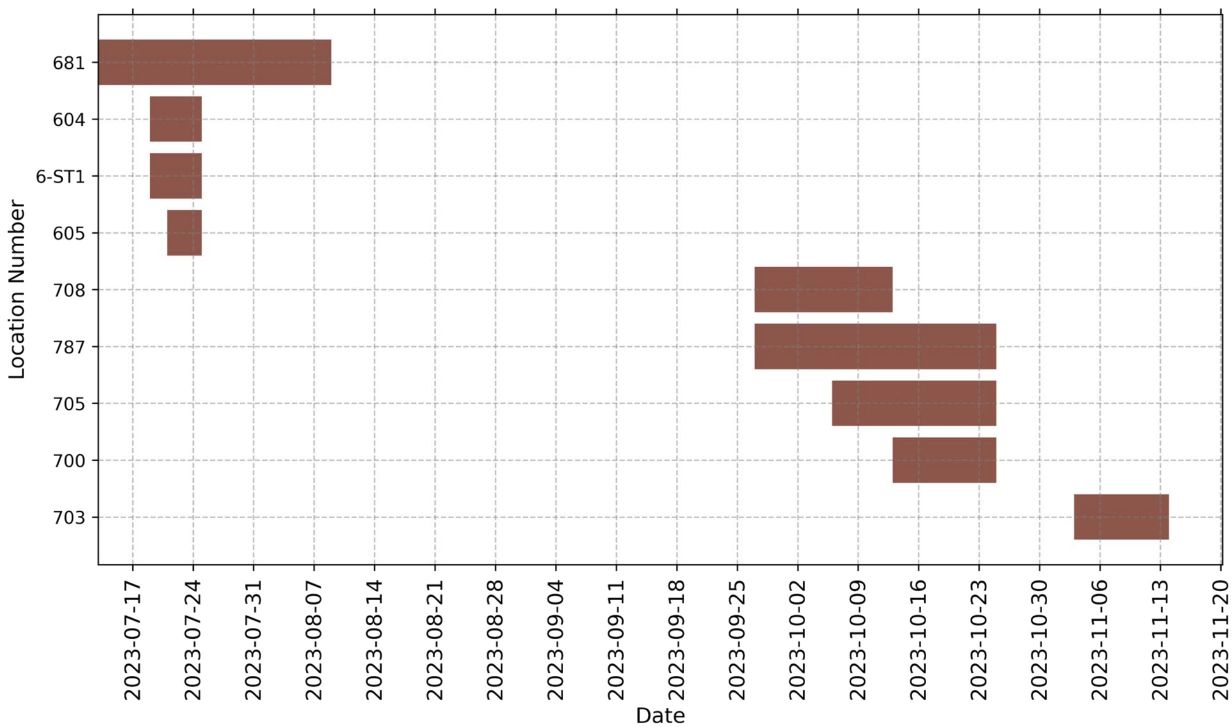


Figure 5.36: Gantt chart for “Hollow Metal Doors and Frames” process step.

In Figures 5.34 through 5.36, simultaneous activity across multiple locations is indicated by concurrent bars. Uniform bar lengths across most locations suggest a standardized time allocation, with exceptions where the duration extends over several weeks, such as the "Cold-Formed Metal Framing" in location 501 (Stair 1 Vestibule). Delays in such locations may stem from strategic decisions rather than production slowdowns. For instance, in case of stair vestibules, the Project O team intentionally left the framing step incomplete as it provided a wider entry into to staircase, facilitating the movement of materials and equipment, and reducing the risk of damage. Project teams use a variety of strategies with different objectives, such as having workable backlog, a backlog work that is ready to buffer against capacity loss and time loss (Ballard and Tommelein 2021).

However, a continuous bar on the Gantt chart does not necessarily correlate with uninterrupted work by a crew. Given the limitations of infrequent data capture and the ability to only detect start of work and no way to detect when work is done, this research can only specify when work was noted, not its continuity. Continuous monitoring technologies, such as Indoor Positioning Systems (IPS) and surveillance cameras, could bridge this data gap.

In another scenario, work occurs more sporadically and is concentrated in shorter timespans. This can be for many reasons, e.g., when work involves a crew arriving at a site with a prefabricated element that can be installed quickly, or due to a strong dependence on other work on-site and supply chain deliveries to be completed first. In such cases, there may be long spans of time with no work, such as "Hollow Metal Doors and Frames" step in Figure 5.36 with no work during August and September months. Door and frame installation work was both prefabricated with the hardware and was dependent on the finishing of walls.

5.5.1.4 Work Density Analysis

In the work density analysis, I used a combination of location- and process step-based analyses. However, work density is different from the previously described location- and process step-based analyses as the DDPF calculates work density only for steps with a clear start and end. The first date of detection for a step is assumed to be its start date, and detection of the successor step in a process means the end of the step. Thus, steps detected on the first and last capture were not included as the data is not enough to know if the step was tracked for the entirety of the work. Algorithm to identify these start and end dates, and measuring work density is described in Section 5.3.3.

Section 5.4.2 discusses various graphical representations of the workloads (cumulative work density per step by location) such as histograms, bar charts, stacked bar charts, and Gantt charts. Apart from these graphs, I generated two more types of visualizations. These visualizations help to understand the average time spent on different types of work at various locations, providing a clear picture of the distribution of work durations across the dataset.

Figures 5.37, 5.38, and 5.39 summarize the workload distribution categorized by process step, location number, and location name, respectively. Each bar represents a corresponding categorical group, with the height indicating the workload in number of days for that group and averaged across steps and location numbers. A solid red horizontal line across the charts indicates the overall mean workload of 20.44 workdays and the dotted red horizontal lines indicate mean workload plus or minus one standard deviation. The standard deviation of the workload distribution for the whole dataset is 19.03 workdays.

The steps that are outside the one standard deviation range include the first five steps in Figure 5.37. Among these five steps, "Steel Decking", "Facility Storm Drainage Piping", and "Plumbing Piping Insulation" had work in locations that were either hard to access during data collection or often obstructed in the images, such as the staircase, vertical shafts, and space behind enclosed walls. Hard and sporadic access led to inaccurate calculation of their workloads. For steps including "Low-Voltage Electrical Power Conductors and Cables", and "Acoustical Tile Ceilings", work took a long time as the scope of a step might be divided into several smaller steps for the crews on-site. For example, with ceiling tiles, device tiles are installed early to allow for coordination with other trades, but some tiles are left open for access and other inspection activities.

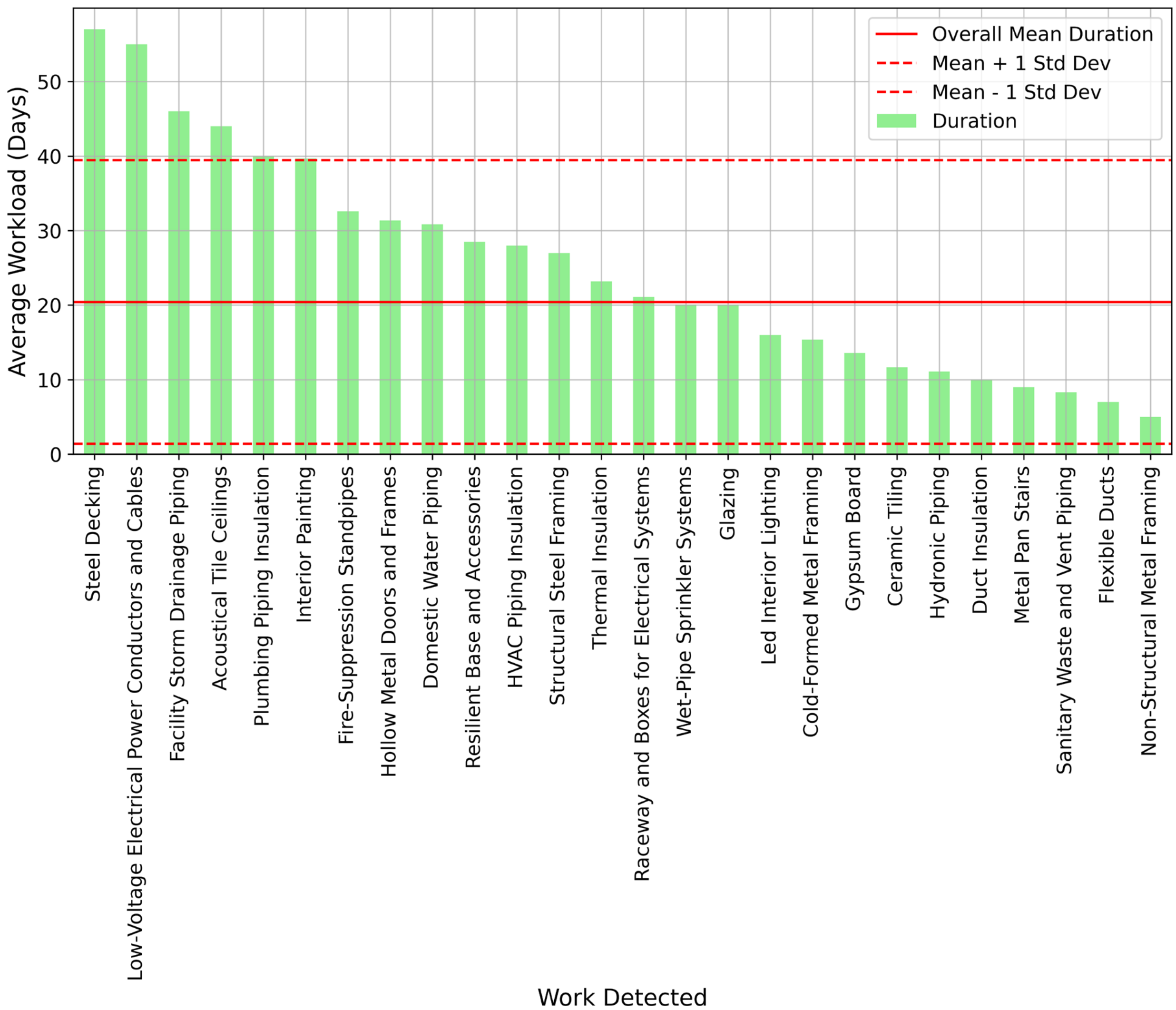


Figure 5.37: Average workload distribution by process step detected.

Similarly with Figures 5.38, and 5.39, workloads for staircases and elevator lobbies were above the one standard deviation range. Here, staircases were hard to access during data collection or often obstructed in the images. The staircase- and elevator lobby locations were planned as workable backlog and were at the end of the built-out sequence for a floor.

Although Figures 5.37, 5.38, and 5.39 were helpful in presenting the workload distribution across one dimension, they are not accurate as limiting to one dimension means a loss of accuracy by averaging in other dimensions. Thus, Figures 5.40 and 5.41 present a heatmap-like two-dimensional plot that represents the workload values in a matrix where locations are on one axis, and process steps on the other, and the color intensity reflects the workload in days. These figures quickly show which step takes the longest, how they are distributed across locations, and how they visually compare across both dimensions. Figure 5.40 uses the location number and Figure 5.41 uses the location name on their y-axis.

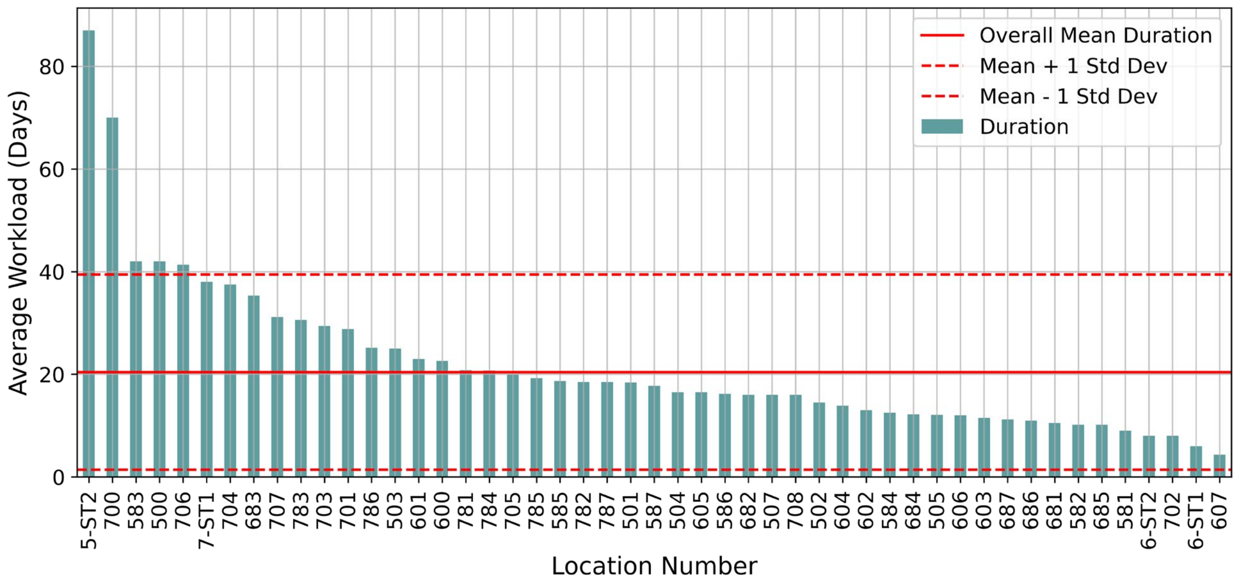


Figure 5.38: Average workload distribution by location number.

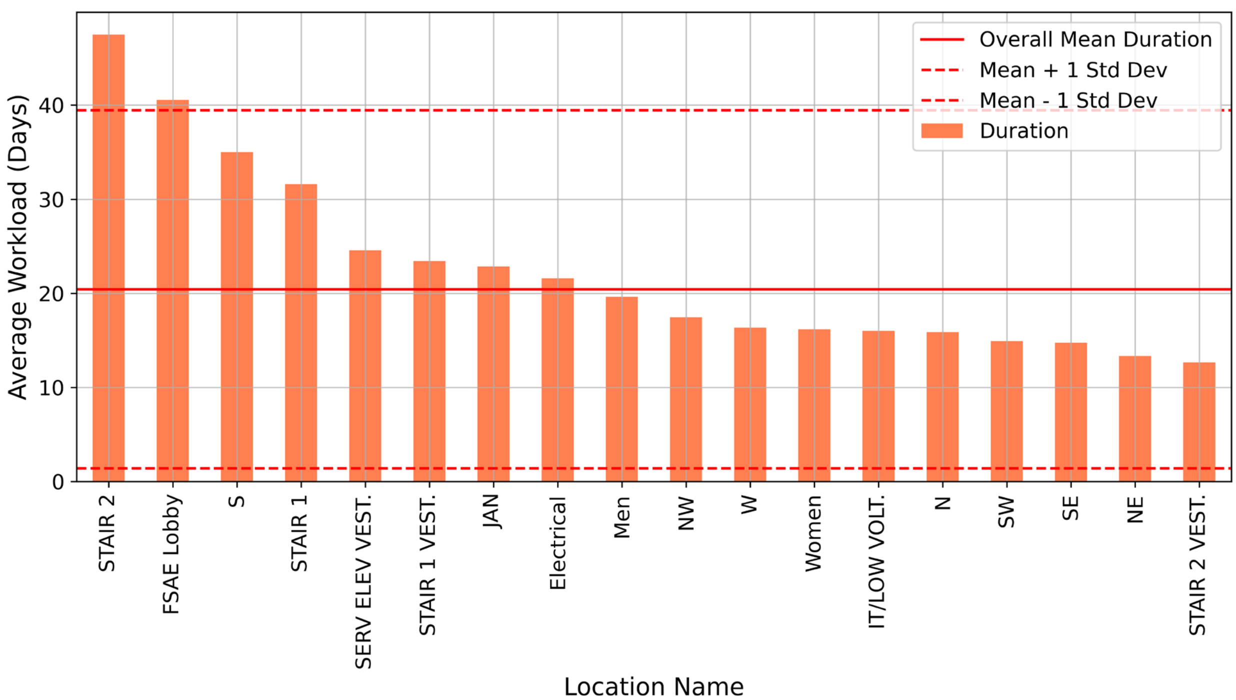


Figure 5.39: Average workload distribution by location name.

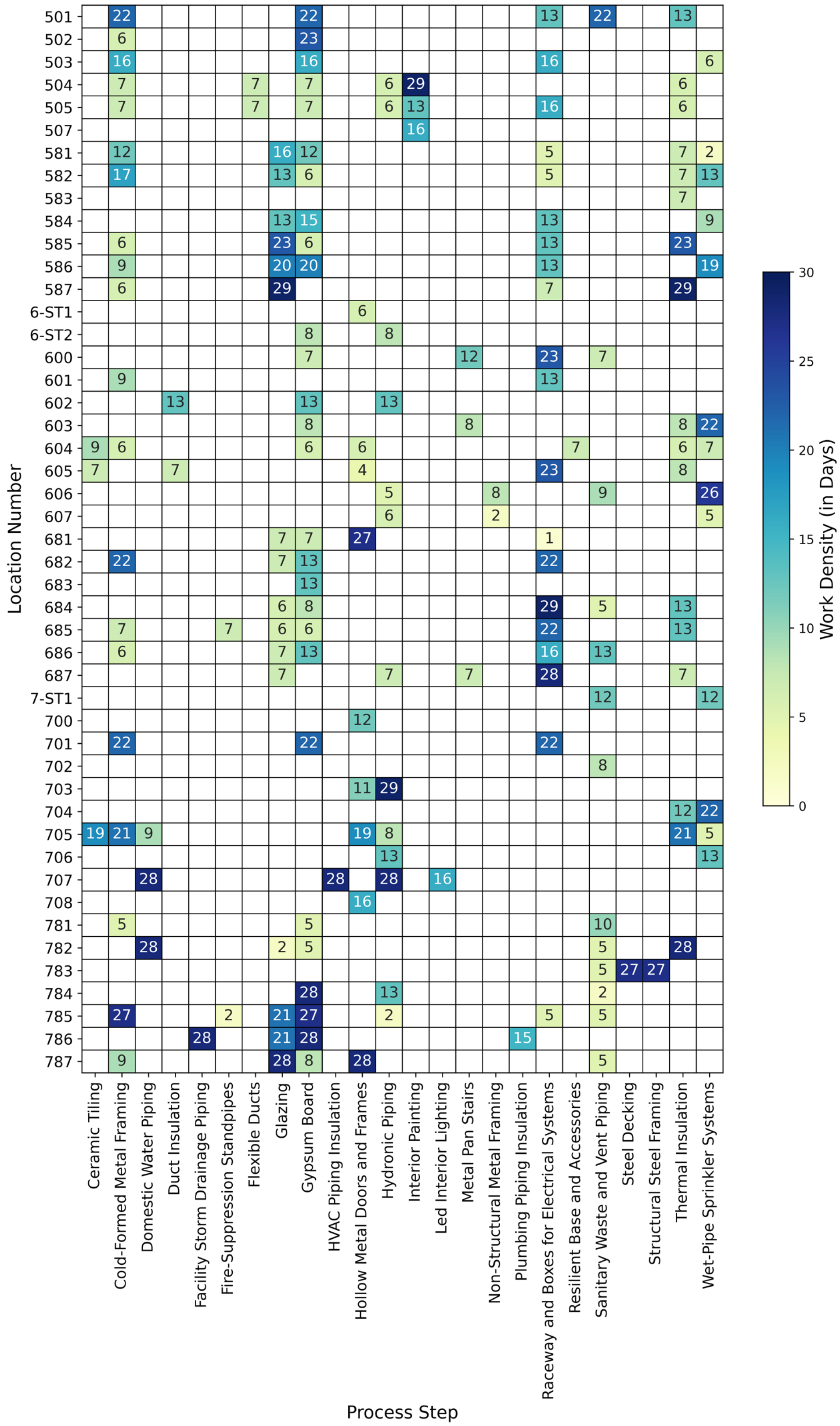


Figure 5.40: Work density by location number (shown on vertical axis) and process step (shown on horizontal axis).

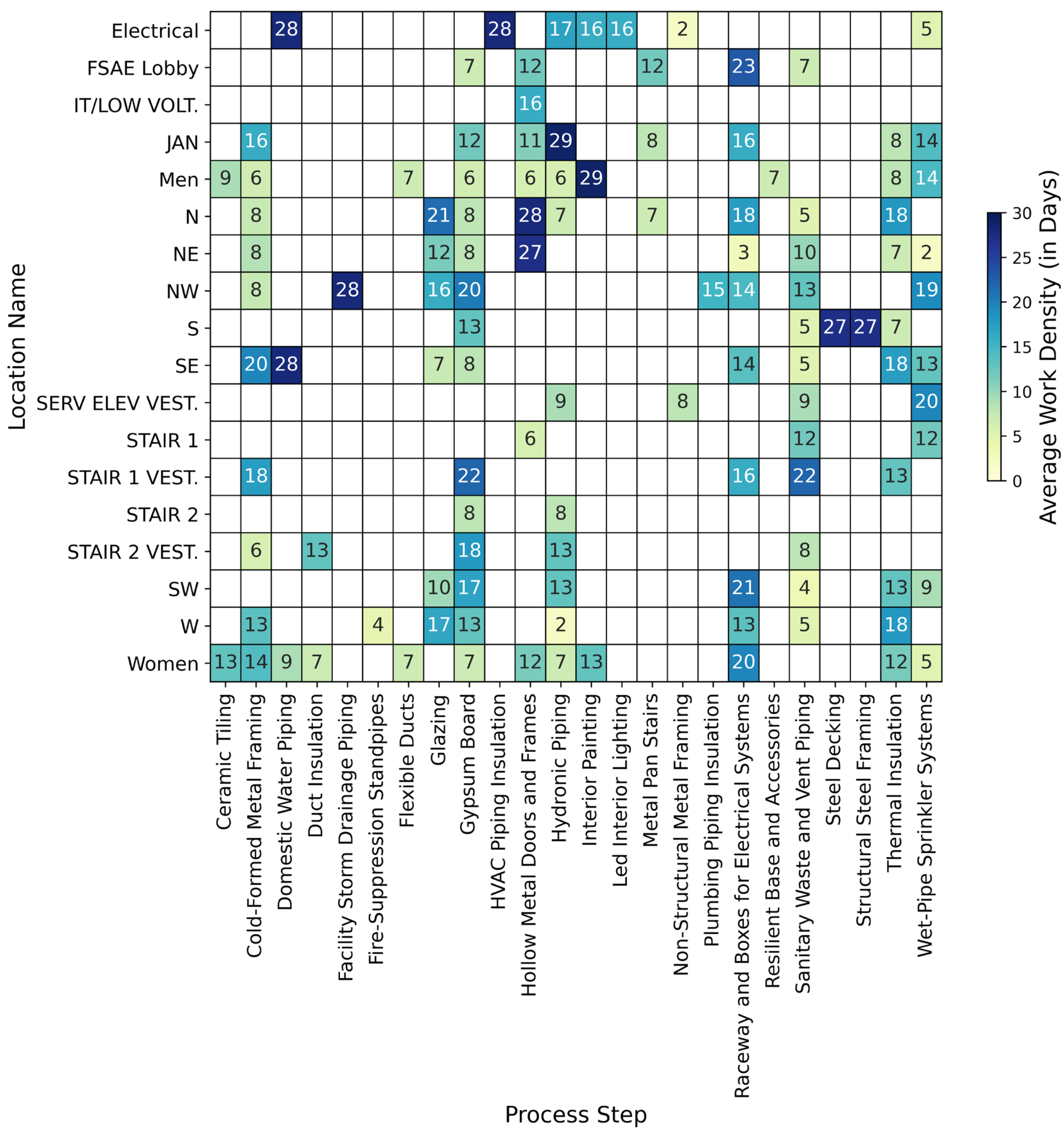


Figure 5.41: Average work density by location name (shown on vertical axis) and process step (shown on horizontal axis).

By studying the work density distribution across locations and steps, I gathered insights about workload distribution. These insights are helpful in production planning, as will be covered in Chapter 6.

5.5.2 Analysis of Production Performance Dashboard

The dashboard developed using Looker Studio proved instrumental in reporting the processed data by means of an actionable tool, displaying information via intuitive graphs, heat maps, and Gantt charts. This tool enabled real-time monitoring and management of production performance, enhancing the project team's ability to make informed decisions for timely course corrections.

5.5.2.1 Expert Opinion

During the development and implementation of the dashboard for Project O, user interviews and user feedback played an integral part in including expert opinion. These users included project team personnel. Insights gathered from their opinion helped me understand the existing production control procedure and the anticipated value addition with the proposed dashboard.

The project team indicated that images captured for work detection were also helpful in substituting for physical site visits to gather updates, while also serving as a photo-documentation tool. The documentation functionality provided remote site access to project stakeholders not working on-site, such as the management team, project owners, and consultants, and gave them assurance as a tool to go back in time for root-cause analysis in case of issues or potential litigation.

The workflow adapted well to the team's weekly planning and control meetings. In their original procedure, data collection commenced on Fridays with the superintendent, foremen and field engineers walking the site to verify the week's scheduled work status. The superintendent would then coordinate and update the schedule, focusing on started-, completed-, and on-target work. Final updates were made on Monday before the weekly coordination meeting on Tuesday. This multiple day manual procedure was replaced with a few hours long walk by one field engineer or me. The walk was accompanied by data capture with a 360° camera on StructionSite's VideoWalks application.

Other than tracking activities for the week, the superintendent made sure the schedule meets major milestones and the critical activities are not delayed. This was achieved by monitoring critical activities (with zero total float) and near-critical activities (with low total float). Since the automated tracking did not synchronize with the schedule, the responsibility of gauging production performance to meet milestones and calculating float was missing and the project team suggested it as an area of improvement. Integration of material delivery and storage management was also identified as a potential improvement area.

5.5.2.2 Questions to Ask the Dashboard

The production performance dashboard helps users find information to guide their production control decisions. The effectiveness of the dashboard depends on knowing the right questions to pose to the dashboard. During its development and implementation, I identified some questions users might ask.

For the situational awareness sub-component, questions include:

- Which steps or trades are currently active in a particular location or location type?
- In which locations is a step (or steps assigned to a single trade) working?
- What was the recent activity within a specific timeframe (e.g., the past week or day)?
- Which locations saw activity in the last specified timeframe?
- What was the last step or trade to work in a particular location or location type?
- Where did a step or trade most recently start work?

For the production parameters sub-component, questions include:

- What are the actual production parameter values for the site's implemented production system? This question can be sub-divided into the following questions:
    - How many steps (*S*) are there in a process, for a location? (put boundaries on a process)
    - How many zones (*Z*) have had work detected?
    - What is the workload (*W*) for a process step in a location?
    - What is the operable takt (or workload peak) (*T(Z)*) for a process?
- Which step has the highest workload and could be a bottleneck?
- What does the distribution of step cycle times look like within a location?
- How does a step's cycle time vary across locations, location types, or floors?
- For takt-based projects, how do actual step cycle times compare to customer- or target takt?
- Are any steps failing to meet the customer takt?
- Which steps are under- or overloaded?

For the production metrics sub-component, questions include:

- How well is the production system performing as per the metrics? This question can be sub-divided into the following questions:
    - What is the operable takt (or workload peak) (*T(Z)*) for a process?
    - What is the lead time (duration of a process) (*D*) for a specific location, location type, or floor?
    - What is the variability in workloads for all steps across all zones in a process?
    - What is the throughput (number of steps completed over time) for a specific location, location type, or floor?
- Does the process location flow demonstrate timely work space handoffs?
- What is the composition and proportion of workloads by step at each location?
- What is the typical sequence of steps (process map) for a location type, and does it vary?
- Are there any steps that occur out of their expected order?
- How does a step (or trade) move across various locations, location types, or floors?
- Is there a consistent vertical flow of steps across floors? or does it vary?
- Is there a vertical flow of steps across the floors in a location or location type?

These structured questions can guide users in using the dashboard effectively, facilitating decision-making for production control.

5.5.3 Assumptions and Limitations

5.5.3.1 Work Density Calculations

The work density calculation algorithm used in the DDPF assumes work progresses seamlessly from one step to the next without delays or idle time—a scenario that is ideal but not always realistic, as seen in Project O. This assumption is in line with takt production systems, where steps are performed back-to-back as they move from one location to another.

The DDPF's methodology assumes sequential finality of process steps. That means the start of a step indicates the previous step has been completed in that location, leading to a sequence of steps with no delays—what is termed a finish-to-start relationship with no lag. The algorithm uses the first detection date as the step's start and the next step's first detection date as its finish, assuming the duration of a step (time between start and finish) to be the work density.

However, work space handoffs are rarely ideal in practice. Planners often introduce a capacity buffer in the takt plan to accommodate a reliable handoff between steps and to mitigate schedule variations. Frandson et al. (2014) categorized these variations as schedule noise, which doesn't impact the overall takt sequence, and schedule variance, which can disrupt subsequent takt sequences, potentially causing delays.

The algorithm also simplifies the process by assuming a linear process with one single path. In a takt plan, a crew associated with only one step is allowed to work in the location at a time, i.e., trade stacking is not allowed. For a deterministic schedule, the merge bias effect increases the probability of being delayed due to the cumulative effect of parallel steps having to finish on time for the successor step to start on time (Dodin and Sirvanci 1990). By planning an exclusively linear sequence of steps, a takt plan eliminates the merge bias effect, increasing plan reliability. The algorithm is able to identify parallel steps in a location but assumes all steps finish at the same time, thus ignoring the merge bias effect.

In the real world, a takt plan encompasses multiple processes and therefore requires decoupling buffers, such as time buffers, to mitigate the downstream propagation of variability. For parallel processes, this time buffer can be placed at the end of the takt plan, similar to the "Calculated End Buffer" described by Dlouhy et al. (2019). The buffered time can be derived from the time saved with takt, allowing it to be used as planned or opportunistic slack to manage complexity (Formoso et al. 2021, Saurin et al. 2021).

Furthermore, the algorithm struggles with steps at the boundaries of the data capture period, potentially underestimating work density if a step started before data capture began or missing it entirely if a step ends after the last capture date. To rectify this, adjustments could be made to incorporate user input for start and end dates or better align data capture dates with the schedule to compare as-planned versus as-done.

Improving the algorithm involves addressing these limitations. Adapting it to the specific conditions of the production system or increasing the frequency of data capture, through more frequent walks or using a different tracking technology, could lead to more accurate work density calculations. These potential enhancements are avenues for future research.

5.5.3.2 Frequency of Data Capture

The chosen technology solution, 360° camera-based tracking, required a person to walk the locations on-site to collect data. I defined the frequency of data capture as the number of times a location is documented on the 360° camera per unit of time.

Figure 5.42 illustrates the effect of data capture frequency on the work density calculation as per the algorithm used (Section 5.3.3). The comparison spans a range of frequencies, from once daily to once every five workdays (once per workweek) with increments of one day, and an outlier example of once every eight workdays.

5 day takted process (with no underloading)

Latest detected step:

Frequency of data capture (once every...)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 day (=1/1)	A	A	A	A	A	B	B	B	B	B	C	C	C	C	C	D	D	D	D	D
2 days (=1/2)	A		A		A		B		B		C		C		C		D		D	
3 days (=1/3)	A			A			B			B			C			D			D	
4 days (=1/4)	A				A				B				C				D			
5 days (=1/5)	A					B					C					D				
8 days (=1/8)	A								B								D			
Actual Work	A	A	A	A	A	B	B	B	B	B	C	C	C	C	C	D	D	D	D	D
Day#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Week 1					Week 2					Week 3					Week 4				

Inferred Duration (days):

Frequency of data capture (once every...)	A	B	C	D
1 day (=1/1)	5	5	5	5
2 days (=1/2)	6	4	6	4
3 days (=1/3)	6	6	3	5
4 days (=1/4)	8	4	4	4
5 days (=1/5)	5	5	5	5
8 days (=1/8)	8	8	ND*	4
Actual Work	5	5	5	5

Delta (days):

A	B	C	D
0	0	0	0
-1	1	-1	1
-1	-1	2	0
-3	1	1	1
0	0	0	0
-3	-3	ND*	1

Delta = Actual Duration - Inferred Duration

non-takted process

Latest detected step:

Frequency of data capture (once every...)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 day (=1/1)	A	A	A	A	B	B	B	B	B	B	B	C	C	C	D	D	D	D	D	D
2 days (=1/2)	A		A		B		B		B		B		C		D		D		D	
3 days (=1/3)	A			A			B			B			C			D			D	
4 days (=1/4)	A				B				B				C				D			
5 days (=1/5)	A					B					B					D				
8 days (=1/8)	A								B								D			
Actual Work	A	A	A	A	B	B	B	B	B	B	B	C	C	C	D	D	D	D	D	D
Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Week 1					Week 2					Week 3					Week 4				

Inferred Duration (days):

Frequency of data capture (once every...)	A	B	C	D
1 day (=1/1)	4	7	3	5
2 days (=1/2)	4	8	2	6
3 days (=1/3)	6	6	3	5
4 days (=1/4)	4	8	4	4
5 days (=1/5)	5	10	ND*	5
8 days (=1/8)	8	8	ND*	4
Actual Work	4	7	3	6

Delta (days):

A	B	C	D
0	0	0	1
0	-1	1	0
-2	1	0	1
0	-1	-1	2
-1	-3	ND*	1
-4	-1	ND*	2

Delta = Actual Duration - Inferred Duration

*ND =No duration inferred

Figure 5.42: Comparison of data capture frequency to work density calculation.

The examples in the figure showcase a process consisting of steps A through D, executed over 20 workdays (4 workweeks). The example in the top half operates on a 5-day takt schedule (with no underloading for simplicity), whereas the bottom half operates a non-takted schedule with steps of various durations, all with a finish-to-start relationship. In both examples, tracking technology is used to identify the latest detected step at every instance of data capture as per their corresponding frequency of capture. The frequency values range from 1 (once daily) to 0.125 (once every eight days). The latest detected step is the newest step identified on-site, reflecting the latest "Actual Work" done on the site. These detected steps inform the algorithm's calculations of a step's start, finish, and inferred duration. The comparison of the inferred durations at different capture frequencies against the actual durations reveals discrepancies (delta) from the actual durations.

In the takted example, the data shows that the accuracy of the algorithm decreases as the frequency of data capture decreases, with an exception when the time between subsequent captures matches the takt. If trades execute their tasks without delays and work spans the entire takt period, matching the data capture frequency to the takt cycle minimizes errors while minimizing data collection efforts. This highlights the ease of control when using takt, as it not only reduces performance variability but also the variability in control points, such as regular handoffs.

The algorithm requires detection of subsequent steps to determine a step's finish and thus its duration. If a step's duration is shorter than the time between captures and there is no capture during the step's execution, the step will be missed, and no duration will be inferred. Therefore, I assume the finish of the process is known and assign it as a special case to the last step in the process. In the takted example, step C is missed when captured once every 8 days; step D is assumed to end on the last day, and the sequence of steps is inferred as A, B, and D. In the non-takted example, step C is missed when captured once every 5 or 8 days.

For accurate work density calculations, the data capture frequency must be equal to or greater than the throughput of the production system, i.e., the reciprocal of the shortest step cycle time or the takt. This approach does not hold for non-takted processes, where varying step durations complicate the accuracy of work density calculations. For processes without a takt or repeating cycle times, daily data collection is preferable to track work progression without missing steps and to identify the exact start of subsequent steps. If daily data collection is not possible, the frequency should be adjusted to best accommodate the variability in step durations by analyzing each scope of work and the time needed to complete it. If a step takes less than a day, more frequent or even continuous data capture is required to achieve a high level of accuracy.

In line with the weekly planning routine of Project O, and typical in many construction projects, I assumed a week as the period of time. For Project O, I determined that a minimum frequency of one capture per week was necessary, based on the scope of work and the time needed to complete it. Frandson and Tommelein (2014a) used a daily colored progress report for takt production control, aligning it with daily huddles, a common practice on projects.

5.5.3.3 Limitations in Line of Sight

Dealing with technical errors, such as inaccuracies in data localization caused by connectivity problems described in Section 5.2.2, required troubleshooting the synchronization between the camera hardware and the mobile application, and refinements in the data processing procedure. However, vision-based tracking technologies have their inherent limitations.

The 360° camera used in this research could detect only work that was visible and within its line of sight. Consequently, I ensured the VideoWalk path for data capture covered all necessary locations and accounted for work concealed by obstacles. Constant path adjustments therefore had to be made to capture the evolving state of the construction site to the extent possible.

Figure 5.43 shows an example screenshot from the StructionSite application. The screenshot presents two frames aimed at the men's bathroom (location number 505) on the fifth floor of Project O. The left frame, dated July 6, 2023, shows a clear view from outside the room into the bathroom area, with visible utilities, including sanitary plumbing and overhead work. The right frame, dated November 14, 2023, depicts how drywall installation has concealed the room. By this date, the utilities were now hidden even from inside the room, behind internal walls and ceiling tiles.

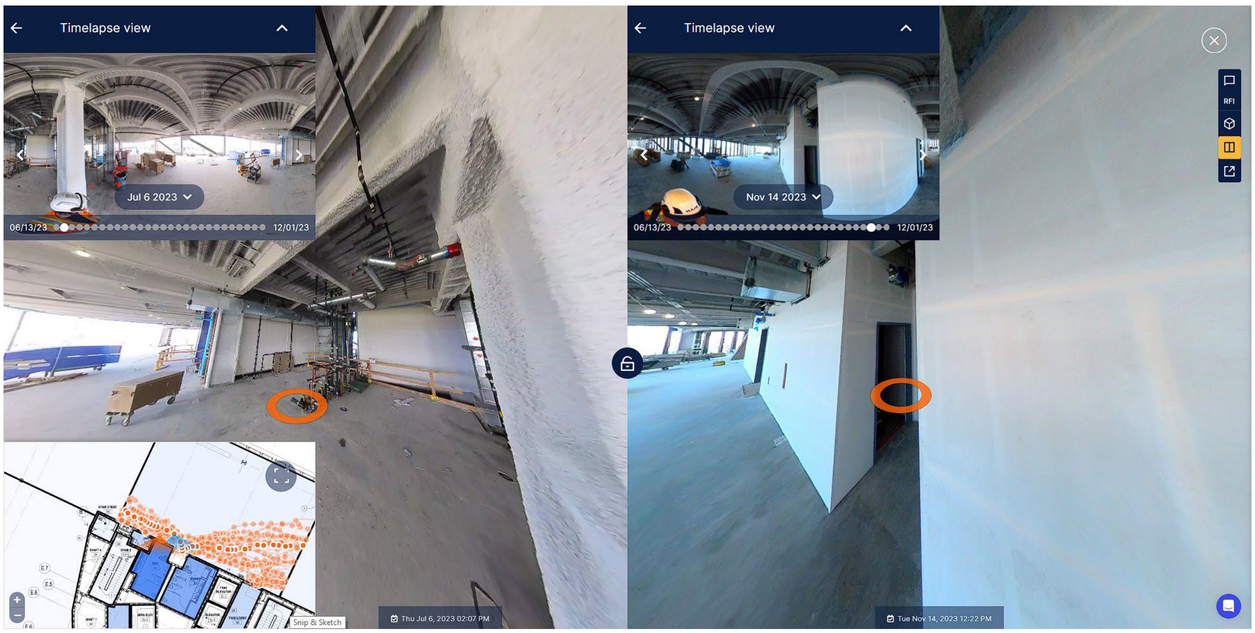


Figure 5.43: Screenshot of StructionSite 360° VideoWalks from Project O case study level 5, in front of location number 505 (men's bathroom), comparing July 6, 2023 (left frame) and November 14, 2023 (right frame) with the captured image pins on a floor plan (bottom left) (taken from https://app.structionsite.com/, visited 02/21/2024).

Although the camera could no longer capture the concealed utilities, adjustments to the data capture route—such as entering the room and walking behind obstructions—ensured continued coverage of the work. This limitation can also be overcome by using other tracking technology solutions that do not rely on line of sight and instead use signals that can penetrate through walls. During technology selection in Section 2.4.2.5, I found IPS to be the best performer under the technology characteristic factor of permeability and coverage, making it a better fit to track work that will likely be concealed at some point in time.

5.5.3.4 Control on Takted Projects

The Project O case study did not use takt production, thereby limiting the use of the production control's takt-specific features. In future projects where takt production is implemented, it will be essential to test the previously unused production parameters and metrics. The parameters include the customer or demand takt (T_c), the process duration or lead time (D), and planned takt (T).

The metrics designed to compare actual performance (cycle time) against the planned target (lead time) will be crucial. This comparison can be conducted at the step level by measuring the step cycle time against the planned takt (T), and similarly, analyses can be extended to process and project levels. Additional metrics that assess performance relative to takt targets—such as cumulative lost capacity for each step, service levels, and handoffs—are also outlined in Section 3.3.2 and should be thoroughly tested to enhance control and efficiency in future takted projects.

5.5.3.5 Control Actions

Although the dashboard provided production performance data to the project team, I have not provided any guidance on implementing control actions for production management. An additional feature could be the implementation of alerts and notifications to flag schedule deviations or resource constraints. Production performance expectations and management styles differ from project team to project team. Thus to enable this functionality, a live connection to the project's scheduling tools and proactive human input would be necessary. This can allow for management at the level of the schedule used for control and measuring against benchmarks and targets set by the project team.

It is recommended that future research explore the development of heuristics for production control, as well as other production design choices that planners could use to guide production toward the desired outcomes. These heuristics could provide a structured approach for users to interpret production metrics, make informed control adjustments to production parameters, and monitor the system's evolution over time.

In the next chapter, I will use the processed data from this chapter and describe the data processing steps taken to convert it into a historical dataset. This processing is a critical step for the planning component of the DDPF by facilitating the application of data-driven methods in the production planning of future projects.

Chapter 6 Data-Driven Production Planning

This chapter elaborates on the development of the production planning component within the DDPF, initially introduced in Chapter 4. It details the method devised and the proof-of-concept training and testing of a ML model tailored for predicting work density to support production planning. The method and the ML model are demonstrated through application on the data from a case study Project O.

Section 6.1 outlines the data processing procedure employed in the Project O case study. The procedure is broken down into two components: (1) the data wrangling, analysis, and storage component (Section 6.2) and (2) the work density component, which includes data preprocessing for ML and the implementation of ML-based work density prediction (Section 6.3). The procedure is described in detail with the intent to create a method that supports data-driven production planning. Finally, Section 6.4 reports the results and insights from the two components of the method development.

6.1 Data Processing Procedure

Figure 6.1 presents an overview of the data processing procedure in two components: (1) at the top is "Data Wrangling, Analysis, and Storage", and (2) at the bottom is "Work Density". The procedure follows the framework outlined in Figure 4.3 of Section 4.3. Each of these represent a component of the DDPF shown in Figure 4.3, and later illustrated in detail in Figures 6.2 and 6.7, respectively.

The procedural flow, from top left to bottom right, is depicted through arrows and the sequential steps are numbered in yellow circles. Steps 1 through 4 are covered earlier in Chapter 5 (see Figure 5.1). Steps 5 through 8 describe the data processing for production planning. This procedure uses some of the raw data collected during the project execution (steps 1 and 2, see Section 5.2) and some of the datasets generated from the production control data processing procedure (step 3, see Section 5.3). The flow chart shown above dotted components in Figure 6.1 represents the associated element of the DDPF (from Figure 4.3), and the flow of data between these elements.

To effectively use ML algorithms for identifying patterns and accurately capturing real-world complexities without undue oversimplification or assumptions, it is essential to have a large quantity of high quality data. Although in the proof-of-concept, the quantity of the data is limited to Project O (Section 5.2), the quality of the data can be further improved after the collection through data wrangling and preprocessing. Data wrangling was already defined and described in Section 5.3. Data preprocessing here involves techniques to prepare data for ML training and testing, including handling missing values, normalizing data, encoding categorical variables, and removing duplicates and irrelevant data. Thus, the input datasets go through wrangling and analysis (step 5) before being stored as historical data (step 6), described in Section 6.2. I used Project O's data on a ML model by preprocessing the data (step 7) and then training and testing the ML model (step 8), described in Section 6.3. For a given set of input features, the trained ML model predicts work density which can then be used with the WDM tools, such as Visual Workload Leveling and Zoning (ViWoLZo) tool to create a takt production plan, as described in Chapter 3.

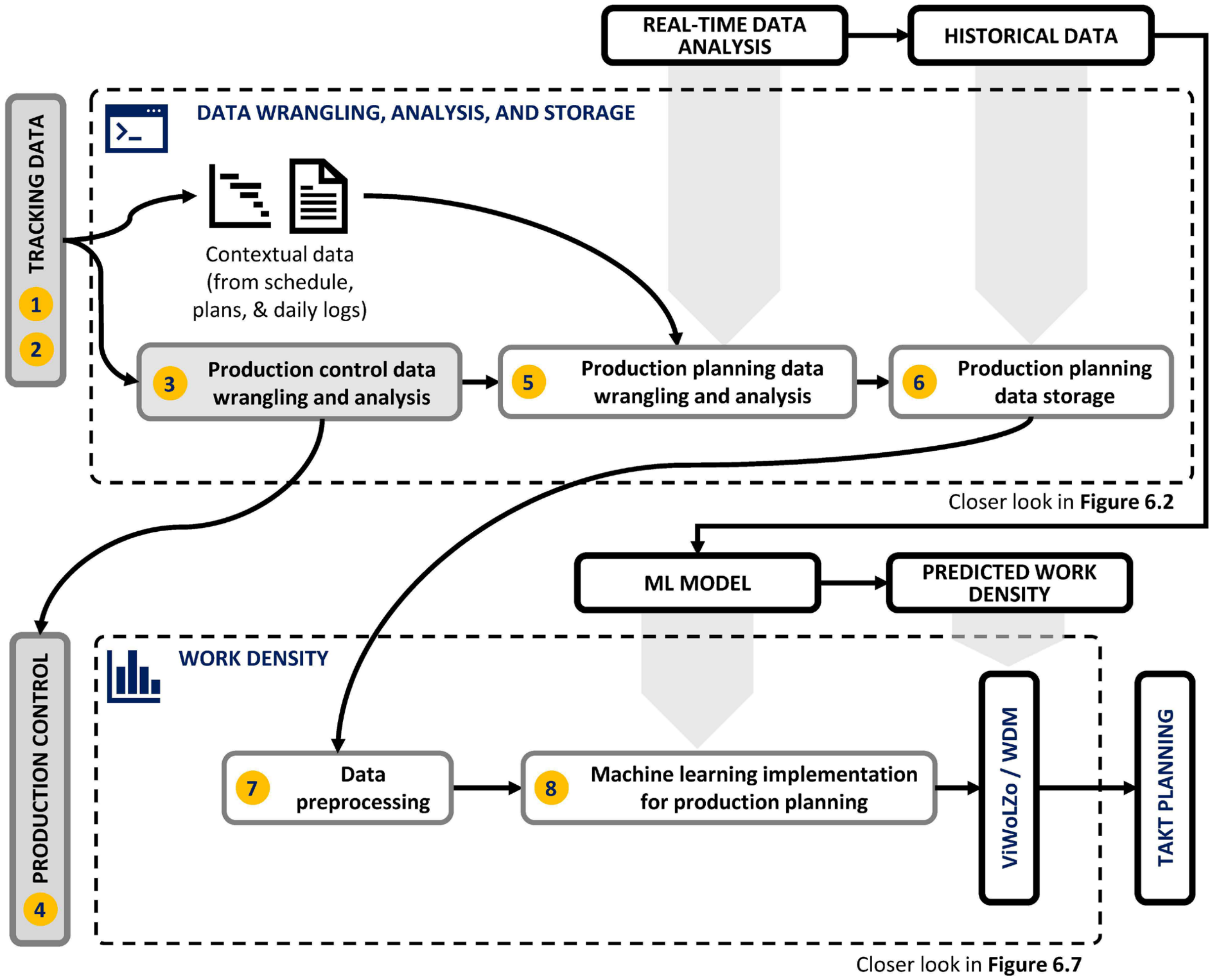


Figure 6.1: Overview of the data processing procedure for production planning.

Next, I take a closer look at each step, explaining the data structuring decisions made, processing actions taken, and outputs generated.

6.2 Data Wrangling, Analysis, and Storage

Figure 6.2 provides a closer look into the data wrangling, analysis, and storage component of Figure 6.1 (top), detailing the steps involved and the output generated at each step. Figure 6.2 is divided in two halves: (1) at the top is "Data Processing Steps" and (2) at the bottom is "Output example" corresponding to each step of the data processing procedure.

The procedure takes raw data from steps 1 and 2 to generate three datasets, namely the work density-, the daily log-, and the location dataset, as described in the following sub-sections. These datasets are merged as part of the data wrangling and analysis in step 5. Finally, the merged dataset is stored as a historical production database in step 6. Section 4.4.3 delineates the technology stack used for steps 5 and 6.

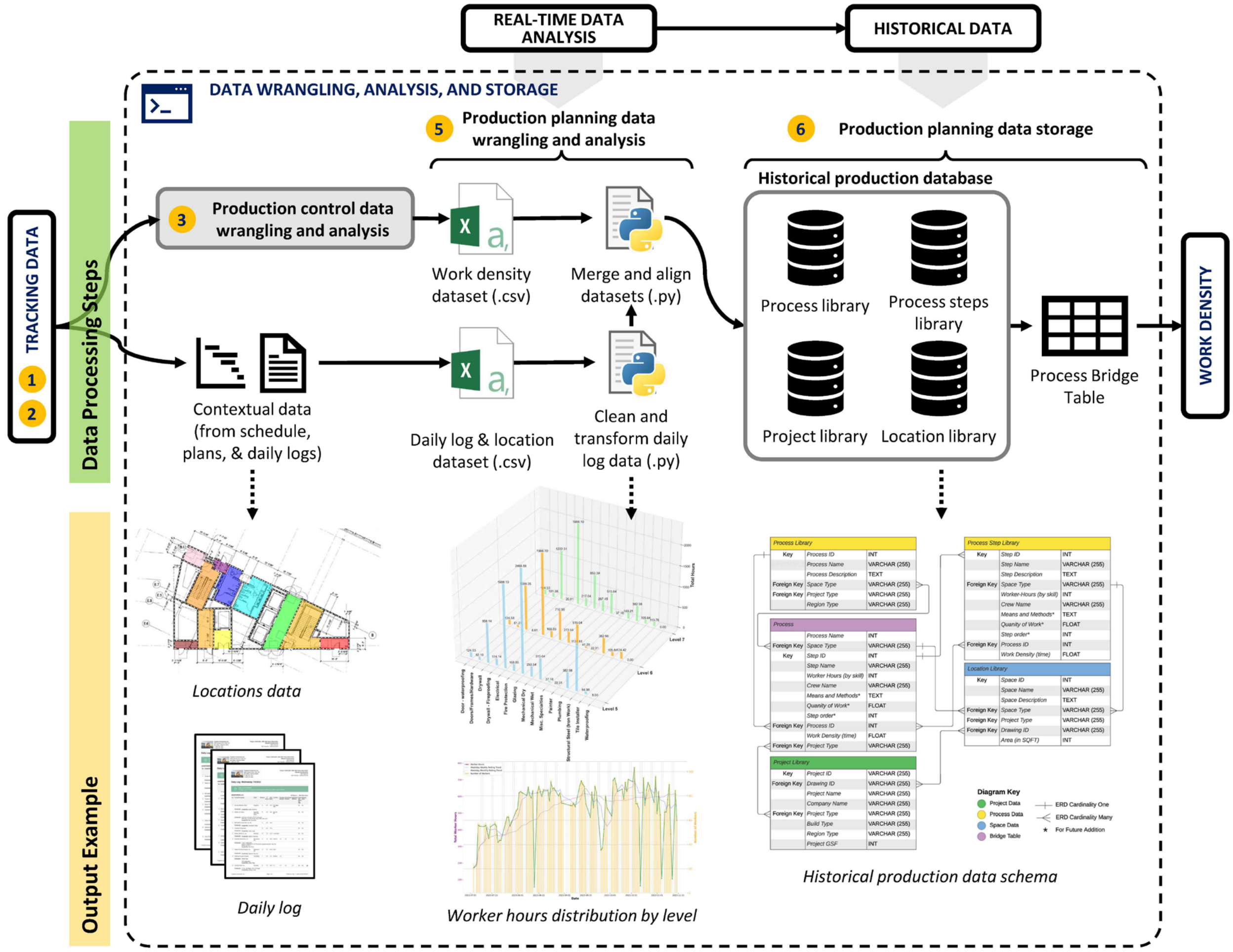


Figure 6.2: Data wrangling, analysis, and storage component of the data processing procedure for production planning.

6.2.1 Work Density Dataset

In Section 5.3.3, I transformed the work detection data (collected in step 2) to calculate the work density for a specific process step in a specific location (step 3). I generated a work density dataset by merging the calculated work density values to the set of input features related to the product (e.g., features of the work's locations and the project) and the process (e.g., features of the process steps, involved crew, and applied means and methods). This dataset is used in step 5 by merging and aligning it with other contextual datasets, as will be described in the subsequent sections.

The distribution of work density is presented in Figures 5.37, 5.38, and 5.39, categorized by location name, location number, and detected process step, respectively. I analyzed these distributions to assess data conformity to expected patterns and identify outliers. This transformation served two primary purposes: initially, to facilitate the integration of this dataset with other input datasets, and subsequently, as detailed in Section 6.3, to inform the preprocessing step of the machine learning implementation.

6.2.2 Daily Log Dataset

In Section 5.2.1, I described manual data collection (step 1) for Project O. The step included collecting contextual data from three sources including the project's daily log. This data was gathered using the Daily Log tool by Procore, a project management cloud-based platform (Procore 2023). The project team reported daily work on the tool, including several data points beyond a simple worker time sheet. Each day each trade reported the scope of work they had performed, the location(s) of their work, the total number of workers on-site, hours worked, breakup of total workers based on their level of experience and role (foremen, journeymen, and apprentices), weather conditions and associated delays, and deliveries of material on-site.

From the project's daily log data, I extracted the data matching the scope of this research, filtering the log to: (1) observations made during the study period, i.e., the range of dates during which I collected the production tracking data (July 3, 2023 – November 14, 2023), (2) observations of scopes of work physically located in the spatial scope of the study (on levels 5, 6, and 7 of Project O), and (3) observations belonging to trades and scopes of work being tracked by StructionSite's work detection software. The final extracted data included a total of 708 individual observations and the following data fields (features): date, trade company name, trade name (scope of work), total number of workers, hours worked (hours worked per worker per day), man-hours (which is the product of the number of workers and number of hours, referred to as worker-hours in this research), location of work, number of foremen, number of journeymen, number of apprentices, and weather delay (binary response of yes or no if there was a delay on that day or not).

Figure 6.3 shows the distribution of total worker-hours per day (green colored line chart on left y-axis) and total number of workers per day (yellow colored bar chart on right y-axis), both obtained by summing all workers, from all trades and locations included in the case study. Typically a worker's day has 8 worker-hours barring small variations. Thus, both charts—total worker-hours and number of workers—follow a similar distribution. Weekends, characterized by vertical dotted lines, represent periods of no or few number of workers on-site. For some weekends with scheduled work, it was usually limited to one trade's scope, and thus shows huge drops in worker-hours line chart. The chart also shows worker-hour trends using rolling average on a weekly basis (blue line) and monthly basis (purple line), only considering while work on weekdays. These trend lines show a ramp up and steady presence of workers in the research locations.

Figure 6.4 shows the distribution of the total worker-hours (green line chart on left y-axis) and the average number of workers (yellow bar chart on right y-axis) grouped by trade over the duration of the case study. For anonymity, the trade company names are referred to by their scope of work. The figure shows the uneven distribution of workers involved, with electrical, drywall, and glazing trades having the greatest number of workers on-site.

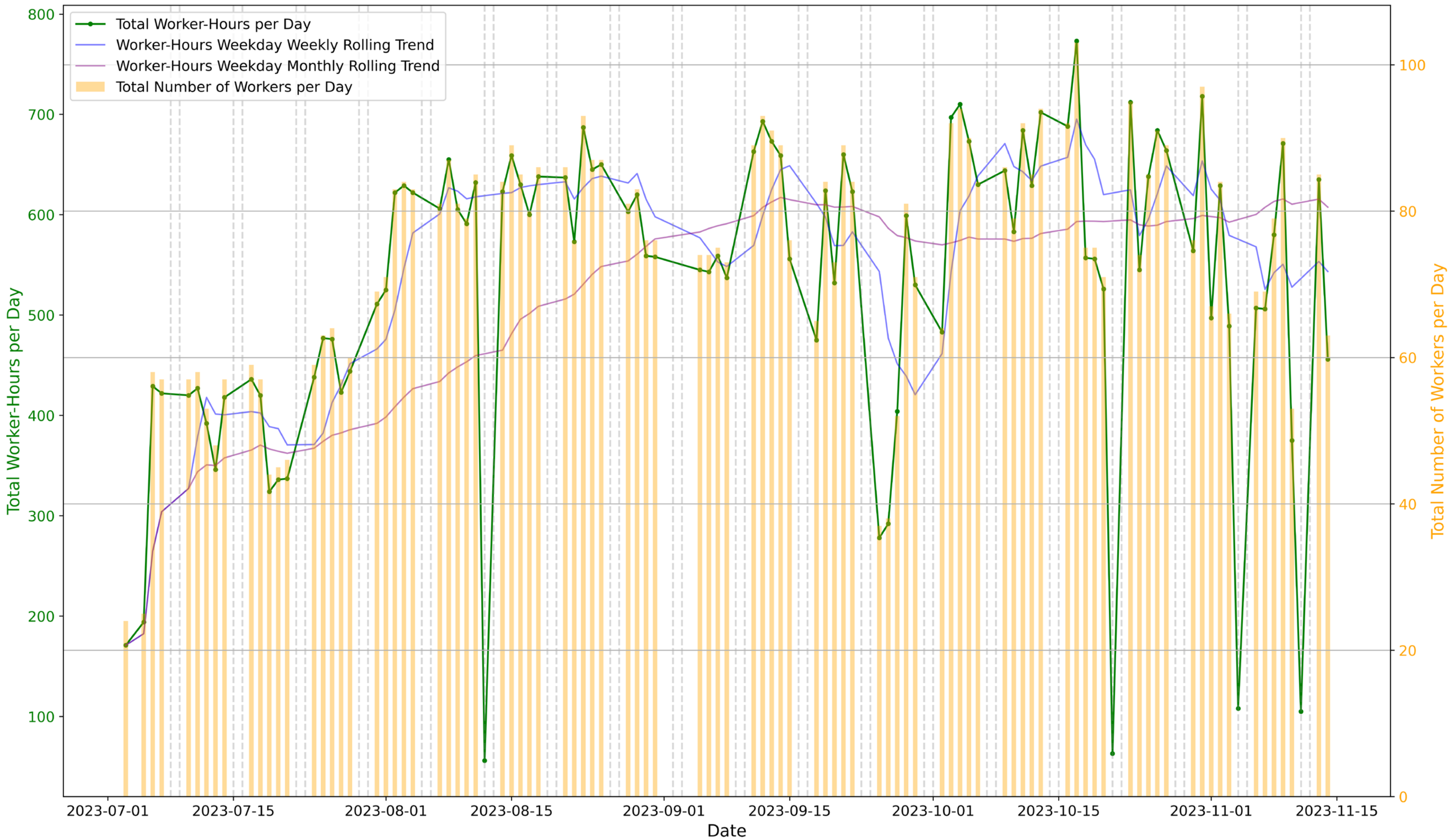


Figure 6.3: Daily distribution of total worker-hours and total number of workers on Project O.

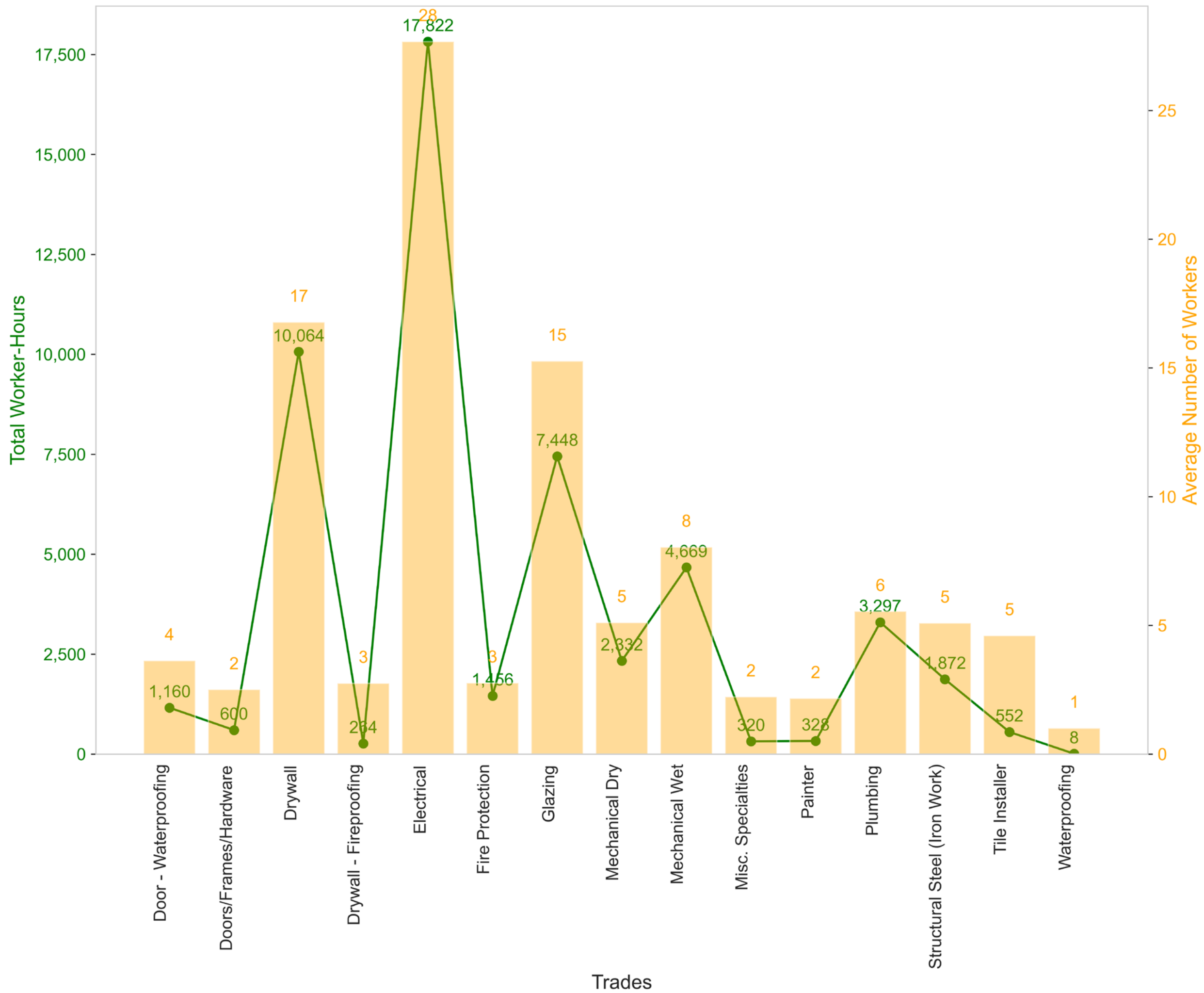


Figure 6.4: Total worker-hours and average number of workers by trade for the duration of the case study.

The data extraction process necessitated several transformations to cleanse and organize the dataset, namely:

(1) Calculating worker-hours by roles by trade on-site on a given day. The daily logs recorded the number of hours worked per day and the total number of workers by trade. However, the data on the division of workers by role contained missing values. Frequently, reports from trade would specify only the total number of workers, omitting the distribution across these three roles. The three roles used include:

1. Foreman is a supervisory role, responsible for overseeing journeymen and apprentices and ensuring that work is performed efficiently and safely.
2. Journeyman possesses full proficiency and is authorized to work independently, having completed formal apprenticeship training.
3. Apprentice is a worker in training under the supervision of a journeyman, aiming to attain full proficiency.

Most production planning models and tools, including ViWoLZo (Section 3.2.4.4), account for only the total number of workers when considering their impact on the production. Given the expected differences in proficiency by role, describing the number of workers by roles makes it possible to incorporate the impact of proficiency on the production rates and work density. To achieve this level of data description, the division of number of workers by roles needed complete data. Thus, this transformation started by filling in the missing or incomplete data for the division of number of workers by roles. For this, I used a data wrangling technique, called data imputation, to replace missing data with substituted values. With imputed number of workers by roles, I calculated the division of worker-hours by role on-site on a given day. This transformation is essential for maintaining the integrity and usability of the data, as many ML models require complete data to function effectively.

Based on my general understanding of construction labor practices, I address the missing data by distributing the total number of workers reported among the three roles on observed proportions within each trade. Imputation of the missing data used the following data transformation algorithm:

1. Calculate the mean values for "Foreman Workers", "Journeyman Workers", "Apprentice Workers", and "Total Number of Workers" columns for each "Trade" individually, taking values from rows where a distribution is present.
2. Determine the proportionate factors for each role for each trade relative to "Total Number of Workers": calculate the "Foreman Factor" as the mean of "Foreman Workers" divided by the mean of "Total Number of Workers", and similarly calculate "Journeyman Factor" and "Apprentice Factor" for each "Trade".
3. Employ these factors to impute missing values in the "Foreman Workers", "Journeyman Workers", and "Apprentice Workers" columns by multiplying the factor by the corresponding "Total Number of Workers" value for each missing entry.
4. Generate new columns ("Foreman Hours", "Journeyman Hours", "Apprentice Hours") by multiplying the imputed role counts by the "Hours" column to provide a detailed breakdown of hours worked per role per day.

(2) Distributing worker-hours across various floor levels and locations. I based the distribution of worker-hours across various floor levels and individual locations as per the spatial distribution and repetition of work on the project. I used this transformation done for situations where the daily log was reported as aggregate for multiple floors, instead of individual floors. Given the similarity in floor plans and workload on most levels, I presumed that the distribution of worker time would be uniform across these levels. However, the first floor and the roof, which feature distinct floor plans and significantly more work, required adjusted calculations. This involved identifying the levels where work occurred and assigning worker time equitably across repetitive floors (levels 2 to 7) and allocating 1.5 times the allocation of the repetitive floors to the first floor and the roof. Based on this distribution, I computed the hours for levels 5, 6, and 7. The employed methodology is outlined in the following data transformation algorithm:

1. Calculate Number of Floor Levels: Create "Modified Number of Levels" column that derives a modified count of levels from the "Location" column. It increases by 1 for each listed level; however, for the first floor and the roof, it adds 1.5 instead.
2. Initialize and Set Level Factors: Introduce "Level 5 Factor", "Level 6 Factor", and "Level 7 Factor" columns, initially set to 0. Subsequently, for each row containing "Location"

values of “5”, “6”, or “7”, calculate the corresponding column (“Level 5”, “Level 6”, “Level 7”) to 1 divided by the “Modified Number of Levels”. This calculation provides a proportional factor representing the time spent on each of the three levels.

3. Generate Detailed Workload Distribution: Create nine new columns by multiplying the level factor columns (“Level 5 Factor”, “Level 6 Factor”, “Level 7 Factor”) with “Foreman Hours”, “Journeyman Hours”, and “Apprentice Hours”. Each combination corresponds to the respective worker-hours dedicated to levels 5, 6, and 7.

Figure 6.5 shows a box plot of the transformed data, comparing the distribution of total worker-hours by roles across levels 5, 6, and 7. It appears that journeymen have a wider range of hours worked across all levels compared to foremen and apprentices. The foreman role shows a consistent median across all levels, whereas the journeyman and apprentice roles exhibit some variability in their medians, particularly at level 5. This is in line with the larger floor area on level 5 compared to levels 6 and 7 which have atrium cutouts, as described in Section 5.2.1. The atrium space spanning on all three levels needed to be accessed through level 5 adding more work. Outliers are present in all roles and levels, but they are most noticeable in the journeyman role, suggesting sporadic spikes in the number of hours worked.

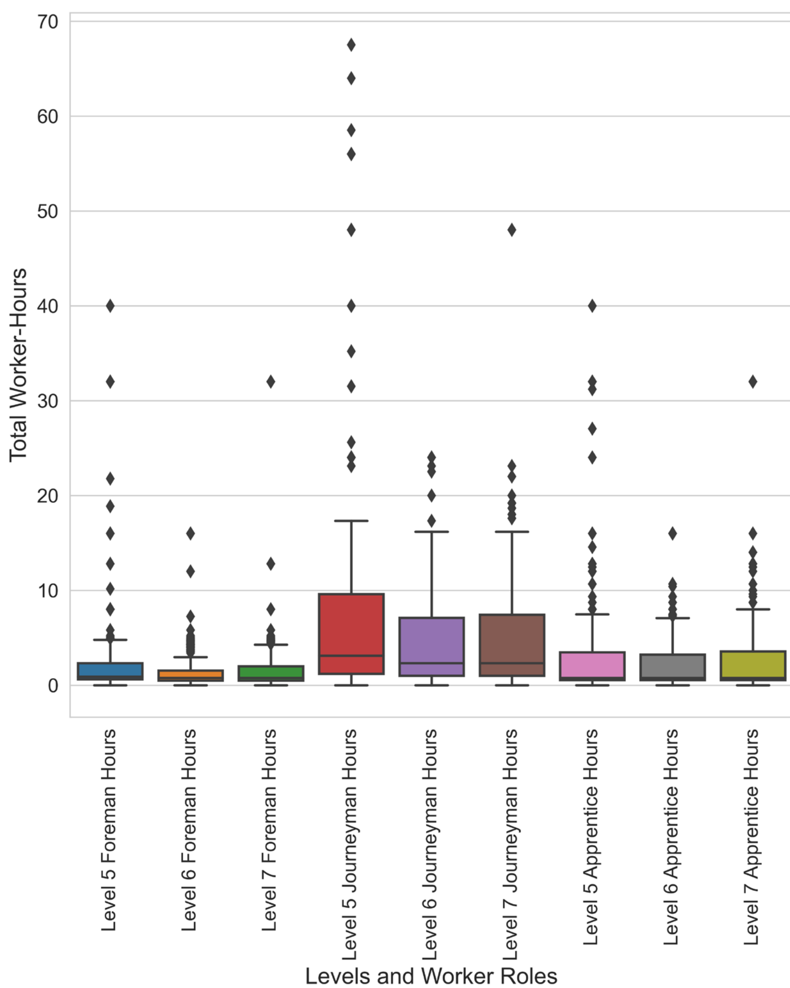


Figure 6.5: Comparison of total worker-hours by level and roles.

Figure 6.6 shows a three-dimensional (3D) bar chart with each bar presenting the total worker-hours spent by trades at a given floor level, with all worker roles combined. The heights of the bars show some outliers. Electrical trade shows the most significant time spent by workers, and a maximum on level 7, as all the utilities were connected from level 7 to the utility plant located on the roof. Structural steel, prominent on level 5, does not register many worker-hours on levels 6 and 7 because of the atrium that spans across all three levels but is counted only in level 5, from where it is accessed.

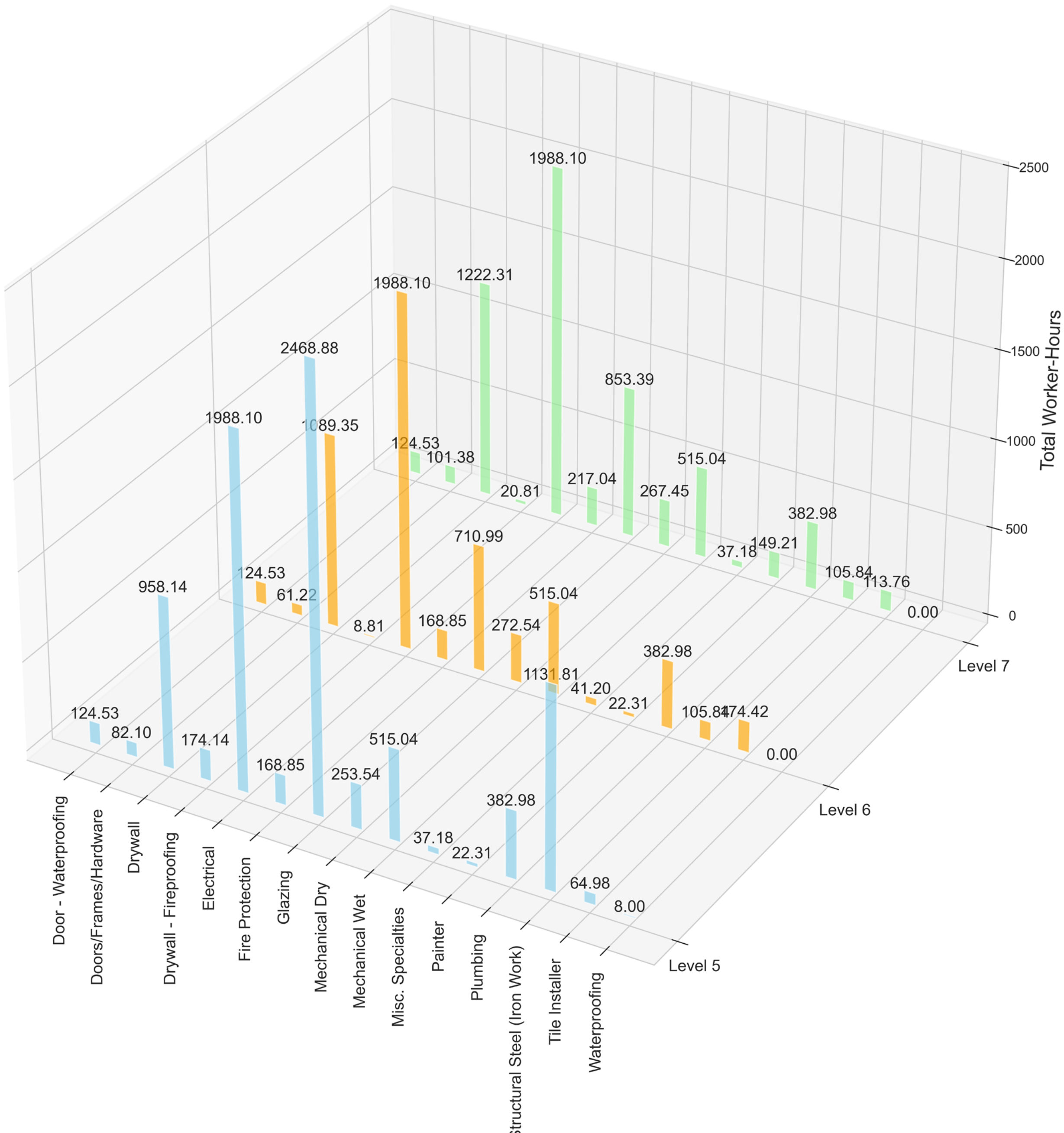


Figure 6.6: Total worker-hours distribution by trade for levels 5, 6, and 7.

(3) Dropping irrelevant fields. This final transformation on the daily log dataset involved the removal of fields that were either consistently empty or irrelevant to predicting work density. Although the initial dataset included daily reports on the weather, which can influence worker productivity and thus production rates (Ibbs and Vaughan 2015), the specific case study recorded no days with adverse weather conditions or related delays. With no representative data to understand the influence of weather on production, this proof-of-concept did not consider the potential impact of weather conditions on production outcomes.

6.2.3 Location Dataset

In Section 5.2.1 I described manual data collection of contextual data from three sources, of which location data was one. The data characterizes individual rooms and different open spaces divided into zones across floor levels 5, 6, and 7 (see Table 5.1 for overview). No vertical shafts were included in the study as it would have been difficult if not impossible to capture work in such locations using the 360° camera-based VideoWalks. Such locations get closed-in and are hard to access horizontally from all floors. Additionally their flow and scope of work is generally different from the other workflows to complete the interior buildout.

For the ML training, I chose location type (as a categorical variable) and area of the location (as a continuous variable in square feet) as features to represent a location. Location type is indicative of the work environment characteristics, with processes for each type of location generally being consistent. For example, construction work in bathrooms typically involves challenges such as limited space and the need for specialized waterproofing and plumbing, whereas work in lobbies and staircases may require consideration for high foot traffic and material movement, often resulting in delayed finishes. The area of a location usually affects the quantity of work and is also tied to environmental characteristics; for instance, larger rooms or open spaces facilitate easier access for equipment and material storage than smaller rooms or bathrooms.

6.2.4 Merging Datasets

Table 6.1 summarizes the four datasets used for production planning. I merged three datasets, called work density-, daily log-, and location dataset, and then used the merged dataset to generate input and target features for the ML training process. I also used a fourth dataset, called trade and step dataset, as a map to connect work detected in the work density dataset to the trades and their scope of work in the daily log dataset.

Before merging the data, I checked all the datasets for fields with no values (called Null values). Table 6.1 shows the work density dataset containing several observations with the "Duration" feature being Null. The high number of observations with no value is the result of work having been detected at the beginning and the end of the study (explained in Section 5.3.3), so that the start and the end of these steps were not identified. Since the duration corresponds to the work density and thus is the target feature for the prediction, I dropped the observations with Null values in "Duration" in this dataset. I also converted the "Duration" values from days to hours based on 8 hours of work every day, to be able to match them with the work-hours in the daily log dataset.

Table 6.1: Production planning datasets, their features, and description of the data.

Datasets	Features	Data description
1. Work Density Data	1. Location Number 2. Location Name 3. Work Detected 4. Original Detection Date 5. Start Date 6. End Date 7. Duration	465 observations, 223 non-Null values for "Duration"
2. Daily Log Data	1. Date 2. Trade (Scope Responsible) 3. Level 5 Foreman hours 4. Level 6 Foreman hours 5. Level 7 Foreman hours 6. Level 5 Journeyman hours 7. Level 6 Journeyman hours 8. Level 7 Journeyman hours 9. Level 5 Apprentice Hours 10. Level 6 Apprentice Hours 11. Level 7 Apprentice Hours	709 observations, no Null values
3. Location Data	1. Location Number 2. Location Name 3. Location Type 4. Area (ft^2)	54 observations, no Null values
4. Trade and Step Data	1. Work Detected 2. Trade Company Name 3. Trade (Scope Responsible)	29 observations, no Null values

I merged the data in several stages, adhering to specific merging criteria to maintain the combined dataset's integrity and relevance, as follows:

1. Spatial and Temporal Integration: I merged the work density data, containing detailed temporal information about various detected scopes of work, with the locations data. This merge was based on a common identifier linking work activities to specific spatial locations, enriching the dataset with spatial- (e.g., location type and area) and temporal dimensions (e.g., dates of work and duration).
2. Incorporation of Procedural Context: I further merged the integrated dataset from the previous step with the trade and process step data, based on a shared descriptor of work activities. This merge introduced a procedural layer to the dataset, linking each work detected to a specific trade and step.
3. Worker Allocation Integration: To analyze worker allocation, I introduced three new variables to the dataset, representing different levels of workforce roles (foreman hours,

journeyman hours, and apprentice hours). I integrated the daily log data, which contains detailed records of workforce allocation across different roles and locations for steps of work. I conditioned this merge on a shared step descriptor and a temporal alignment between work detection and daily logs, ensuring accurate association of worker data with corresponding work density data.

4. Conditional Data Population: After creating the unified dataset, I applied conditional logic to populate the labor allocation variables with data from the worker log dataset. This logic considered the spatial identifier's prefix to determine the appropriate source columns for labor hours, reflecting a nuanced approach to labor allocation that varies by project location. This conditional allocation ensured accurate attribution of labor hours to each work activity, based on specific project location codes.

Following a structured approach for data preparation, merging, and conditional processing to integrate spatial, temporal, procedural, and labor dimensions into a single dataset, the transformed data is stored as historical production data for analysis and to train ML models.

6.2.5 Historical Production Database

The development of a proof-of-concept ML-based production planning application is helpful in demonstrating the potential benefits and feasibility of the DDPF approach, but improving the performance of this ML model requires data from more than a single project. This requires a larger quantity and variety of data in a standardized structure; hence I propose the design of a historical production database.

To incorporate a standardized way of storing and using the data for future production planning efforts, in Section 4.2 I described a data schema that supports DDPF. Figure 4.2 shows the Entity Relationship Diagram (ERD) representation of this schema. This schema is implemented in the production planning data processing procedure to store the data in a historical production database containing four libraries (Figure 6.2 step 6), mirroring the four entity tables in Figure 4.2. These libraries are the (1) process-, (2) process step-, (3) location-, and (4) project library.

The production planning data wrangling and analysis step, outlined in Figure 6.2 step 5, enhances the quality of the raw data through post-collection transformations. This step results in a merged dataset, which serves as the foundation for creating the bridge table that links four libraries. In Section 6.2.4, I detail the creation of four datasets—work density, daily log, location, and trade and step—and their subsequent merge into a single dataset. These datasets for each project are stored in the first three historical data libraries: the process-, process step-, and location library. When data from multiple projects are combined, the bridge table, referred to as the "Process Table" forms a comprehensive database cataloging unique processes for each combination of space types and project types.

However, since I utilized data from only one project, Project O, for the proof-of-concept production planning component, I did not use the project library in the subsequent steps of ML implementation. Furthermore, the proof-of-concept did not include certain data fields from the proposed data schema due to limitations in scope and the practical implementation constraints encountered on Project O. These omitted fields are identified with an asterisk in Figure 4.2.

6.3 Machine Learning-based Work Density Prediction

Figure 6.7 provides a closer look into the data-driven work density prediction component of Figure 6.1 (bottom), detailing the steps involved and the output generated at each step. The procedure takes data from the "Process Table" in the historical production database (Figures 4.2 and 6.2 step 5).

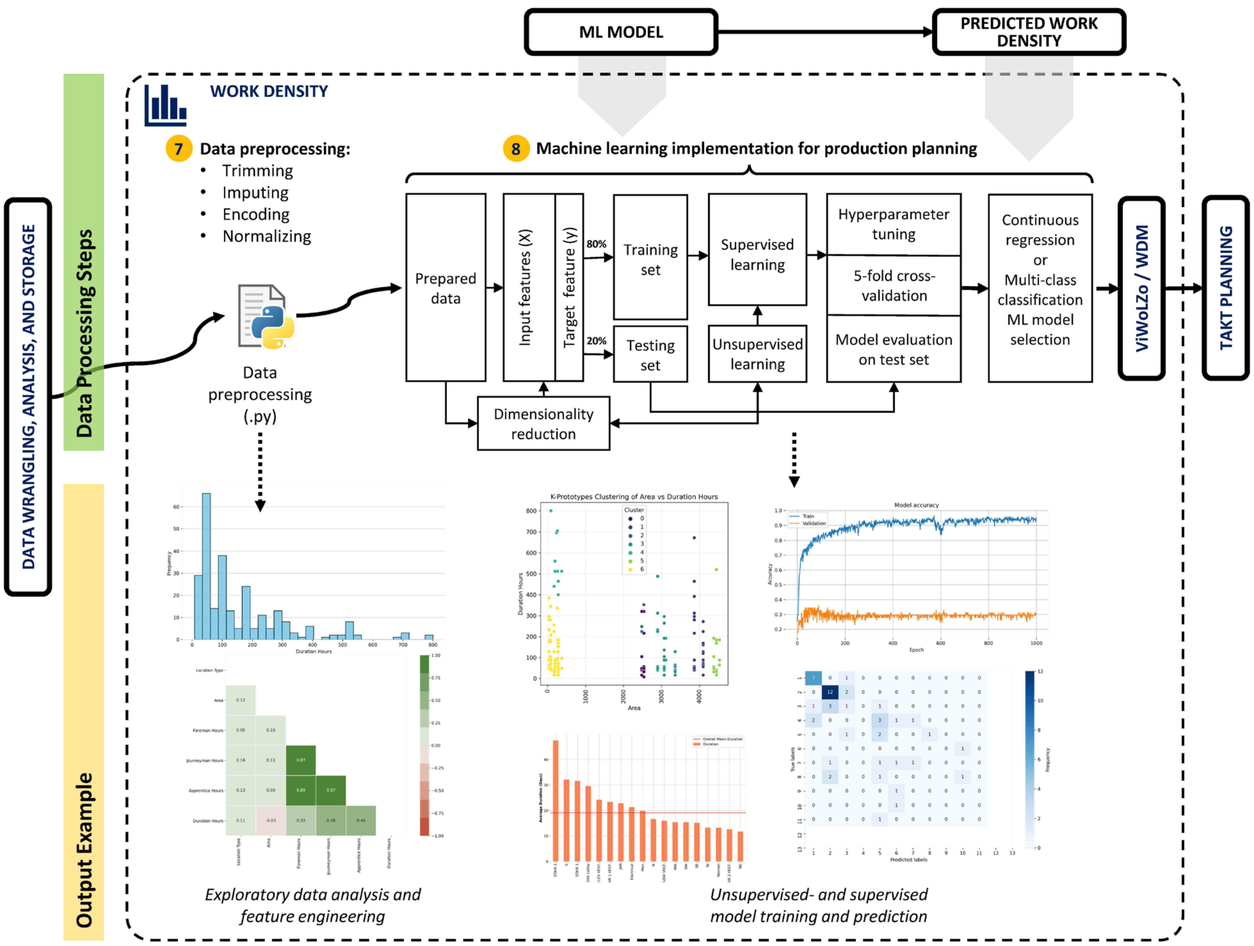


Figure 6.7: Work density component of the data processing procedure for production planning.

Section 6.3.1 describes various data preprocessing transformations (Figure 6.7 step 7) made to make the data ready for ML models and other data-driven analysis methods. Section 6.3.2 describes the implementation of ML for production planning (Figure 6.7 step 8), describing the different unsupervised- and supervised learning methods used. Section 4.4.3 delineates the technology stack used for steps 7 and 8.

6.3.1 Data Preprocessing

In the data preprocessing step (Figure 6.7 step 7) I prepared the data for analysis, enhancing the dataset's quality and ML model's prediction capability. I used the following preprocessing transformations: (1) removing inconsistencies by trimming, (2) handling missing values by imputing, (3) converting categorical variables by encoding, and (4) adjusting all features to the same scale by normalization (aka. standardization). Analysis of the data during the implementation of this step and the resultant data at the end of it supported the exploratory data analysis (EDA), which is discussed in Section 6.4.1.1. These data transformations result in selection and extraction of useful features, collectively referred to as feature engineering, that improve the ML model's ability to discern patterns and make accurate predictions.

6.3.1.1 Trimming

The preprocessing step involved data exploration by analyzing the collected dataset to understand its overall distribution and to identify inconsistencies. This analysis included examining data formats and statistical properties such as mean, median, quantiles, and standard deviation. This was essential to spot any outliers that could potentially compromise the accuracy of the predictive models. Recognizing the impact of these outliers, I opted to remove them from the dataset, a process known as trimming (aka. truncation). As part of trimming:

1. I cleaned the data by removing anomalous records, such as observations with missing values, to avoid the complications that could arise from imputing missing data based on potentially flawed assumptions.
2. I further cleaned the dataset by eliminating outliers. These were identified according to industry-expected values, especially noting that the work density distribution contained numerous anomalies due to the limitations inherent in the method I used to calculate it (explained in Section 5.3.3). Locations and scopes of work with incorrect work density values due to intermittent work or infrequent data capture created observations with large work density, e.g., work in the stair case which was captured infrequently due to limited access during data capture. For work density, captured in the "Duration Hours" feature, values ranged from 0 to 800 hours. I applied a cutoff at 200 hours, equivalent to 25 8-hour workdays, as illustrated in Figure 6.8 where the frequency distribution of work density in duration hours is depicted with the applied cutoff.
3. Lastly, I made a strategic decision to remove certain features from the dataset that were unlikely to contribute to the final prediction of work density or that were already fully represented by another, more suitable feature. For instance, features "Location Number" and "Location Name" were dropped as they did not add any contextual information helpful for predictive modeling. Moreover, I chose not to employ time-series analysis for prediction since it was not aligned with the problem at hand, and the data was neither sufficiently long-term nor captured frequently enough, leading to the exclusion of "Original Detection Date", "Start Date", and "End Date" features from the analysis.

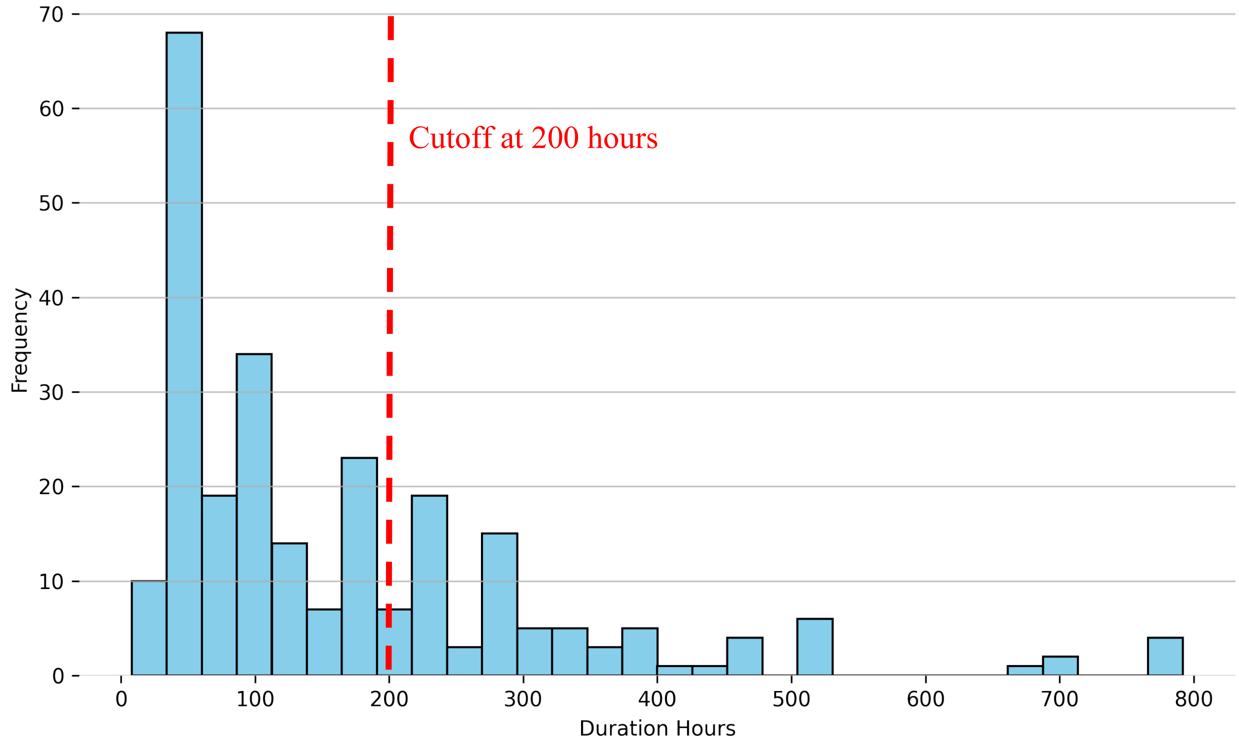


Figure 6.8: Frequency distribution of work density dataset (“Duration Hours”) in worker-hours with cutoff at 200 hours.

6.3.1.2 Imputing

Imputing tackles the challenge of missing values within the dataset. Methods range from simple deletion, where observations with missing values are entirely removed from the dataset to more nuanced methods. Mean or median imputation for numerical variables involves replacing missing values with the mean or median of the available data, which helps maintain the overall distribution. Mode imputation for categorical variables replaces missing values with the most frequent category. Additionally, a new category can be created specifically for missing categorical values, allowing the model to treat missing category as a potentially informative feature. These techniques help ensure that the dataset remains comprehensive and usable for analysis or modeling, without losing any data observations and reducing the dataset’s dimensions.

During the data wrangling step, I had already imputed features including “Foreman Hours”, “Journeyman Hours”, and “Apprentice Hours”, for which I used a custom algorithm to maintain the distribution of workers between the three roles (see Section 6.2.2 and Figure 6.2 step 5). In my data exploration during the data preprocessing step, I only found “Duration Hours” to have missing values (Table 6.1). As this was the target variable for the ML model, imputing these missing values was not an option because it can introduce bias and distort the true patterns in the data, leading to inaccurate model predictions and compromised model integrity. Consequently, I removed observations with missing “Duration Hours” from the dataset.

6.3.1.3 Encoding

Categorical variables are not compatible with many ML algorithms, which typically require numerical input. To ensure these variables are available for use in a compatible format, I employed encoding techniques tailored to the nature of each variable.

For nominal variables, variables with categories that do not have a specific order to them, I used one-hot encoding method, by creating binary features to represent the presence or absence of each category without implying any order of relationship. This resulted in several new features for a single feature, e.g., the five unique categories of "Location Type" expanded into multiple features namely "Location Type – Bathroom", "Location Type - Lobby/Corridor", "Location Type - Open Area", "Location Type – Room", and "Location Type – Staircase".

Despite the challenges posed by one-hot encoding, such as the potential for increased dimensionality and computational cost, I considered it manageable due to the dataset's modest size. I recognize that for larger datasets in the future, it might be necessary to either remove these one-hot encoded features or consider label encoding to mitigate computational constraints. Unlike one-hot encoding, label encoding converts the categorical columns into numerical ones without adding a column for each category.

For ordinal variables, variables with categories that can be ordered or ranked, I used ordinal encoding method, by assigning a unique integer to each category, preserving the inherent ranking within the features. Ordinal, or ordered categorical, encoding is a type of label encoding where the labels are numerically ordered, though the intervals between consecutive labels are not necessarily consistent. None of the input features were ordinal. However, to facilitate the use of multi-class classification ML models, I transformed the target feature "Duration Hours" into ordinal classes.

I divided the range of 200 worker-hours into five equal bins, each representing increments of 40 hours, equivalent to one working week with five days of eight worker-hours each. This bin size, aligned with the duration of takt supports weekly planning and control, while also providing sufficient observations to represent all five ordinal categories in the ML training process. Although day-long bins of eight worker-hours could offer more precision, data from Project O did not have enough number of observations for effective ML training and would significantly increase the complexity and computational demands of the models.

The numerical features "Area", "Foreman Hours", "Journeyman Hours", "Apprentice Hours", and "Duration Hours" remained unaltered in their original form.

6.3.1.4 Normalization

To address the influence that differing scales of variables might have on algorithms that are sensitive to feature magnitude, such as Support Vector Machines (SVM) and k-means, I implemented feature scaling techniques. Scaling was essential for two reasons. First, it counteracts the potential overshadowing effect of variables on larger scales versus those on smaller scales, ensuring that features such as "Area", which operates on a scale ranging from 41 ft^2 to 4526 ft^2, do not unduly influence the learning process compared to a time-based feature such as "Foreman Hours", which ranges from 0.38 hours to 320 hours. For example, without scaling, the large range of the "Area" variable could dominate the model's calculations, rendering the "Foreman Hours" less impactful despite its relevance. Second, it facilitates the model's learning from all features uniformly, including those that had to be one-hot encoded, with values of 0 or 1. These measures bolstered the performance of the ML models in the next step and sharpened their predictive accuracy.

For the non-categorical features, I applied the standardization function by subtracting the mean and scaling to unit variance. The binary features resulting from one-hot encoding were inherently scaled by their binary nature.

6.3.2 Machine Learning Implementation for Production Planning

In the ML implementation step for production planning, I developed an ML workflow (Figure 6.7 step 8) that began with applying unsupervised learning algorithms to the data prepared at the end of preprocessing step. I utilized these algorithms to understand the data to enhance ML implementation for work density prediction in this research and for future improvement of the DDPF. With an enhanced understanding of the data, I then applied supervised learning algorithms to predict work density based on specific product- and process features. For details on the types of ML algorithms and their intended applications, refer to Section 2.4.4.

The unsupervised learning algorithms facilitated further feature engineering, extending beyond the initial data preprocessing step. This part of the ML workflow involved correlation-, feature importance-, and clustering analysis. These analyses helped in extracting meaningful features from the dataset, generating interaction terms to capture relationships between features, and applying dimensionality reduction techniques to identify the most impactful features (Russell and Norvig 2010, p. 694). I discuss the results of these analyses in Sections 6.4.1.2 to 6.4.1.4.

I used several unsupervised learning algorithms, including dimensionality reduction methods including Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE), and clustering methods including k-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and k-prototypes. I discuss the implementation of these methods in Section 6.3.3.

I applied supervised learning algorithms to predict work density as regression and classification problems. Selecting the right ML model and tuning its parameters was crucial to balance underfitting or overfitting, and to optimize model flexibility, complexity, and interpretability (Russell and Norvig 2010, p. 709). The goal of predictive modeling was to develop a model that provides optimal prediction accuracy suitable for production planning and strong generalization capabilities across the feature set. Such a model should offer precise predictions not only for the data it was trained on but also for unseen data.

I used several supervised learning algorithms, including linear models including Linear Regression and Linear Discriminant Analysis (LDA), tree-based Ensemble models such as Gradient Boosting Regressor (GBR) and Random Forest Regressor, deep learning models including Deep Neural Networks (DNN), and a variety of Ensemble methods combining multiple algorithms. These models were trained for regression and classification tasks suitable for their respective architectures. The implementation of these methods is further discussed in Section 6.3.4, with their results detailed in Sectio 6.4.2.

6.3.3 Unsupervised Learning

6.3.3.1 Dimensionality Reduction

Dimensionality reduction is an unsupervised learning technique that transforms data from high-dimensional spaces (large number of features) to lower-dimensional ones while preserving most of the variability (i.e., information) in the original data. I used dimensionality reduction technique, initially to explore the prepared data and later to analyze the data generated from other ML models. This approach aimed to iteratively enhance the ML implementation for work density prediction.

For the initial exploration to identify the distribution of data through visualizations and to identify most important features, I used PCA. PCA is a statistical technique that transforms a set of possibly correlated variables into a smaller number of uncorrelated variables called Principal Components (PCs). PCs are eigenvectors of the data's covariance matrix, computed by eigendecomposition of the covariance matrix (Hastie et al. 2009, p. 534). This results in identifying the directions (PCs) that are orthogonal (i.e., independent of one another) and along which the variance in the original data (i.e., information) is maximized. The first PC contains largest variance, followed by consecutive PCs with as many PCs as there are dimensions in the feature space (i.e., the number of features in the original data). Figure 6.9 shows a line plot with explained variance for each individual PC, called a Scree Plot. The explained variance for PC1 is 0.1021 (i.e., 10.21%) and keeps reducing until it approaches zero for the last PC44.

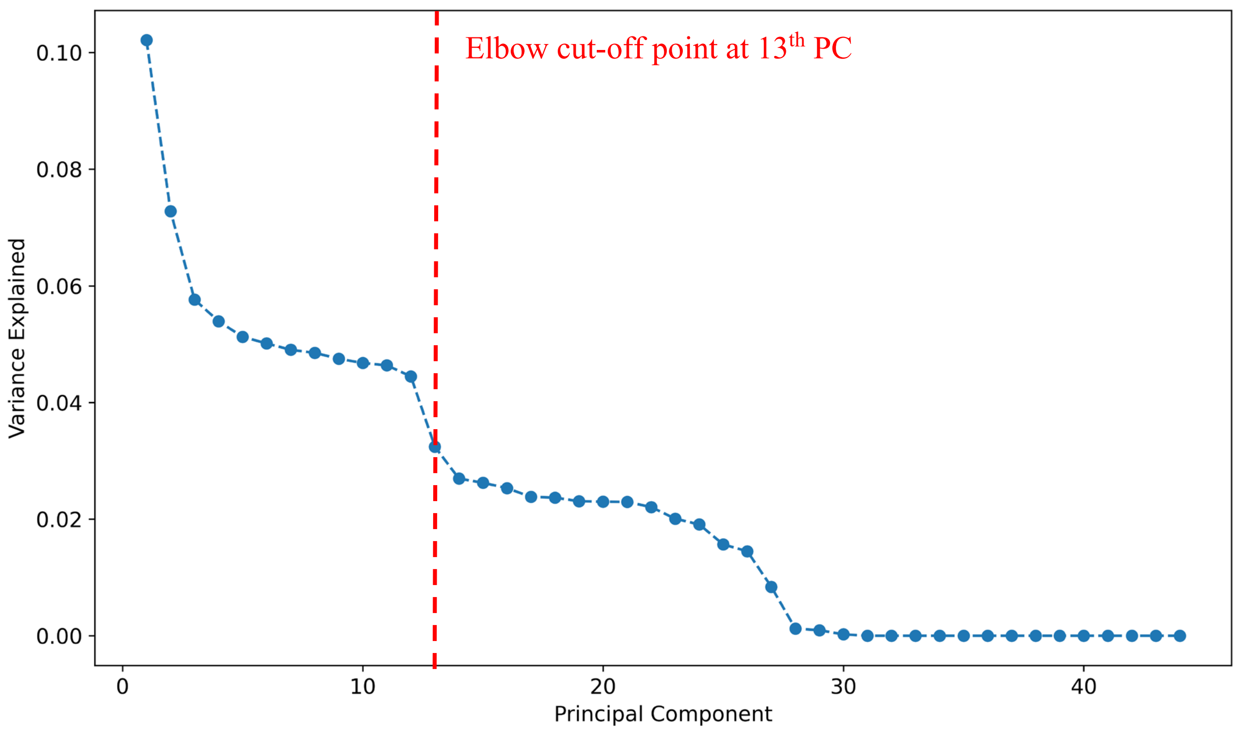


Figure 6.9: Scree plot: variance explained for each Principal Component (PC).

I used the scree plot in Figure 6.9 as a diagnostic tool to check whether PCA worked well on the "Process Library" dataset from Project O or not, with the idea being to reduce the number of dimensions without losing a lot of information. The figure shows the first few PCs captured most of the information with a long tail of PCs capturing nearly no information. I also used the plot to select the PCs to keep. Usually, an ideal curve should be steep, then bends at an "elbow"—used as the cut-off point—and after that flattens out. With multiple noticeable elbows on the plot, I decided to cut-off at the 13th PC (dotted red line) as the first 13 PCs cumulatively explained approximately 70% of the total variance in the data. This demonstrates that PCA can be used to reduce the number of dimensions in the "Process Table" dataset, without losing a lot of information.

Results from PCA, summarized in Table 6.2, show the first 13 PCs and the most important features for each PC. The most important feature to a PC means that the loading (coefficient) of that feature to the PC vector is the largest in magnitude compared to other features. Loading represents the weight or contribution of that feature to the PC. Largest loading to the PC means the feature contributes most significantly to the variance explained by that PC. The "Importance" score quantifies the extent of contribution of each feature, with higher values indicating a stronger impact.

Table 6.2: Principal Component Analysis (PCA) results with top Principal Components (PCs) and their corresponding most important features.

Principal Component	Explained Variance	Most Important Feature	Importance
PC1	10.21%	Foreman Hours	0.36
PC2	7.28%	Location Type - Open Area	0.38
PC3	5.76%	Trade - Drywall	0.55
PC4	5.39%	Trade - Plumbing	0.28
PC5	5.13%	Trade - Electrical	0.45
PC6	5.01%	Work Detected - Hydronic Piping	0.38
PC7	4.90%	Trade - Mechanical Wet	0.49
PC8	4.85%	Work Detected - Thermal Insulation	0.38
PC9	4.75%	Work Detected - Metal Pan Stairs	0.58
PC10	4.68%	Trade - Painter	0.57
PC11	4.64%	Trade - Mechanical Dry	0.54
PC12	4.45%	Work Detected - Raceway and Boxes for Electrical Systems	0.34
PC13	3.24%	Trade - Misc. Specialties	

The results shown in Table 6.2 illustrate how each PC helps to characterize different aspects of the dataset. For example, PC1, explaining 10.21% of the variance, shows the highest loading from "Foreman Hours", suggesting a strong influence of this feature on the variance in the data. The next most important feature is the "Open Area Location Type", whereas important features after that include trades such as Drywall, Plumbing, Electrical, etc. and the steps they are involved in, namely hydronic piping, thermal insulation, etc.

The breakdown in Table 6.2 helps identify which features most significantly impact variance in the data, guiding further data processing and feature selection for modeling efforts. Despite this, the explained variance and importance scores reveal that no single feature stands out as significantly important. More detailed analysis of the feature importance is discussed in Section 6.4.1.3.

Figure 6.10 displays a 3D PCA projection of the "Process Library" dataset from Project O using the first three PCs, with a color gradient representing the duration hours for each data point. The 3D plot illustrates a very weak separation of data points based on the duration hours feature. The distribution seems to have high duration hours data points (colored red) in the bottom right corner and a concentration of low duration hours data points (colored blue) in the top left corner, with a very weak semblance of distribution from high to low duration hours in the bottom right to top left direction. It appears that data points with lower duration hours share similar features and cluster together, whereas those with high duration hours show variation in features and are spread out.

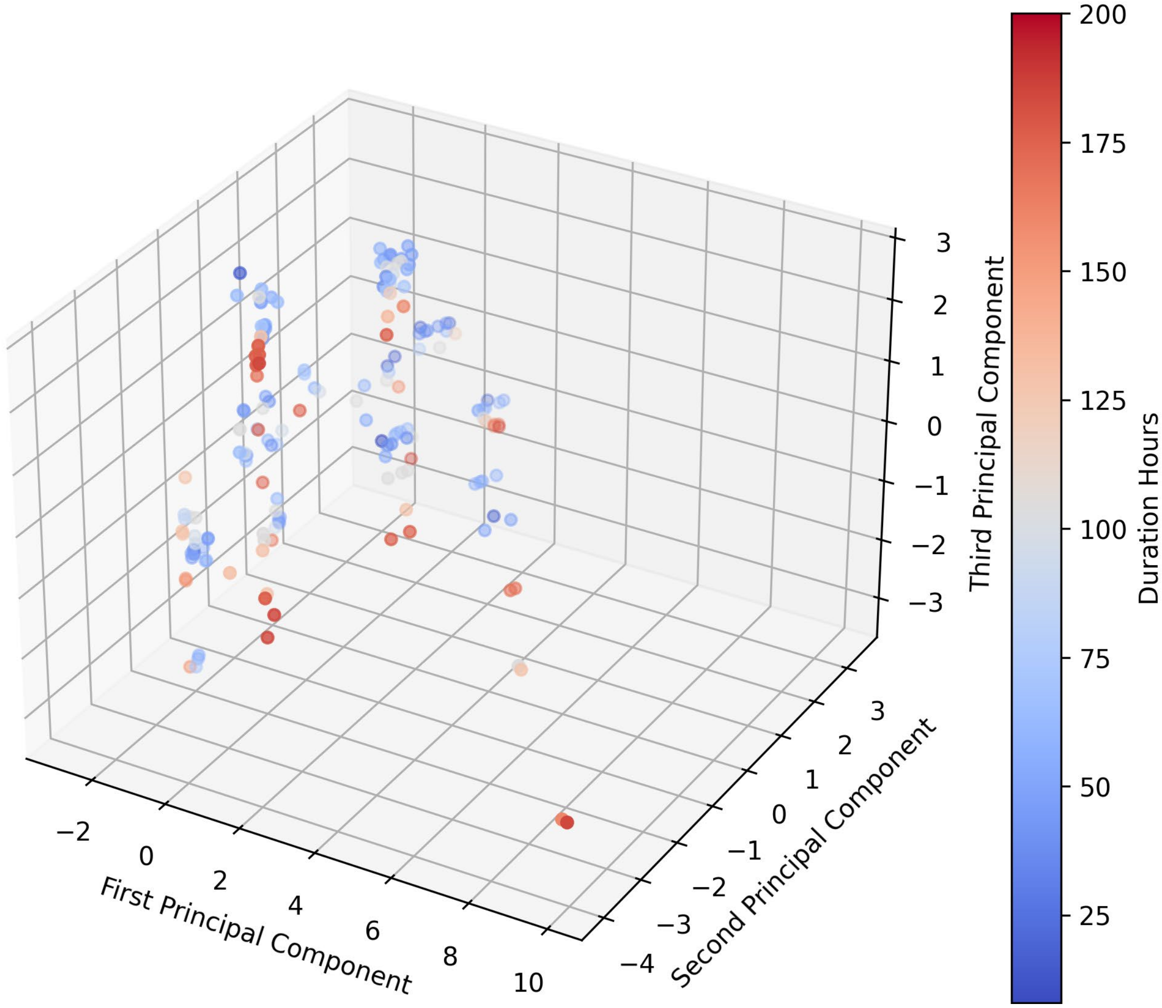


Figure 6.10: 3D Principal Component Analysis (PCA) projections of the "Process Library" dataset from Project O using the first three PCs with color gradient based on duration hours.

Figure 6.11 presents a better visual with two-dimensional (2D) PCA projections of the same dataset using all combinations between the first four PCs, again with a color gradient representing the duration hours. This plot shows separation of high duration hours data points (colored red) in the bottom part of the PC1 vs PC2 subplot, and in the left parts of the PC2 vs PC3 and PC2 vs PC4 subplots. However, some high duration hours data points are mixed with low duration hours data points (colored blue). In the PC1 vs. PC2 subplot, a noticeable gradient from blue to red indicates a correlation between the first two principal components and duration hours, a trend also visible in other plots but most pronounced in the direction of PC1- and PC2 axis. This becomes evident in the separation of data points and the direction of the gradient matching the orientation of PC1 or PC2 in plots where they are orthogonal to other PCs. Similar to Figure 6.10, high duration hours (red) data points are more spread out, while the low duration hours (blue) data points seem to cluster more tightly.

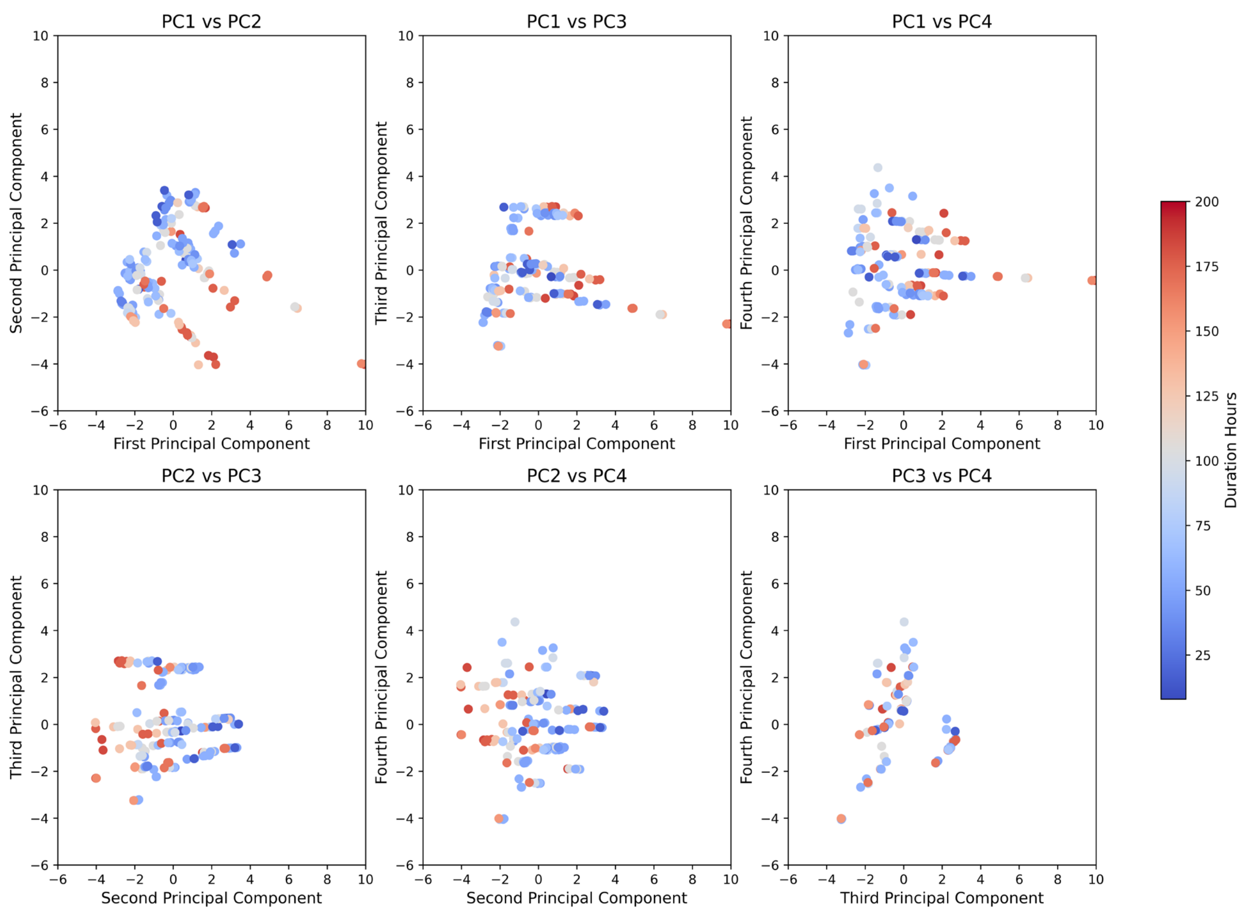


Figure 6.11: 2D Principal Component Analysis (PCA) projections of the "Process Library" dataset from Project O using all combinations between the first four PCs with color gradient based on duration hours.

The PCA visualizations reveal significant variability in the data along the PCs, especially for PC1 and PC2, capturing essential information of the dataset. There is a clear pattern where data points with higher duration hours are more dispersed, suggesting that duration hours are a significant factor contributing to the dataset's variability. Conversely, lower duration hours tend to cluster more, indicating less variability and potentially more uniformity in the data points with shorter durations.

The 3D PCA projection with PC1, PC2, and PC3 (Figure 6.10) captures 23.25% of the information, whereas the 2D projection PC1 vs PC2 subplot (Figure 6.11) captures 17.49% of the information. This is not enough information for the plots to reveal separation to distinguish differences in the duration hours of the data points. For the first two PCs which show the best separation of data points with respect to duration hours, features "Foreman Hours" and "Location Type - Open Area" are found to be most important. I used the knowledge of feature importance with PCA-based visualizations to understand the separation of the data along the PCs, results from which are discussed in Section 6.4.1.3.

Additionally, I employed dimensionality reduction along with other models within the ML workflow (Figure 6.7 Step 8) for simplifying and visualizing results of clustering algorithms and selecting input features for supervised learning methods, as discussed in their respective sections.

6.3.3.2 Clustering

Clustering, also called data segmentation, is an unsupervised learning technique used for the study of patterns and natural groupings within the data, facilitating the identification of similarities among the data points based on the similarity of features (Hastie et al. 2009, p. 501). I used clustering algorithms to enhance the understanding of the prepared data and the prediction of work density through classification models (Figure 6.7 step 8).

Central to implementation of clustering algorithms is measuring the degree of similarity (or dissimilarity) between the individual data points being clustered. A clustering algorithm attempts to group the data points based on the definition of similarity supplied to it. Hence, the determination of the most suitable clustering algorithm and the definition of similarity is contingent upon the data's unique characteristics and the analytical objectives. The prepared dataset included:

- A continuous numerical target feature (specifically, the numerical "Duration Hours" in target feature scenario 1).
- A blend of one-hot encoded categorical variables and continuous numerical variables as input features.
- A relatively small dataset size but with a high dimensionality due to numerous features.

To identify suitable algorithms for the given dataset, I considered:

- Dimensionality: Having higher dimensional data (number of features is comparable to number of data points) can render distance metrics in clustering less meaningful. Using dimensionality reduction or feature selection techniques prior to clustering can prove advantageous.
- Mixed Data Types: It is preferable to utilize algorithms that can inherently accommodate mixed data types (numerical and categorical) to avoid extensive preprocessing.
- Dataset Size: The small size of the dataset diminishes concerns about computational efficiency, thus allowing for the exploration of more computationally demanding algorithms.

Based on these considerations, I found these following clustering algorithms would be suitable:

- k-means: This algorithm is a popular initial choice due to its simplicity and computational efficiency, because of its simple measurement of similarly that is based on the Euclidean distance between data points (Hastie et al. 2009, p. 509). It is excellent for quick, coarse segmentation of data clusters.
- DBSCAN: This algorithm excels in identifying clusters of arbitrary shapes and detecting outliers, and it is less susceptible to the curse of dimensionality compared to centroid-based methods (Ester et al. 1996). However, optimal parameter selection is critical and often requires careful tuning or domain-specific insights.
- k-prototypes: This algorithm is an amalgamation of k-means and k-modes, tailored for datasets that include both numerical and categorical data. It is especially effective for handling one-hot encoded features, making it a robust choice for my dataset.

To apply these algorithms, the initial step involved preparing the data to ensure it is suitable for clustering. This preparation includes scaling the features to normalize their ranges. Unlike k-means and DBSCAN, the k-prototypes clustering algorithm accommodates datasets that contain both categorical and numerical features. Therefore, for the k-prototypes algorithm, it is not necessary to one-hot encode categorical variables, as the algorithm can handle these data types natively.

For both k-means and k-prototype algorithms, a prespecified number of clusters is used. To find an optimal number of clusters, I utilized the elbow method, which involves calculating the sum of squared distances (inertia) for each possible number of clusters. Similar to the scree plot (Figure 6.9) used for PCA, the "elbow" point, i.e., the point on the curve where the rate of decrease in inertia sharply changes, suggests the most appropriate number of clusters.

In contrast, the DBSCAN algorithm does not require the number of clusters to be specified in advance. However, the DBSCAN algorithm requires ε (epsilon), the maximum distance between two samples for considering them to be in the same neighborhood, and the minimum number of samples required for a point to be identified as a core point. Selecting suitable values for ε and the minimum number of samples involved using the k-distance graph. The graph plots the distance to the (minimum sample -1)th nearest neighbor for each point, and the ideal value for ε is equal to the distance value at the "elbow" point or the point of maximum curvature. After establishing the optimal parameters, I clustered the data and analyzed the resultant patterns. Utilizing DBSCAN with ε set to 6 and a minimum of 5 samples per cluster, I visualized the clusters using PCA for dimensionality reduction.

Figure 6.12 illustrates the clustering outcomes using k-means, DBSCAN, and k-prototypes. Using PCA and t-SNE, dimensionality reduction methods, the figure visualizes high-dimensional data into two dimensions (PCs and t-SNE features) (Maaten and Hinton 2008). Each algorithm segmented the data into seven clusters, labeled from cluster 0 to cluster 6. Observations form these plots include:

- The clustering plots from k-means (Figure 6.12 top left) and DBSCAN (Figure 6.12 top right) algorithms show substantial overlap between clusters, indicating less effectiveness in distinguishing the clusters.

- The DBSCAN plot also reveals a high number of noise points (marked with purple in the "Cluster 0" category), indicating that DBSCAN struggled to form meaningful clusters in this dataset.
- The k-prototypes (Figure 6.12 bottom center) plot displays more clearly defined clusters with less overlap, highlighting its effectiveness in handling datasets with both numerical and categorical features. The visualization reinforces the finding that k-prototypes is the most suitable algorithm for this particular dataset, providing distinct and well-separated clusters that enhance the understanding and predictive capability of the data.

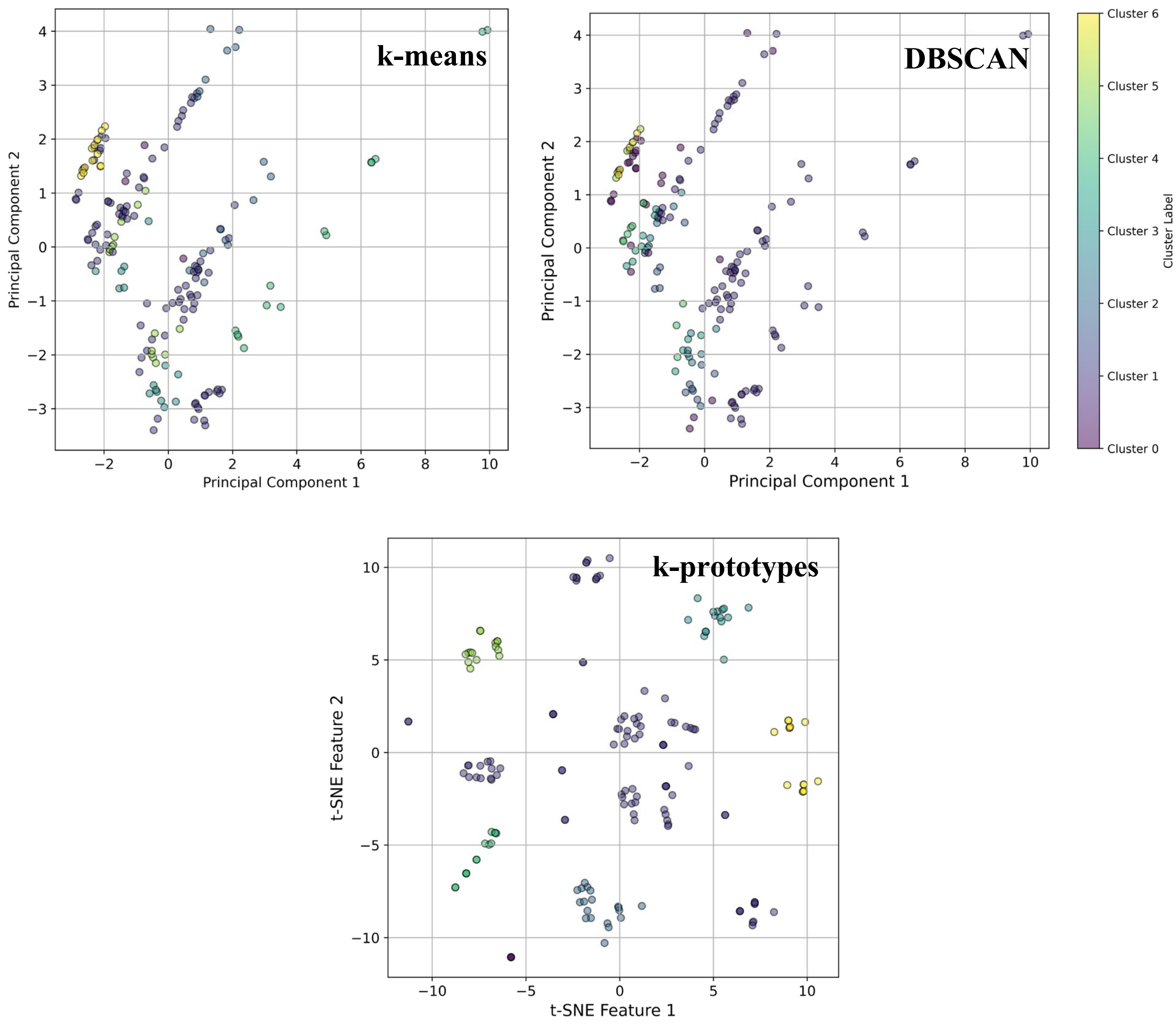


Figure 6.12: k-means (top left), DBSCAN (top right), and k-prototypes (bottom center) visualization of clusters.

For the k-prototypes algorithm, the analysis also involved identifying centroids, which consist of both numerical and categorical components. The numerical centroids are the mean values of numerical features for each cluster, whereas the categorical centroids represent the most common categories within each cluster. This dual centroid composition aids in understanding the distinct groups within the dataset. The results of the k-prototypes algorithm are discussed in Section 6.4.1.2.

6.3.4 Supervised Learning

6.3.4.1 Prepared Data

After preprocessing (Figure 6.7 step 7), the “Process Table” dataset transformed to become fit for ML application, changing its dimensions from 9 features and 262 observations to 44 features and 175 observations. In the ML workflow (Figure 6.7 step 8), I prepared the dataset for supervised learning by dividing the data into input features, labeled as “X”, and the target feature, labeled as “y”. The dataset consists of 44 features, with 43 serving as input features. These input features include continuous numerical variables such as “Area”, “Foreman Hours”, “Journeyman Hours”, and “Apprentice Hours”, alongside categorical features including “Work Detected”, “Location Type”, and “Trade”. For regression models, I used the “Duration Hours” as the target feature, which quantifies work density in continuous hours. For multi-class classification models, I used “Duration Category” as the target feature, which categorizes duration into ordinal classes in 40-hour increments, representing a range from 0 to 200 hours of work density across five classes.

To enhance model performance and prevent overfitting, I split the input features (“X”) and target feature (“y”) into independent training- and testing datasets at an 80:20 train-test ratio (Figure 6.7 step 8). This split produced training dimensions of 140 observations and 43 features for inputs, with a corresponding 140 observations for the target, and test dimensions of 35 observations and 43 features for inputs, with a corresponding 35 observations for the target. This split is essential for assessing the model’s performance and ensuring its generalizability.

6.3.4.2 Model Training Process

6.3.4.2.1 Tyes of Prediction Models Used

To support the objective of predicting work density, I implemented various supervised learning methods for predictive modeling where a set of independent variables are used as inputs, and through pattern recognition, generate an output (i.e., the dependent variables). Supervised learning-based predictive modeling aims to construct a pattern recognition model that excels in both prediction accuracy and generalizability (Hastie et al. 2009, p. 9). This involves avoiding underfitting, where the model does not adequately learn the training data, indicated by high training errors, and overfitting, where the model learns the training data too well but performs poorly on new data, evidenced by high testing errors.

I used a variety of supervised learning algorithms, with different levels of complexity and flexibility. On one hand, simpler and inflexible algorithms, such as Linear and Logistic Regression, can discern data patterns within the constraints of their predefined linear assumptions. On the other hand, more complex and flexible algorithms such as Random Forest, Neural Network (NN), and SVM offer the versatility to model nonlinear relationships without having to make such rigid assumptions. However, this flexibility comes with its own drawbacks, as it can lead to models that are complex, potentially overfitted, and less interpretable (Russell and Norvig 2010, p. 709).

The algorithms that I used for work density prediction can be classified under the following groups of models:

1. Linear models:
    a. Linear Regression: This method estimates the relationships between variables by minimizing the difference between the predicted values and actual values, drawing a line of best fit onto the data points (Draper and Smith 1998).
    b. Linear Discriminant Analysis (LDA): Used primarily for classification, LDA assumes linear boundaries between classes (Hastie et al. 2009, p. 106). Here, I transformed "Duration Hours" into a binary class (high or low) based on its median value.
2. Tree-based Ensemble models:
    a. Gradient Boosting Regressor (GBR): Used for regression, which involves predicting a continuous outcome variable based on one or more predictor variables. It is part of the Ensemble methods (see item 4 in this list), specifically an implementation of boosting that builds on the principle of converting weak learners into strong ones sequentially.
    b. Random Forest Regressor: This method is a type of Ensemble learning technique that constructs multiple decision trees during training and outputs the average prediction of the individual trees (Biau and Scornet 2016, Probst et al. 2019). It is particularly useful for handling non-linear data with high variability.
    c. CatBoost: CatBoost is an algorithm for gradient boosting on decision trees, designed to handle categorical variables with minimal preprocessing (CatBoost 2024a). It provides robust solutions to overfitting through systematic random permutations of data.
    d. XGBoost: XGBoost stands for eXtreme Gradient Boosting and is an advanced implementation of gradient boosting that has proven effective across many types of prediction problems. It is renowned for its efficiency, flexibility, and the capability to handle sparse data (Shwartz-Ziv and Armon 2022).
3. Deep Neural Network (DNN) models: Used for both regression and classification. A DNN is an Artificial Neural Network (ANN) with multiple layers between the input and output layers, hence called "deep". The architecture of DNN models allows them to be flexible with the types of input data and its use to accurately solve various types of problems. They usually perform better than other models when working with unstructured data (Gorishniy et al. 2021). Several types of deep learning models exist, but their application on this research was limited as they were not found suitable for the type and size of data, further discussed in Section 6.4.3.3.2.
4. Ensemble methods: These methods combine multiple base algorithms including linear regression, ridge regression, lasso regression, and several others into a composite predictor to reduce variance and bias, enhancing the prediction accuracy (Hastie et al. 2009, p. 605).

I implemented these groups of models for regression and classification tasks, tailoring them to fit their respective architectures. I prepared the data according to the specific requirements for each task, as detailed in the following sections.

6.3.4.2.2 *Regression-Based Prediction*

I employed regression-based prediction techniques to predict work density on a continuous numerical scale in worker-hours. The prediction is the estimated cycle time (in hours) for a step in a location. The primary objective was to develop a model that can predict the time required to complete a scope of work given a set of features representing process, step, and location, making it suitable for production planning purposes.

I started with Linear Regression to establish a performance baseline due to its simplicity and interpretability. To improve prediction accuracy, I then explored more complex models, including GBR and Random Forest Regressor, both of which construct Ensemble learners from Decision Trees to enhance predictions by reducing variance and bias. Additionally, I implemented XGBoost for boosting and a DNN Regressor to capture nonlinear relationships within the data. To further enhance the model's accuracy, I adopted an Ensemble method that combines predictions from multiple models, leveraging the strengths of each to achieve superior predictive performance.

Default hyperparameter settings for these models cannot guarantee their optimal performance, especially on a specific dataset. To improve performance results, I used five-fold cross-validation along with hyperparameter tuning to optimize performance and generalizability of these models.

6.3.4.2.3 *Classification-Based Prediction*

I employed multi-class classification-based prediction techniques to predict work density in five ordinal classes, each spanning 40 worker-hours corresponding to one standard working week. This classification scheme allowed me to transform the regression problem into a more manageable categorical framework with a somewhat practical class size that can match predictions on a week-long interval, suitable for takt plans with takt of one week or longer. This class size also allows to accommodate samples for each class in the training and test sets, necessary for correctly fitting the models on the training dataset.

I started with LDA which, by assuming Gaussian distributions and equal covariance across classes, served as an effective linear classifier for establishing baseline accuracy. Subsequently, I implemented a DNN Classifier to leverage its capability in capturing complex, non-linear patterns that LDA might miss. Finally, to maximize predictive performance, I employed an Ensemble method that integrated outputs from both the LDA and DNN models along with other classifiers.

Similar to regression-based prediction, I used five-fold cross-validation and hyper parameter tuning to improve the performance of these models.

6.3.4.2.4 *Sparse Identification of Nonlinear Dynamics (SINDy) Approach*

Apart from the direct implementation of supervised learning methods on the prepared data, I also applied the Sparse Identification of Nonlinear Dynamics (SINDy) approach, designed by Brunton et al. (2016). SINDy is particularly effective for systems where the dynamics are nonlinear and governed by a sparse subset of influential features among a potentially large pool. This makes it ideal for identifying the underlying equations of dynamic systems with numerous variables, assuming that only a few are truly significant.

Given the nonlinear nature of the input data and the prominence of a few critical features, I applied SINDy to model the production system dynamics. The one-hot encoded categorical and numerical attributes of the dataset presented a suitable case for such nonlinear modeling techniques. Nonetheless, the limited size of my dataset posed a challenge, as SINDy requires a substantial amount of data to accurately discern the sparse set of impactful predictors.

To initiate the SINDy application, I first conducted a polynomial transformation of selected features up to the third degree, incorporating interaction terms. Based on insights from PCA-based feature importance analysis (Section 6.4.1.3), correlation analysis (Section 6.4.1.2), and clustering analysis (Section 6.4.1.4), I selected four features: Area, Foreman Hours, Journeyman Hours, and Apprentice Hours. These were combined in various configurations to generate candidate functions that capture the dynamic interplay among them, expanding the dimensionality to twenty dimensions to encapsulate more complex relationships.

Subsequently, I applied sparse regression to identify the key nonlinear dynamics influencing the resultant output feature—work density. Utilizing PCA helped pinpoint the most crucial polynomial features generated during the transformation. Table 6.3 lists the top ten factors from this polynomial transformation, detailing their explained variance and relative importance.

Table 6.3: Most important factors in the SINDy transformed polynomial using Principal Component Analysis (PCA).

Principal Component	**Explained Variance**	**Most Important Factors**	**Importance**	**Importance x Explained Variance**
PC1	0.8972	Area × Journeyman Hours × Apprentice Hours	0.1267	0.1137
PC2	0.0607	Area^2	0.4611	0.0280
PC3	0.0257	Apprentice Hours	0.4331	0.0111
PC4	0.0070	Journeyman Hours	0.3597	0.0025
PC5	0.0041	Foreman Hours	0.4117	0.0017
PC6	0.0026	Area	0.5740	0.0015
PC7	0.0010	Area	0.3751	0.0004
PC8	0.0006	Area × Apprentice Hours	0.3181	0.0002
PC9	0.0003	Apprentice Hours	0.5250	0.0002
PC10	0.0002	Foreman Hours	0.3508	0.0001

The final step involved selecting the most significant factors from Table 6.3 for inclusion in the new dataset for supervised model training. This enriched dataset comprised the newly identified input features alongside the original target feature. Polynomial transformation, while not a prediction method in itself, serves to enrich the feature set, enabling linear models to capture non-linear relationships. Thus, I employed linear and logistic regression for regression and classification tasks, respectively. Additionally, I utilized Neural Networks and Ensemble methods to ensure robust model training and predictive accuracy, maintaining consistency with previously described methods.

6.3.4.2.5 Ensemble Methods

Ensemble learning involves two primary tasks: creating a diverse group of base ML models from the training data and integrating them to form a comprehensive predictor (Hastie et al. 2009, p. 605). To ensure the Ensemble model is tuned to the data, I took the following steps:

1. **Choosing the Constituent Base Models:** I started by selecting a diverse set of models to include in the Ensemble. The models chosen were the top performers in regressions and classification-based prediction separately. A variety of models ensures that the Ensemble leverages different strengths and compensates for individual model weaknesses.
2. **Optimizing Model Selection:** I employed a mix of cross-validation and performance metrics analysis to iteratively refine which models to include in the final Ensemble. This involved testing various combinations to identify the subset that yielded the most accurate predictions.

   The models considered for this optimization process were:

   a. Regression Models: Linear Regression, Ridge, Lasso, Elastic Net, SVR, K-Neighbors Regressor, Random Forest Regressor, GBR, XGB Regressor, CatBoost Regressor, and MLP Regressor.
   b. Classification Models: Logistic Regression, Ridge Classifier, SVC, K-Neighbors Classifier, Random Forest Classifier, Gradient Boosting Classifier, XGB Classifier, CatBoost Classifier, and MLP Classifier.
3. **Selecting the Estimators:** For each model selected, I conducted hyperparameter tuning using grid search and random search methods to pinpoint the best estimators. I used Linear Regression, Ridge, Lasso, and Elastic Net as the potential estimators. This tuning was crucial to reducing prediction errors and maximizing accuracy.
4. **Ensemble Construction and Evaluation:** The final Ensemble was constructed by integrating the optimally tuned estimators. I explored various Ensemble strategies such as stacking, bagging, and boosting to determine the most effective integration technique. I evaluated the performance of the Ensemble model to confirm it surpassed the performance of the individual models.

The results of these supervised learning methods are analyzed and reported in Section 6.4.2.

6.3.4.3 Model Optimization

As part of the machine learning workflow (Figure 6.7 step 8), I optimized the ML models through a combination of cross-validation and hyperparameter tuning to ensure robustness and enhance predictive accuracy. Given the limited number of observations available for training and testing (Section 6.3.4.1), I employed K-fold cross-validation, specifically using 5-fold cross-validation which uses part of the available dataset to fit the model, and a different part to test it (Hastie et al. 2009, p. 241). For cross-validation, I split the training dataset into five equal parts, using four for training and one for validation in each cycle, and systematically rotating the validation subset to confirm model performance on unseen data.

Determining the optimal hyperparameter settings for each model was crucial for unbiased assessment of a model's predictive power. Hyperparameter tuning is essential for not only improving model performance on training datasets but also ensuring effective generalization to new, unseen data (Schratz et al. 2019). Although many ML models often do not require tuning, for the ones that do, I evaluated various combinations of hyperparameters to find the optimal settings to optimize their performance. Initially, I established a baseline set of parameters for each model. Depending on the model and specific parameters, I made incremental adjustments, compared either to the baseline or the most recently identified high-performing set of parameters. In cases involving extensive combinations of parameters, I employed search techniques to find the best configuration.

For simpler models such as Linear Regression, tuning was typically confined to adjusting regularization parameters by using variants including Ridge or Lasso. Regularization is crucial as it helps reduce variance and increases robustness, preventing overfitting and thereby enhancing the model's ability to generalize (Friedman et al. 2010). In the case of LDA, I primarily adjusted the solver type and occasionally employed shrinkage techniques.

For more complex models such as GBR, I tuned multiple parameters including the number of trees, learning rate, and tree depth. For DNN, I made adjustments to the network architecture. Utilizing tools including Scikit-learn's MLPRegressor and MLPClassifier, I tuned various hyperparameters such as the sizes of hidden layers, the activation function for these layers, the solver for weight optimization, the alpha L2 penalty (a regularization term), the initial learning rate for updates, and the maximum number of iterations during training. For parameter tuning, I employed GridSearchCV to test every possible combination of hyperparameters from a predefined grid and RandomizedSearchCV to sample configurations from the parameter space. Both methods used 5-fold cross-validation to ensure thorough testing.

As described in Section 6.3.4.2.4, for the SINDy approach, I optimized the application through careful selection of features and hyperparameter tuning. Initially, I employed sparse regression to determine the most critical dynamics affecting work density, using PCA to pinpoint essential polynomial features. The final hyperparameter tuning involved selecting the most significant polynomial features for inclusion in a new dataset, which then underwent supervised learning hyperparameter tuning like the models descried above. For Ensemble methods (Section 6.3.4.2.5), I optimized the composition of the Ensemble through trial and error, selecting appropriate models, model estimators, and tuning parameters for techniques such as bagging and boosting. This active and iterative process of hyperparameter tuning led to significant improvements in most models' performance.

The optimal hyperparameters identified for each model are reported in Section 6.4.2.1.

6.3.4.4 Model Evaluation Metrics

I evaluated models using a variety of performance metrics, individually selected for the regression and multi-class classification models, to assess the predictive accuracy and robustness of the developed models.

For regression models, the predicted values were evaluated against the actual values using the following three metrics:

1. The Mean Square Error (MSE) measures the average of the squares of the errors, i.e., the average squared difference between the actual (y_i) and predicted ($\hat{y}_i$) values for all the data

points (n). It measures the variance of the residuals, i.e., the difference between the actual and predicted values (Draper and Smith 1998). It is given by Equation 6.1.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6.1}$$

2. The Root Mean Square Error (RMSE) measures the square root of MSE. It measures the standard deviation of residuals. It is given by Equation 6.2.

$$\text{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i} - \hat{y}_i)^2} \tag{6.2}$$

3. The coefficient of determination (R^2) represents the proportion of the variance in the dependent variable which is explained by the regression model. It was used as the goodness of fit and is given by Equation 6.3.

$$R^2 = 1 - \frac{\sum_i(\mathrm{y_i} - \hat{y}_i)^2}{\sum_i(y_i - \bar{y}_i)^2} \tag{6.3}$$

The MSE provides a measure of the average squared difference between the estimated values by the prediction model and the actual value measured using DDPF, indicating the model's prediction error. A lower MSE value indicates a better fit to the data. The RMSE is the square root of MSE and offers a measure of error in the same units as the target variable, i.e., in hours, which makes it intuitively easier to interpret. The coefficient of determination, or R^2 score, which can range from -∞ to 1.00, provides a measure of how well future samples are likely to be predicted by the model. An R^2 score close to 1 indicates a model that explains a large portion of the variance in the response variable.

For classification models, the predicted classes were evaluated against the actual classes on the test set. A binary confusion matrix was used with four kinds of results including True Positives (*TP)*, True Negatives (*TN)*, False Positives (*FP)*, and False Negatives (*FN)*. The results from the matrix were used to calculate the following four performance metrics:

1. Accuracy measures how often a ML model correctly predicts the outcome. It is given by Equation 6.4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{6.4}$$

2. Precision measures how often a ML model correctly predicts the positive class. It is calculated by dividing the number of correct positive predictions (true positives) by the total number of instances the model predicted as positive (both true and false positives). It is given by Equation 6.5.

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{6.5}$$

3. Recall measures how often a ML model correctly identifies positive instances (true positives) from all the actual positive samples in the dataset. It is calculated by dividing the number of true positives by the number of positive instances, i.e., true positives (successfully identified cases) and false negative results (missed cases). It is given by Equation 6.6.

$$Recall = \frac{TP}{TP + FN} \times 100\% \tag{6.6}$$

4. F1 score measures the average of precision and recall, where the relative contribution of both metrics is equal to F1 score. It is given by Equation 6.7.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6.7}$$

Accuracy measures the proportion of true results (both true positives and true negatives) in relation to the total number of cases examined, providing insight into how well the model performs across all classes. This metric is particularly relevant when the costs of false positives and false negatives are similar, or when class distribution is balanced. Precision, which measures the accuracy of positive predictions, becomes critical when the cost of a false positive is high. For example, overestimating work duration might lead to unnecessary resource allocation and higher costs. Precision reflects the proportion of correct positive predictions among all positive predictions made.

Recall measures the model's ability to identify all relevant instances within a dataset, becoming crucial when the cost of missing a positive case (a false negative) is significant. For example, underestimating work duration can result in rushed jobs and potential safety issues. The F1-Score, which is the harmonic mean of precision and recall, balances these two metrics, providing a single measure that is useful in situations where class imbalances might affect the model's performance, ensuring a balanced view of both the precision and recall achievements of the model. All of the four metrics used for classification models are range between 0 to 1 (or 0 to 100%), and typically, a value of > 0.9 (90%) is considered excellent, between 0.8 and 0.9 is considered good, between 0.5 to 0.8 is considered average, and below 0.5 is considered to have a poor performance.

The results from the implementation of the unsupervised- and supervised learning methods are described next with evaluation of the supervised learning models based on the above mentioned metrics reported in Section 6.4.2.2.

6.4 Results and Discussion

6.4.1 Data Analysis Results

This section presents the results from the analyses conducted during the data preprocessing- and unsupervised learning steps, described in Sections 6.3.1 and 6.3.3, respectively. These analyses include exploratory data-, correlation-, feature importance-, and clustering analysis.

6.4.1.1 Exploratory Data Analysis (EDA)

I conducted an EDA on the historical production datasets generated in the data processing procedure (Figure 6.2 step 6). This analysis, part of the data preprocessing step (Figure 6.7 step 7), aimed to understand the characteristics of the data before further processing and the implementation of ML methods (Figure 6.7 step 8). I present the findings of this analysis through various visualizations that explore patterns, anomalies, and relationships among the data points.

Figure 6.13 displays box plots for duration hours, data feature representing work density, categorized by worker role and subdivided into hourly bins based on worker-hours. These bins are equally divided across the range of hours for each role: foreman (0.39–320.00 hours), journeyman (0.89–528.00 hours), and apprentice (0.26–256.00 hours). Each role's plot is further segmented into four bins: low, medium, high, and very high, each covering equal hourly increments based on the range of values for that role. For example, foreman hours are divided into four bins from 0.39–80.29 hours (low) to 240.10–320.00 hours (very high), with each bin spanning 79.90 hours. This segmentation into four bins with a very high bin addresses the significant number of outliers observed towards the higher values in each role, as shown in Figure 6.5.

The distribution in Figure 6.13 shows a generally linear increase in duration hours with rising journeyman and apprentice hours across low to very high bins, with box, quartile, and median values also increasing. Conversely, foreman hours display a relatively flat distribution, suggesting that while the demand for journeymen and apprentices scale with increasing work density, the need for foremen remains relatively constant. This pattern underscores the physical and managerial differences between the roles.

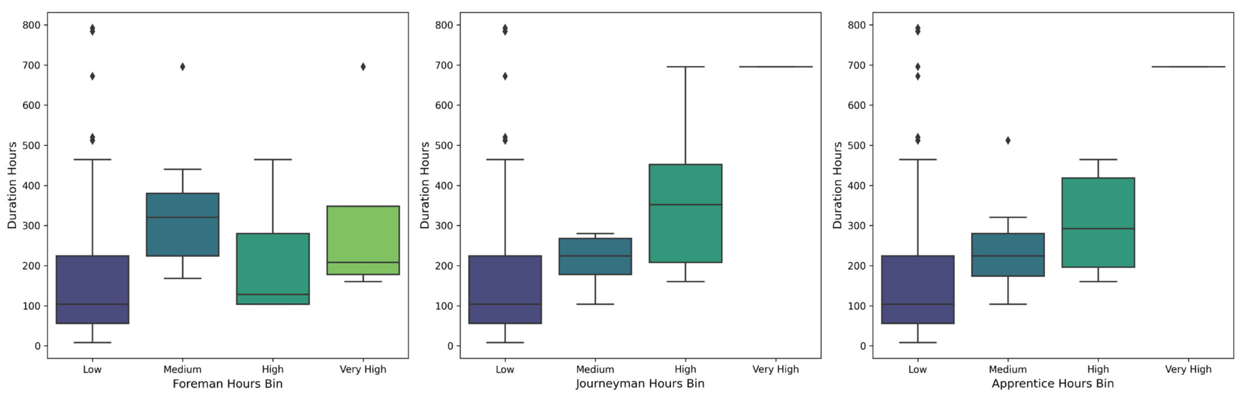


Figure 6.13: Historical production data box plots for step duration hours grouped by role and binned by role-based hours.

Visually, the length of the boxes and whiskers in these plots indicates variability in duration hours per step, segmented by worker role. The variability for foreman hours remains consistent across all bins, whereas journeyman and apprentice hours show greater variability in the low and high hour bins compared to the medium and very high bins.

This analysis validates the expected distribution patterns of workers per role, influenced by craft-specific standards and union agreements. Typically, the ratio of foremen to workers increases with crew size—e.g., one foreman for every 15 workers—and is dictated by union agreements, often making up about 10% of the total workforce. The apprentice to journeyman ratio is higher, typically one apprentice for every four to five journeymen, adhering to state labor codes, local jurisdiction exemptions, and specific apprenticeship standards. For example, according to the California Department of Industrial Relations (2024), "the minimum apprentice hourly ratio of five journeymen hours per one apprentice hour as required by Labor Code 1777.5 (g) is per craft and only includes straight time hours, not overtime. At the end of the project, straight time apprentice hours must equal one hour for every five straight time journeyman hours for each craft."

Figure 6.14 presents a box plot of duration hours segmented by location type (e.g., bathroom, lobby/corridor, open area, room, staircase). As discussed in Section 5.5.1.4, the figure highlights how steps in staircases and elevator lobbies, treated as backlog spaces, exhibit significantly longer durations with high variability. Differences in physical area and work scope across location types including bathrooms, open areas, and rooms also display comparable variability and duration ranges, with rooms showing higher median duration hours despite their smaller physical size compared to open areas. This observation emphasizes that physical area alone is not a reliable indicator of work density, underscoring why conceptual and parametric planning based solely on the physical area is not an adequate measure of work density.

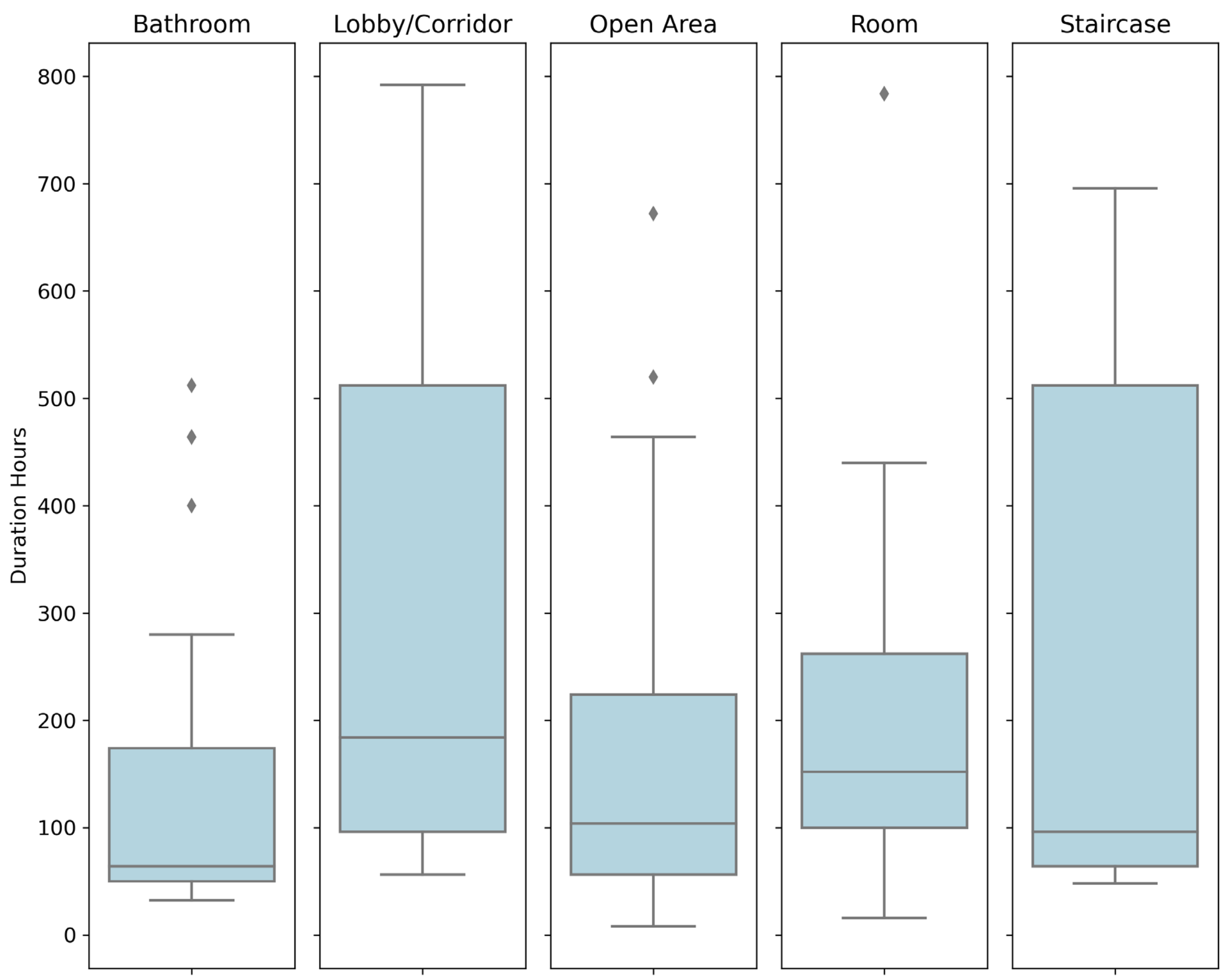


Figure 6.14: Historical production data box plot for step duration hours grouped by location type.

6.4.1.2 Correlation Analysis

For correlation analysis, I used the Pearson Correlation Coefficient (PCC), given by r in Equation 6.8 between two variables x and y. The PCC is used to quantify relationships between variables, where values range from -1 (total negative correlation) to +1 (total positive correlation), with 0 indicating no correlation. A value closer to 1 or -1 suggests a linear relationship between the two variables.

$$\mathrm{r} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{6.8}$$

Figure 6.15 displays a correlation matrix focusing only on numerical features. For categorical features, I calculated the PCCs after one-hot encoding. Given the high dimensionality resulting from 44 encoded features involving 946 unique feature pairs, I limited my discussion to strong correlations (PCC close to -1 or 1) and weak correlations (PCC close to 0).

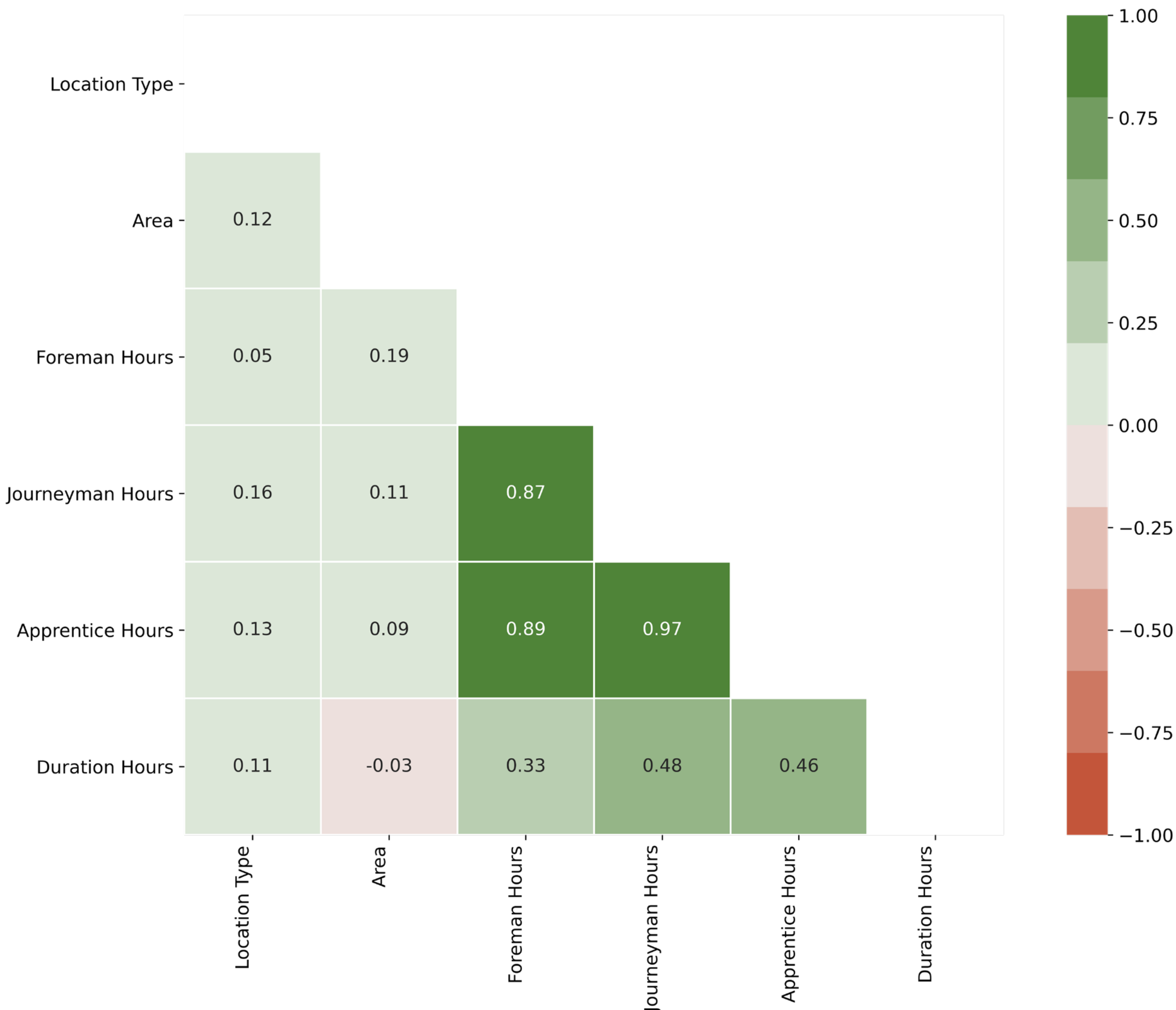


Figure 6.15: Correlation matrix for numerical features only.

In addition to PCC, I also use the results from the PCA to distill correlated features into uncorrelated PCs. Figure 6.16, a correlation circle (aka. variable factor map), visualizes the relationships between original features projected onto a factorial plane defined by the first two PCs (PC1 and PC2), as identified in Section 6.3.3.1. The x-axis represents PC1, and the y-axis represents PC2. The figure includes a unit circle and red arrows originating from the origin. Each arrow represents a feature, with the length indicating how much that feature explains the variance of the data on this factorial plane. Feature arrows that are close to the circle's edge are well-represented by the first two PCs. For clarity, only the features explaining more than 25% (length > 0.25) of the variance are labeled. Feature arrows that point in the same direction are positively correlated, those pointing in opposite directions are negatively correlated, and orthogonal ones indicate no correlation.

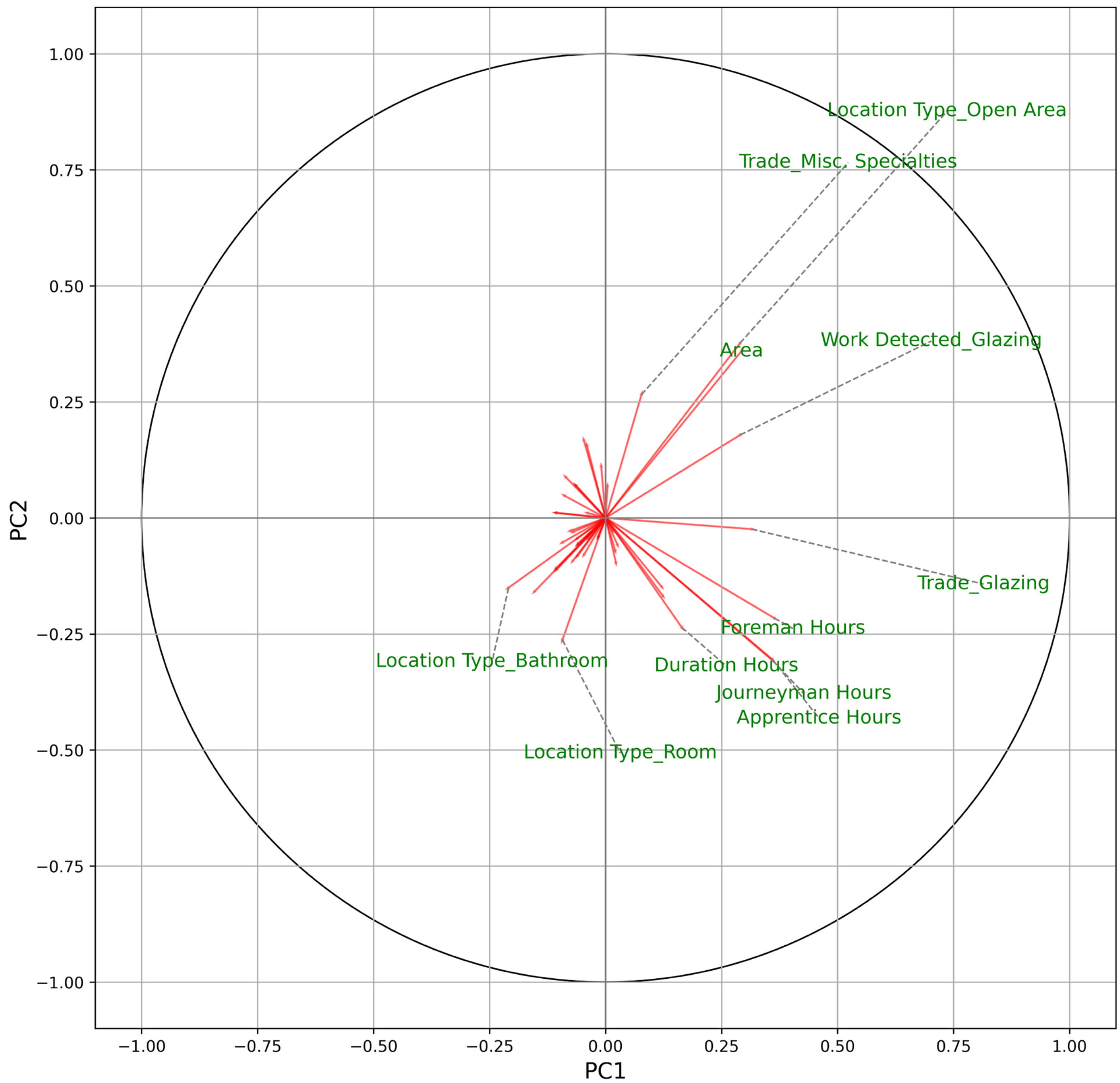


Figure 6.16: Correlation circle (aka. factor map): contribution of each feature to first and second principal components (PC1 and PC2).

Results from this analysis (Figures 6.15 and 6.16) align with those observed in Section 6.4.1.1. Correlations among foreman-, journeyman-, and apprentice hours are strong and positive, influenced by union and general labor agreements. Notably, journeyman- and apprentice hours display an almost perfect correlation with a PCC of 0.97 (Figure 6.15) and arrows of equal length and same direction in the correlation circle (Figure 6.16). Foreman hours is slightly less correlated but still with high correlation (PCC 0.87 and 0.89), highlighting the managerial versus labor-intensive nature of the roles. The correlations between the role-based hours and the target feature, duration hours, also exhibit a similar pattern. Similarly, the correlation between duration hours and journeyman- and apprentice hours is moderate to strong and positive (PCC 0.48 and 0.46, respectively), whereas the correlation with foreman hours ranges from weak to moderate and positive (PCC 0.33). The orthogonal positioning (Figure 6.16) of some feature arrows to the duration hours suggests weak relationships, such as the minimal correlation between the area of a location and duration hours (PCC -0.03 in Figure 6.15).

The analysis of the relationship between work density (represented by duration hours) and all other features clarifies the relative influence of input features on the target feature of work density. Table 6.4 summarizes the top five PCCs between the 43 continuous numerical and one-hot encoded input features against the target feature (duration hours). Worker-hours across all the three roles exhibit the highest PCC to the target, consistent with the results discussed with Figures 6.15 and 6.16. The order of PCC follows the proportion of total hours contributed, with journeyman- and apprentice hours having the strongest and almost equal correlation (PCC 0.48 and 0.46, respectively).

The next most correlated feature to the target is room location type (Table 6.4 and Figure 6.16), possibly due to most data points being of this location type. Future datasets with more diverse location types may help mitigate this bias. Similarly, the Electrical trade and Raceway and Boxes for Electrical Systems steps, having a larger data point representation in the dataset and requiring the greatest number of workers (Figure 6.4), consequently having the largest share of worker-hours (Figures 6.4 and 6.6), show a higher PCC to the target feature.

Table 6.4: Pearson Correlation Coefficient (PCC) between target feature (duration hours), and top five correlated input features.

Feature - 1	**Feature - 2**	**PCC**
Duration Hours	Journeyman Hours	0.48
Duration Hours	Apprentice Hours	0.46
Duration Hours	Foreman Hours	0.33
Duration Hours	Location Type - Room	0.21
Duration Hours	Trade - Electrical	0.18
Duration Hours	Work Detected - Raceway and Boxes for Electrical Systems	0.16

Analyzing the pairwise correlations among all other features is also beneficial. Strong pairwise correlations between input features indicate redundancies, which could be eliminated in future data collection and model training efforts by selecting a single representative feature. Conversely, identifying weak correlations is important for recognizing variability in the data.

Table 6.5 lists the top pairwise correlated features with absolute PCCs greater than or equal to 0.80. An expected pattern within these pairs is the high PCC between trades and their associated steps. This suggests a potential feature redundancy when both trade and step are used in model training, since the definition of a step inherently includes the associated unique trade. However, as steps provide more detailed information and a single trade can work on multiple steps, it is rational to use the step instead of the trade as an input feature. Additionally, to be able to use replace trade feature with step feature only, a standard library of steps and processes is needed, as suggested through the historical production database (Figure 4.2) in Sections 4.2 and 6.2.5.

Table 6.5: Top pairwise correlated (Pearson Correlation Coefficient > 0.80) between all features.

Feature - 1	**Feature - 2**	**PCC**
Trade - Mechanical Wet	Work Detected - Hydronic Piping	1.00
Trade - Drywall - Fireproofing	Work Detected - Thermal Insulation	1.00
Trade - Structural Steel (Iron Work)	Work Detected - Metal Pan Stairs	1.00
Trade - Painter	Work Detected - Interior Painting	1.00
Apprentice Hours	Journeyman Hours	0.97
Trade - Electrical	Work Detected - Raceway and Boxes for Electrical Systems	0.97
Location Type - Open Area	Area	0.96
Trade - Plumbing	Work Detected - Sanitary Waste and Vent Piping	0.93
Trade - Fire Protection	Work Detected - Wet-Pipe Sprinkler Systems	0.92
Apprentice Hours	Foreman Hours	0.89
Foreman Hours	Journeyman Hours	0.87
Trade - Tile Installer	Work Detected - Ceramic Tiling	0.86

Furthermore, worker-hours across the three different roles demonstrate a high degree of correlation. However, their influence can change depending on geography and scope of work as the labor- and union requirements change. Further analysis of these features is required by collecting data from different projects to see the consistency in the distribution so that their representative feature can be simplified. In terms of location types, the open area type is strongly correlated with the physical area of the location. However, it does not show strong correlations with other location types (such as bathroom and room), indicating that it is not redundant. This is also visible in Figure 6.16 with their arrows pointing in opposite directions.

6.4.1.3 Feature Importance Analysis

I analyzed feature importance to assess the relative significance of each feature in an ML model, particularly its contribution to the model's predictive performance. In this research, I quantified the importance of features to gauge their influence on prediction outcomes and used it as a metric in various aspects of model assessment and improvement, including:

1. Feature Engineering: Understanding which features are more important can guide further feature engineering efforts. Using this understanding, future improvement efforts might include creating new features that enhance the effects of already important variables, or improving the representation of features that are currently not contributing much to the model's performance.
2. Data Collection Resource Allocation: In applications where data collection is costly or labor-intensive, feature importance can help prioritize which variables to focus on, thereby improving resource utilization.
3. Model Interpretation: Feature importance analysis provided insights into the underlying decision-making process of the model by highlighting which features have stronger influence on the predicted outcomes. This is particularly valuable in complex models, where understanding how decisions are made can be challenging.
4. Model Simplification: By identifying the most influential features, less important features can potentially be removed without significantly decreasing the model's performance. This simplification can lead to faster training times and reduced model complexity, which often enhances the generalizability of the model.
5. Improving Model Performance: Feature importance can highlight issues such as data leakage (where some features unrealistically aid in prediction because they would not be available in an actual prediction context). Addressing these issues can lead to more robust models.

Next, I describe the different techniques used for the above listed aspects of model assessment and improvement through feature importance analysis, and their results.

For the first and second aspects of feature importance analysis, I employed a PCA-based dimensionality reduction technique to identify features rich in information and capable of distinguishing data clusters. In Section 6.3.3.1, I have reported the preliminary results for dimensionality reduction technique PCA in Table 6.2, where feature importance is indicated by the extent of each feature's contribution towards the PCs, with values standardized to a maximum score of 1.0.

The results in Table 6.2 reports only the top contribution (most important) features, e.g., "Foreman Hours" for PC1 and "Location Type - Open Area" for PC2. This result showed that, for the dataset from Project O, only the first two PCs (PC1 and PC2) account for a substantial proportion of the explained variance, with subsequent PCs contributing significantly less. Thus, I considered only the most important features for PC1 and PC2 for feature importance analysis. To find other features contribution of a PC, I used a loading plot. The loading plot in Figure 6.17 shows the contribution (loading) of each original feature to the PC1, where features with higher absolute loading values contribute more to the corresponding PC. The height of the bars indicates the loading value for each feature. Positive loadings indicate a direct relationship with the principal component, while negative loadings indicate an inverse relationship.

The “Foreman Hours” feature shows largest loading in Figure 6.17, matching the results in Table 6.2. However, other features including “Journeyman Hours”, “Apprentice Hours”, “Location Type - Open Area”, and the process step and trade for glazing, all show similar and positive loading values, indicating they contribute significantly and positively to PC1. Conversely, features such as “Location Type: Bathroom” have moderate negative loadings, indicating they contribute negatively to PC1.

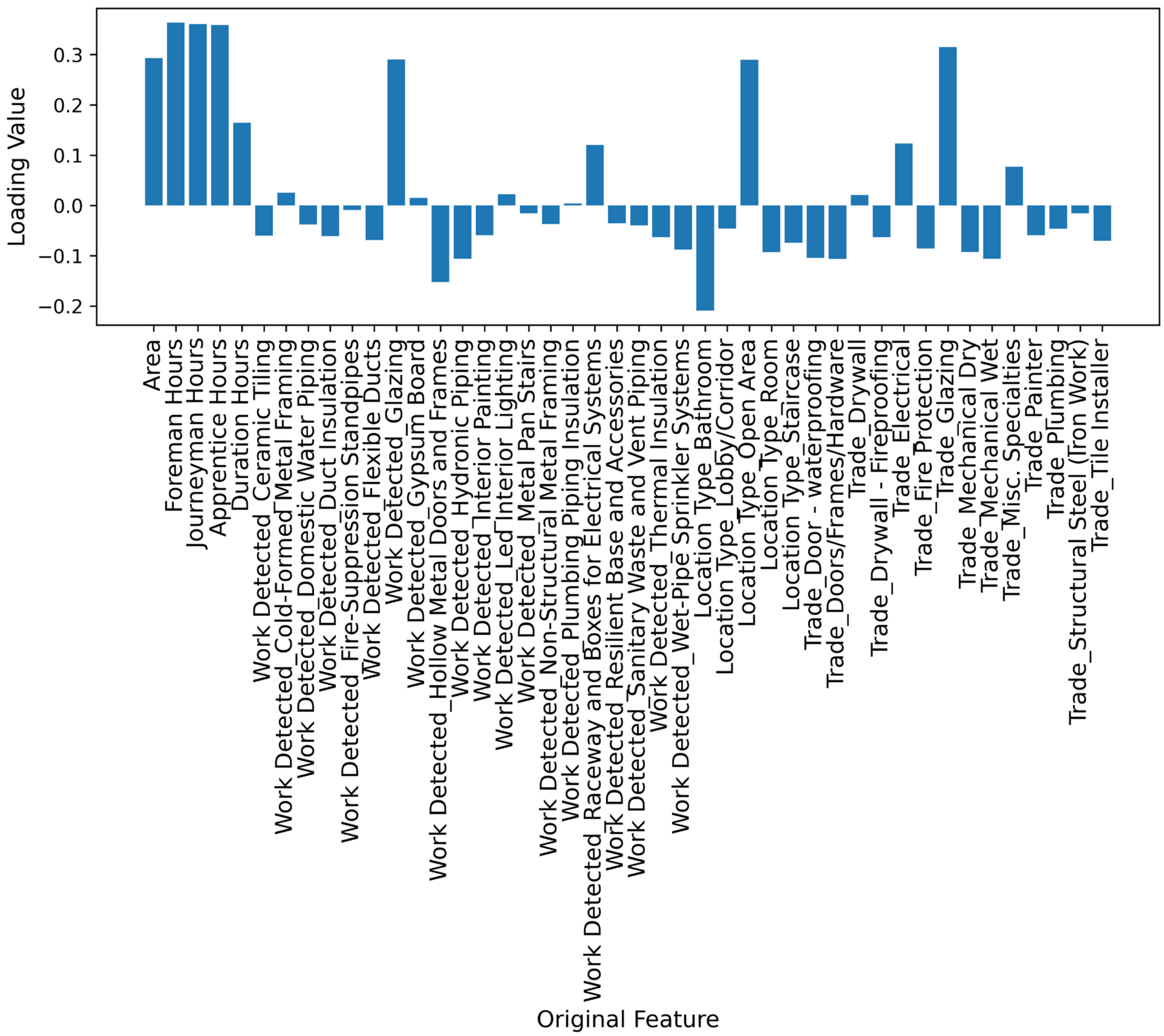


Figure 6.17: Loading plot: loading value of each original feature to the first principal component (PC1).

Figures 6.18, 6.19, and 6.20 display 3D PCA projections of the “Process Library” dataset from Project O using the first three PCs, with each data point colored according to important features identified in Figure 6.17. The plots in Figure 6.18 are colored based on area (left) and location type - open area (right), both showing similar separation for data points with larger areas (colored red) and open area location type (colored red), which represents the only location type with large area. The plots in Figure 6.19 are colored based on work detected - glazing (left) and trade - glazing (right), both showing similar separation for data points with glazing work and glazing trade (colored red). The data points associated with glazing are a subset of data points for open area in Figure 6.18 (right) as the glazing work was only located in these areas around the periphery of the building (Figure 5.3). These plots show how area and scopes of work specific to open area are important features to introduce variation in the dataset and that these features are good differentiator from all the other types of locations and scopes of work.

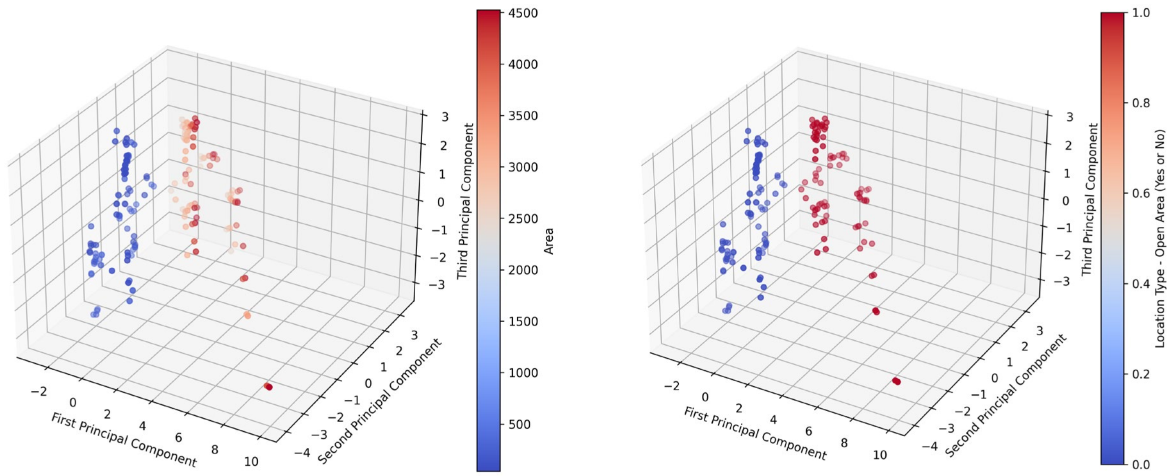


Figure 6.18: Principal Component Analysis (PCA) projections of the “Process Library” dataset from Project O using the first three Principal Components (PCs) with color gradient based on area (left) and location type - open area (right).

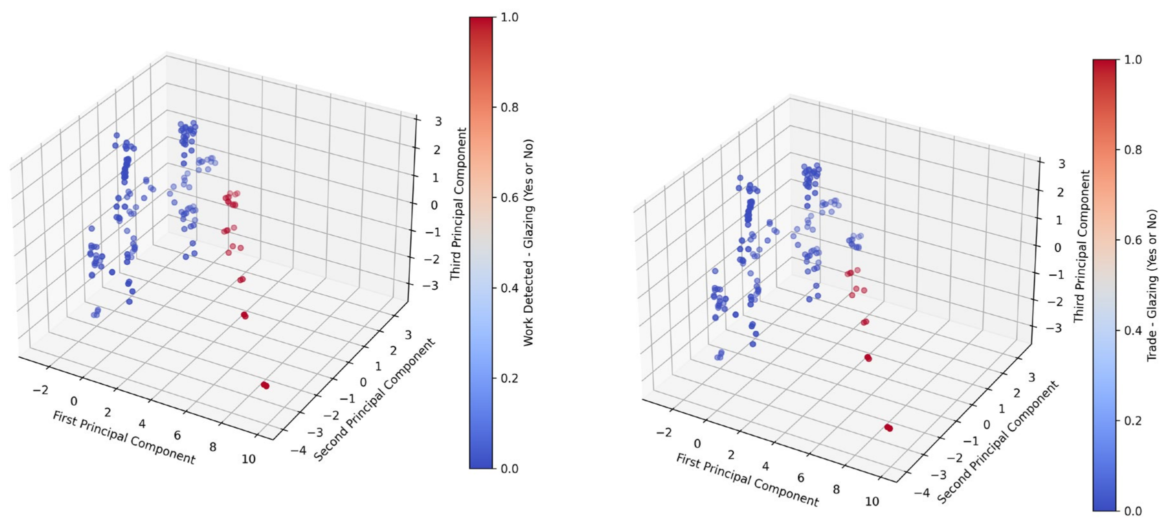


Figure 6.19: Principal Component Analysis (PCA) projections of the “Process Library” dataset from Project O using the first three Principal Components (PCs) with color gradient based on work detected - glazing (left) and trade - glazing (right).

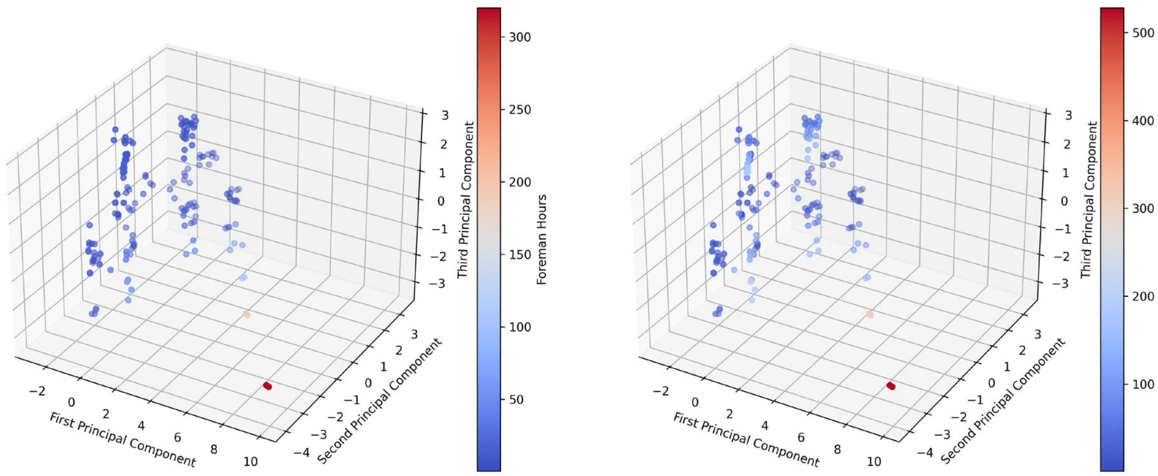


Figure 6.20: Principal Component Analysis (PCA) projections of the "Process Library" dataset from Project O using the first three Principal Components (PCs) with color gradient based on foreman hours (left) and journeyman hours (right).

The plots in Figure 6.20 are colored based on foreman hours (left) and journeyman hours (right), both showing similar separation for data points with higher foreman- and journeyman hours (colored red). The data points with very high foreman-, and journeyman hours are a subset of data points for open area (Figure 6.18 right) and glazing work (Figure 6.19 right).

Although having this clear separation is helpful in understanding the data, it seems to be limited to certain types of steps, trades, and locations, which means other features are not that easy to separate and add variation to the dataset.

For the first, third, and fourth aspects, I utilized PCA to treat the factors of the polynomial generated by the SINDy approach (described in Section 6.3.4.2.4) as dataset features for model training. The polynomial, comprising 70 factors, allowed for focusing on only the most essential factors and creating new features with greater importance, thereby simplifying the dataset, enhancing model performance, and reducing overfitting. Table 6.6 details the analysis results, featuring the first five PCs and their most important features. The SINDy approach allowed creation of new features as part of the polynomial to fit on training data, among which "Area x Journeyman Hours x Apprentice Hours" and "Area^2" are two examples with largest contributions in explaining variance in the first two PCs and the data.

For the third, fourth, and fifth aspects of the analysis, I derived values from model training data. For example, the GBR model, comprising numerous regression trees, is challenging to interpret solely through individual tree analysis. Feature importance was used to determine which features frequently act as split points in the trees. Table 6.7 lists the top five most important features for the GBR model, highlighting the predominant role of worker-hours (by role) and area.

Overall, the feature importance analysis yielded consistent results with two main groups of important features: (1) role-based worker-hours (i.e., Journeyman Hours, Foreman Hours, and Apprentice Hours) and (2) area-related factors (i.e., Area, Location Type – Open Area, and Area^2). While factors related to worker-hours align with findings from the EDA and correlation analysis, those related to area do not, suggesting the former being more important in adding variability to the data.

Table 6.6: Principal Component Analysis (PCA) results for SINDy polynomial factors with first five Principal Components (PCs) and their corresponding most important features.

Principal Component	**Explained Variance**	**Most Important Feature**	**Importance**
PC1	89.72%	Area x Journeyman Hours x Apprentice Hours	0.13
PC2	6.07%	Area^2	0.46
PC3	2.57%	Apprentice Hours	0.43
PC4	0.70%	Journeyman Hours	0.36
PC5	0.41%	Foreman Hours	0.41

Table 6.7: Feature importance analysis resutls for the GBR model with top five most important features.

Feature	**Importance**
Journeyman Hours	0.584
Area	0.128
Foreman Hours	0.106
Apprentice Hours	0.097
Trade - Misc. Specialties	0.013

6.4.1.4 Clustering Analysis

In Section 6.3.3.2, I described the implementation of clustering algorithms used with the objective of understanding the dataset and facilitating classification-based predictive modeling. Among the three algorithms evaluated, the k-prototype algorithm outperformed both k-means and DBSCAN in distinguishing data points based on their inherent properties. The visualization of k-prototype clusters in two-dimensional space, varying combinations of features on the x- and y-axes, and color-coding based on cluster assignments, provided insights into the algorithm's utility in identifying properties. The analysis results, depicted in Figures 6.21 to 6.23, span several scatter plots with each representing different set of features against area, apprentice hours, journeyman hours, foreman hours, duration hours, trade, location type, and work detected.

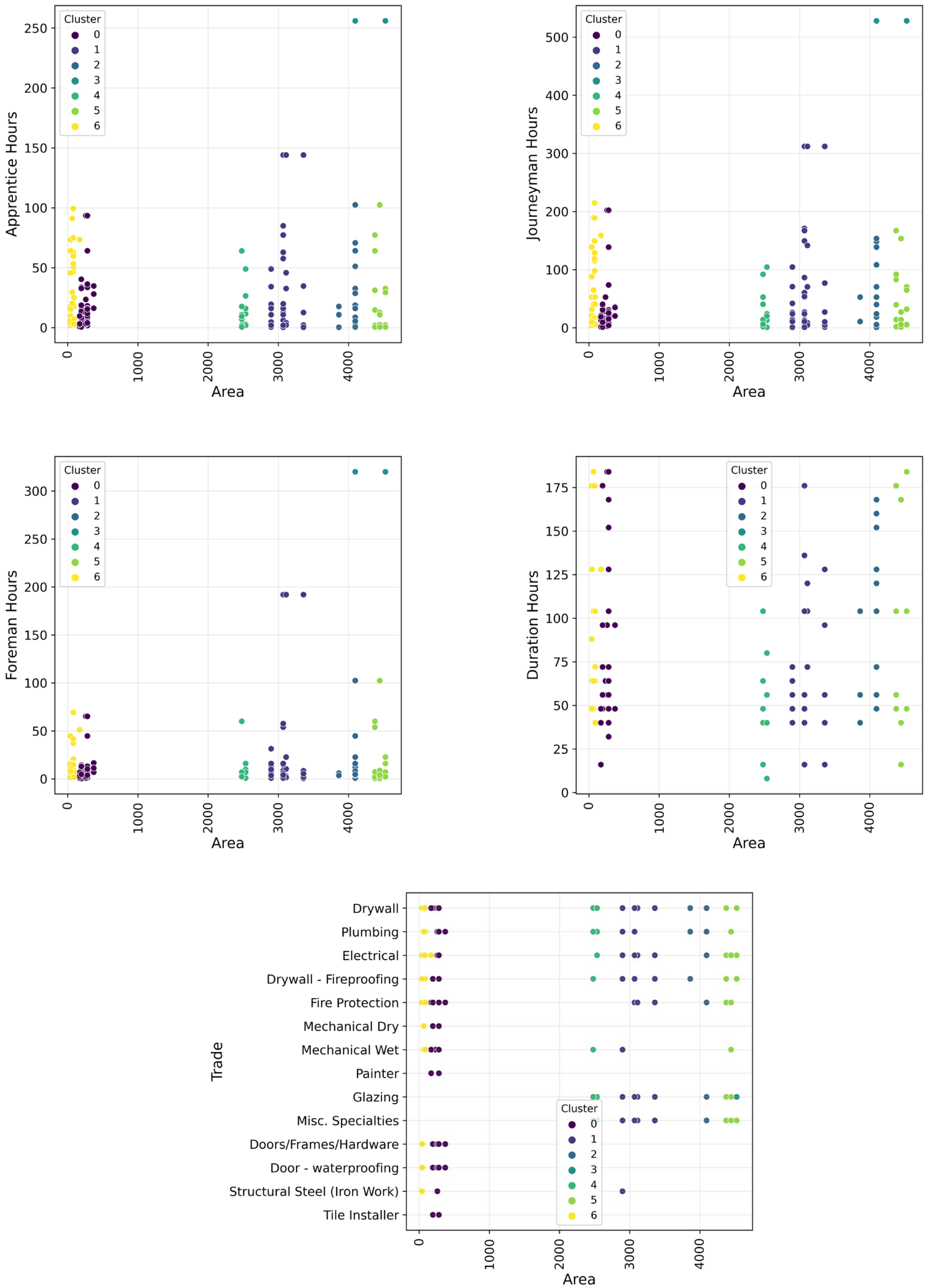


Figure 6.21: K-prototype clustering of scatter plot with apprentice hours (top left), journeyman hours (top right), foreman hours (middle left), duration hours (middle right), and trade (bottom center) against area.

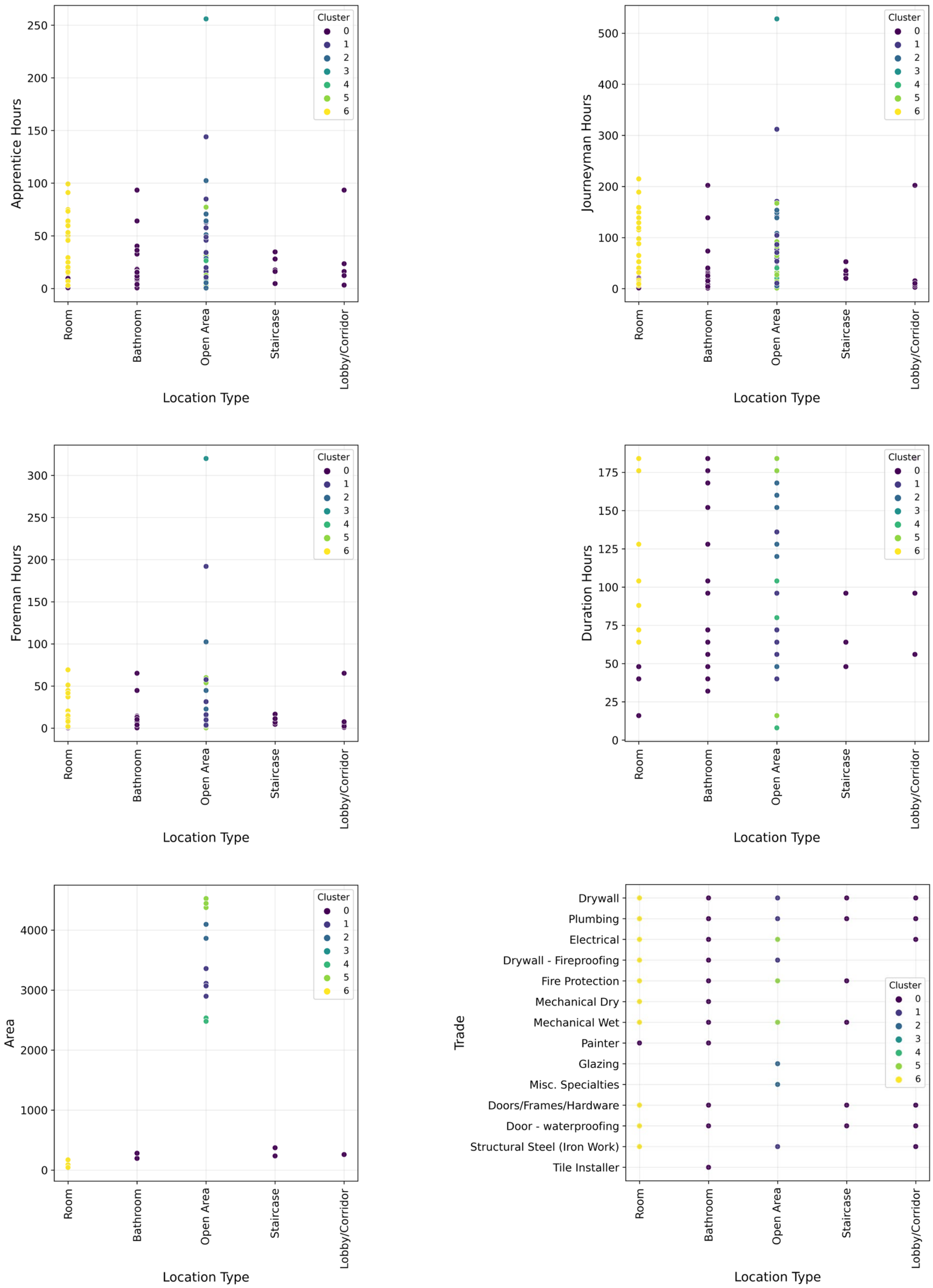


Figure 6.22: K-prototype clustering of scatter plot with apprentice hours (top left), journeyman hours (top right), foreman hours (middle left), duration hours (middle right), area (bottom left) and trade (bottom right) against location type.

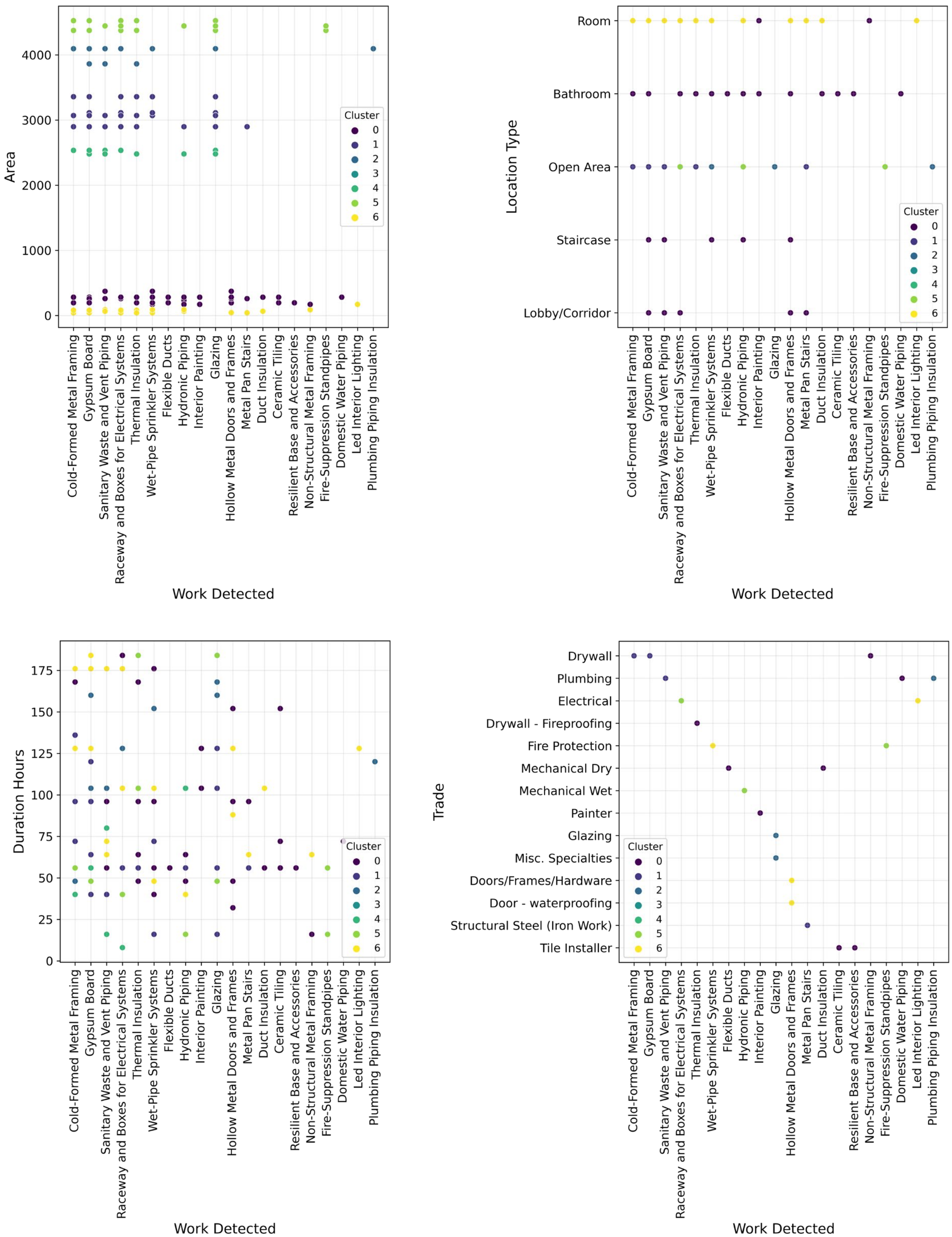


Figure 6.23: K-prototype clustering of scatter plot with area (top left), location type (top right), duration hours (bottom left) and trade (bottom right) against work detected.

Figures 6.21 presents five subplots, each showcasing a different feature—apprentice hours (top left), journeyman hours (top right), foreman hours (middle left), duration hours (middle right), and trade (bottom center)—plotted against the area feature. These plots demonstrate a clear segregation of seven clusters by their physical area. Based on the area range per cluster and the average size of location types (Table 5.1), the open area location type (ranging from 2,500 to 4,500 ft^2) is divided into four clusters, while other types (ranging from 0 to 400 ft^2) are segmented into two clusters. No other features are distinguished by these clusters.

Observations from these distributions suggest several conclusions:

1. Cluster Distribution:
   - There appears to be a correlation between area and worker-hours across different types of roles (apprentice, journeyman, and foreman). Larger areas tend to have more variability in the number of worker-hours, as seen by the spread of clusters in plots where area is large.
   - Certain clusters are more concentrated at lower area values across different worker roles, suggesting that smaller locations might have more predictable or uniform worker-hour requirements.
2. Workforce Trends:
   - Apprentice- and journeyman hours: the distribution indicates that smaller areas typically require fewer apprentice- and journeyman hours, though exceptions exist in specific clusters where the hours are disproportionately high. Subplots for the two roles show almost identical distribution, consistent with the EDA and correlation analysis.
   - Foreman hours: Foreman hours tend to increase with area size but not in a linear manner, suggesting that the need for oversight does not directly correlate with the area of a location.
   - Duration hours: There is a uniform distribution of variability in duration hours relative to area.

Figures 6.22 presents six subplots, each showcasing a different feature—apprentice hours (top left), journeyman hours (top right), foreman hours (middle left), duration hours (middle right), area (bottom left) and trade (bottom right)—plotted against location type feature. All the plots show a clear separation of seven clusters separated by their location type, which is dependent on the area of the location. With some variability, almost all data points of open area location type are grouped in four clusters (clusters 1 through 5), bathroom, staircase, and lobby/corridor location types are grouped in one cluster (cluster 0), and room location type is grouped in one cluster (cluster 6). This clustering correlates with the average location sizes noted in Table 5.1. The duration hours exhibit considerable variation across all location types, thus providing a useful dimension for data sparsity. Conversely, role-based worker-hours do not significantly contribute to data sparsity.

Figures 6.23 presents six subplots, each showcasing a different feature—area (top left), location type (top right), duration hours (bottom left) and trade (bottom right)—plotted against work detected feature, which represents different process steps. The clusters show no clear separation except for area and location type. Observations from these distributions include:

1. Location type: there is significant variation in area and location type relative to the type of work detected, reflecting the specific requirements of different locations within the

project. For instance, electrical- and drywall work is common across all location types, whereas specialized works such as ceramic tiling is unique to bathroom locations.

2. Duration of hours: the duration hours for different types of work show broad variability and cluster intermixing from the perspective of detected work.
3. Trade involvement: Specific trades are associated with particular steps; most trades are linked to one step, a few to two, and only the plumbing trade to three steps of work.

The comprehensive analyses described in this section underscore the relationship between features of the data, which not only enhanced the understanding of the dataset but also helped in applying this understanding in the subsequent stages of model training and testing with supervised learning methods in Section 6.3.4. The evaluation of these prediction models is discussed in the following section.

6.4.2 Supervised Learning Model Evaluation Results

This section presents the results from the implementation of supervised learning methods, as described in Section 6.3.4. These methods include regression-based models, classification-based models, and a combination of the two with SINDy approach. Following sub-sections report the observations from the hyperparameters tuning for these models, described in Section 6.3.4.3, and finally compare the performance of all the models using the evaluation metrics described in Section 6.3.4.4.

6.4.2.1 Hyperparameter Tuning Results

Hyperparameter tuning, as part of the ML workflow for production planning (Figure 6.7 step 8), optimizes the model's parameters to enhance its predictive power and reduce overfitting. For each model, I selected hyperparameters that yielded the least loss and highest accuracy on the validation set to configure the final models.

For regression-based models, the best-performing hyperparameters were identified as follows:

- Random Forest Regressor: Following recommendations from Probst et al. (2019), the optimal settings included 500 trees, using one-third of the total features at each split, and a minimum node size of 5.
- CatBoost: The tuning focused on key parameters such as the learning rate (0.03), tree depth (6), and iterations (1000), based on the ranges suggested by CatBoost (2024b).
- XGBoost: Optimized parameters included the booster type set to 'gbtree', a learning rate of 0.3, a maximum depth of 6, and 3 boosting rounds.
- DNN Regressor: Employing the MLPRegressor, I utilized both grid and random search techniques, selecting the Adam optimizer, a logistic activation function, an alpha value of 0.01, hidden layer sizes of (100,), an initial learning rate of 0.01, and a maximum of 1000 iterations.
- Ensemble: I found Linear Regression to be the best estimator for the Ensemble model. It included models such as Linear Regression, Ridge, Lasso, Elastic Net, SVR, K-Neighbors Regressor, Random Forest Regressor (number of estimators = 100), GBR (number of estimators = 100), XGB Regressor (objective = 'reg:squarederror'), CatBoost Regressor,

and MLPRegressor, all configured with optimal parameters to balance the Ensemble's prediction capability.

For classification-based models, the tuning results were as follows:

- DNN Classifier: Employing the MLP Classifier, I found the best parameters through GridSearchCV to be logistic activation function, an alpha of 0.05, hidden layer sizes of (50, 30, 10), a constant learning rate, a maximum of 10,000 iterations, and the Adam solver.
- Ensemble: I found Ridge to be the best estimator for the Ensemble model. This Ensemble incorporated models including Logistic Regression (maximum iterations = 1000), Ridge Classifier, SVC, K-Neighbors Classifier, Random Forest Classifier (number of estimators = 100), Gradient Boosting Classifier (number of estimators = 100), XGB Classifier (use of label encoder = False and evaluation metric = 'mlogloss'), CatBoost Classifier, and MLPClassifier, all configured with optimal parameters to balance the Ensemble's prediction capability.

Results using these model hyperparameters are reported next.

6.4.2.2 Result Comparison

I evaluated all supervised learning models using their prediction performance on the model evaluation metrics, listed in Section 6.3.4.4.

For regression models, the performance metrics included MSE, RMSE, and the coefficient of determination (R^2), with the predicted work density in hours. Table 6.8 presents the comparative results for the regression-based supervised learning models.

Table 6.8: Results for regression-based supervised learning.

#	Model	MSE	RMSE	R^2
1.	Linear Regression	1,509.98	38.86	0.29
2	Gradient Boosting Regressor	911.52	30.19	0.57
3	Random Forest Regressor	1,079.44	32.85	0.49
4	CatBoost	950.60	30.83	0.55
5	XGBoost	1,269.44	35.63	0.40
6	DNN	1,240.30	35.22	0.42
7	Ensemble	884.83	29.75	0.58
8	SINDy with Linear Regression	1,263.9	35.55	0.45

In terms of performance, the Ensemble model outperformed all other models with an MSE = 884.83, RMSE = 29.75, and R^2 = 0.58. RMSE of 29.75 suggests that the model can predict results with an expected error of 29.75 hours, which is equivalent to 3.72 days of 8 hour work days. Among the various constituent models included in the Ensemble, described in Section 6.3.4.2.5, some key observations include:

- Linear Regression was quickest and most efficient, with a training time of approximately 161 seconds and the best R^2 score of 0.584.
- Other models, including Random Forest and Gradient Boosting, while slower, offered competitive accuracy but required longer training times.
- Ridge and Lasso models individually exhibited strong performance, each achieving an approximate MSE of 885 and R^2 score of 0.58. These results were marginally surpassed by the superior performance of the combined Ensemble model.
- DNN models, although not providing the best fit for this type of structured data, showed a notable discrepancy in performance, highlighting their sensitivity to feature selection and hyperparameter tuning.
- Among the estimators used for the ensemble model, the Ridge estimator performed best, achieving the lowest MSE of 884.83 and R^2 score of 0.58 as reported in Table 6.8.

Figures 6.24 and 6.25 shows scatter plots comparing the actual values versus predicted values for best performing Ensemble model and DNN model respectively. In these plots, each point represents an observation with its actual value on the x-axis and its predicted value on the y-axis. The dashed line represents the ideal case where the predicted values perfectly match the actual values (i.e., the line y = x).

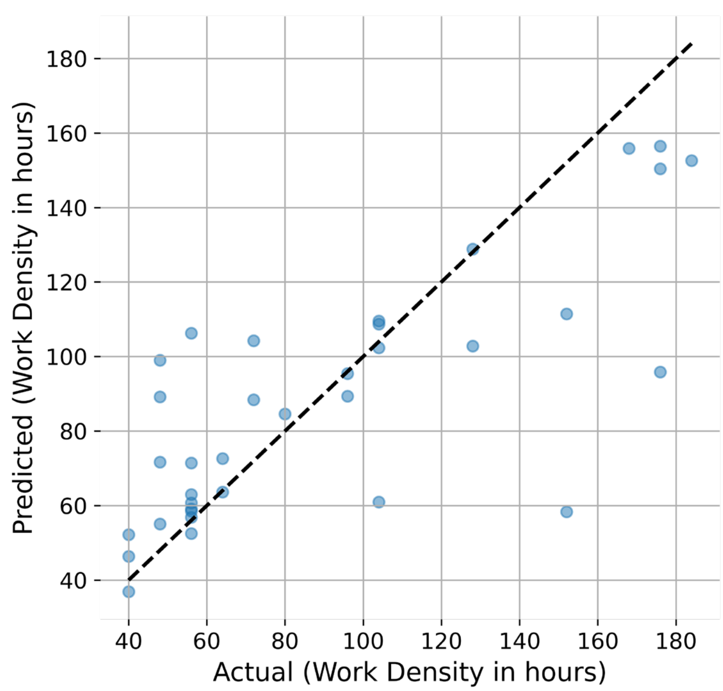


Figure 6.24: Ensemble Actual vs. Predicted Values

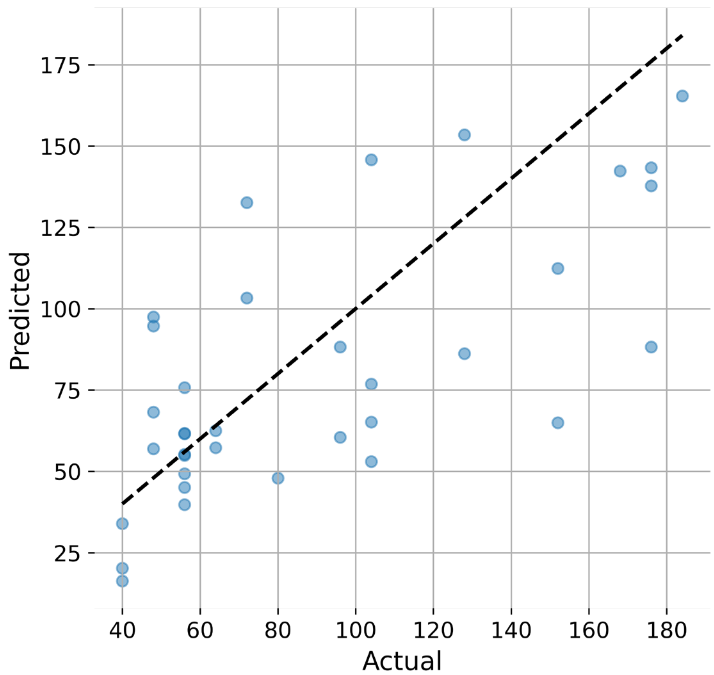


Figure 6.25: Deep Neural Network (DNN) Regression Actual vs. Predicted Values

Figure 6.24 shows the points are more tightly clustered around the dashed line. The plot has a concentration of points close to the origin, indicating that for smaller work density values (<120 hours), the Ensemble model is highly accurate. However, as the actual values increase, the scatter becomes more pronounced, indicating larger prediction errors.

Figure 6.25 displays scatter plots for the DNN model, showing a more dispersed arrangement of points around the dashed line, underlining its poorer performance across all work density ranges compared to the Ensemble model. There are several points far from the dashed line, indicating that the DNN model has a number of significant prediction errors. The overall fit appears to be moderate, with some systematic deviations from the ideal line.

Reflecting on the results in Table 6.8 and Figures 6.24 and 6.25, it is apparent that despite the efficacy of deep learning models with unstructured data, they do not always outperform tree-based models such as Gradient Boosting and Random Forest for medium-sized structured data (10K samples). This is particularly due to DNN's extensive tuning needs and higher computational demands. Studies such as those by Gorishniy et al. (2021) and Shwartz-Ziv and Armon (2022) have demonstrated that in scenarios involving structured data, Ensemble and decision tree-based models often deliver better performance with more practical hyperparameter tuning and lower computational costs.

Table 6.9 provides a detailed comparison of multi-class classification-based supervised learning models utilizing a range of performance metrics, including accuracy, precision, recall, and f1-score. Although only these four metrics are used in evaluation, the metrics used in regression (MSE, RMSE, and R^2) are also included for comparison. These metrics evaluate the model's prediction performance across five ordinal classes of work density, with each class representing a standard work week of 40 hours.

Table 6.9: Results for multi-class classification-based supervised learning.

#	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	R-squared (R^2)
1	Linear Discriminant Analysis	71.70	84.61	66.67	0.75	0.28	0.53	-0.20
2	DNN	54.29	60.39	54.29	0.57	1.03	1.01	0.30
3	Ensemble	74.29	76.41	74.29	0.75	0.89	0.94	0.39
4	SINDy with Logistic Regression	64.15	73.33	66.67	0.70	0.36	0.60	-0.53

In terms of performance, the Linear Discriminant Analysis- and Ensemble model outperformed all other models with comparable results for accuracy (71.70% and 74.29% respectively) and F1-score (0.75 and 0.75 respectively). However, looking at the spread of values across all the metrics, Ensemble model does show more consistent performance, especially with precision and recall, both in 70s and the R^2 score of 0.39. The importance of balancing precision and recall, perhaps because both underestimations and overestimations of work density carry significant consequences. Considering the two, Ensemble exhibited the best performance among the models The model had an MSE of 0.89 and RMSE of 0.94, translating to an error in work density prediction of approximately 37.6 hours (0.94*40), which is equivalent to 4.7 days of 8 hour work days.

However, top performing Ensemble model exhibited an accuracy of 74.29%, which is typically considered average to good score, this level of accuracy suggests that predicting the specific bin of “Duration Hours” (work density) based on the available features poses a significant challenge. The complexity of the task, possible overlap between features across different duration bins, or inherent limitations of the constituent models in the Ensemble in capturing the nuances of this particular dataset could contribute to this outcome.

Among the various models trained, some key observations include:

- Linear Discriminant Analysis (LDA): The model recorded an MSE of 0.28, RMSE of 0.53, and an R^2 of -0.20, indicating that the model does not fit the data well, performing worse than a simple mean-based model.
- Deep Neural Network (DNN): Showed lower performance with an accuracy of 54.29%, precision of 60.39%, and a matching recall, leading to an F1-score of 57.17. Its MSE was 1.03 with an RMSE of 1.01, and a relatively better R2 of 0.30.

Figure 6.26 shows confusion matrix comparing the predicted labels versus true labels for best performing multi-class classification Ensemble model. Each row of the matrix represents the instances in a true class while each column represents the instances in a predicted class.

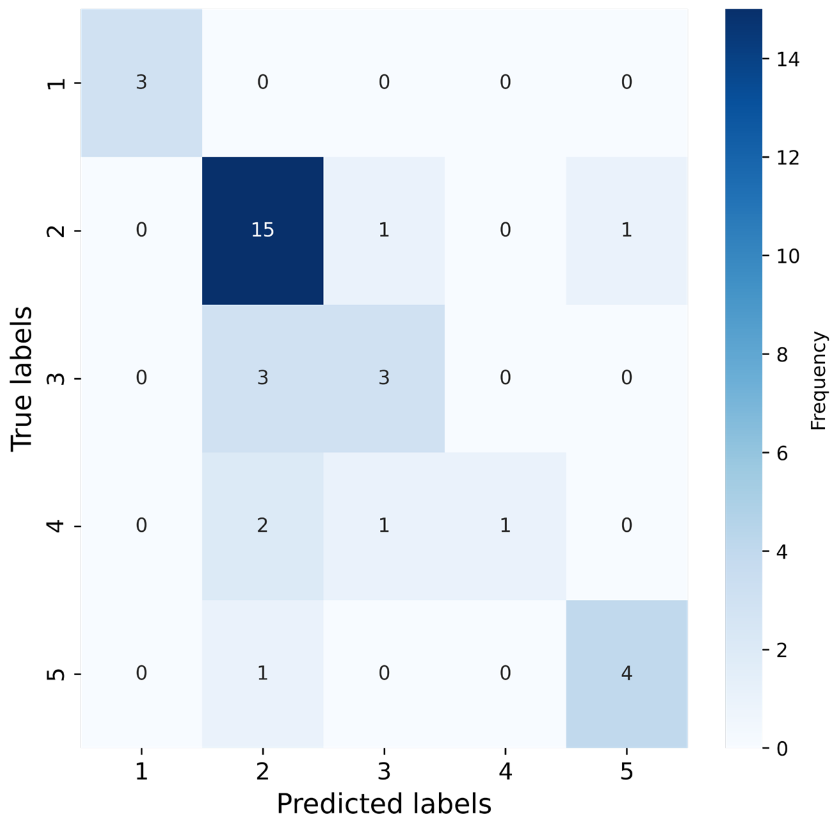


Figure 6.26: Ensemble Confusion Matrix (multi-class classification)

The diagonal elements (true positives) in the confusion matrix (3, 15, 3, 1, 4), represent the number of correct predictions for each class. For example, the first class (labeled as 1) has 3 correct predictions, second class has 15 correct predictions, and so on. The off-diagonal elements (false positives and false negatives) represent the misclassifications.

Analysis of the results class-wise shows that for the first class, 3 instances correctly classified and no misclassifications, which indicates perfect classification for this class. For the second class, 15 instances correctly classified and 6 misclassifications, indicating a high accuracy but with a few errors. Based on this analysis, Classes labeled 1, 2, 4, and 5 show high accuracy with minimal misclassifications, and Class labeled 3 has moderate misclassifications primarily into classes 2 and 4, i.e., off by one class.

Considering results from both regression and classification problem definition, the Ensemble model significantly outperformed the individual models. By integrating multiple predictive perspectives, Ensemble models demonstrate their effectiveness in reducing the likelihood of overfitting and enhancing generalizability across diverse datasets. These results underscore the importance of combining diverse models and meticulously tuning them to optimize predictive accuracy, particularly in complex, structured data environments where Ensemble models can leverage their strength in integration and robustness.

6.4.3 Assumptions and Limitations

The application of ML models inherently requires large amounts of training data to achieve optimal performance. In this research, I collected data from a single case study, which limits the robustness of the model. This constraint underscores the necessity for more extensive data collection and training to enhance the model's accuracy and generalizability in future research.

To better understand the influence of input features on the target feature, work density, I used unsupervised ML methods such as dimensionality reduction and clustering. These methods helped in refining the model training process by identifying features that significantly impact the prediction of work density, thereby improving accuracy. However, learnings from these methods also surfaced several assumptions and limitations, that can be accommodated in future research. These assumptions and limitations are detailed in the following subsections.

6.4.3.1 Workers and Daily Log Dataset

In the construction industry, the roles and experience levels of workers are clearly defined. Among the work roles used in this research (Section 6.2.2), a journeyman is a fully qualified and experienced worker who can perform trade tasks without supervision, having completed an apprenticeship program. In contrast, a foreman or supervising employee not only possesses the skills of a journeyman but also directly supervises physical construction, highlighting their advanced knowledge and supervisory capabilities.

For the missing data on worker-hours distribution by roles, I imputed the time using the distribution of hours for same process step with complete worker-hours by role. This was observed in the EDA (Section 6.4.1.1), where I saw the distribution as expected as per the union and trade rules. These rules can be used as a domain-specific strategy for imputing the number of workers by roles if this division is not included in the data collection. For example, union agreements often specify ratios such as one foreman for every 15 workers or one apprentice for every five journeymen. These ratios ensure proper supervision and training on job sites, influencing the allocation of worker time.

The skills and roles of these workers reflect the complexity and concentration of work density, as observed in the correlation analysis (Section 6.4.1.2). Further research is required to determine if these roles can be effectively combined into a single feature for modeling purposes. Moreover, more than three levels of role and experience might be needed for detailed analysis. Clear distinctions in the impact of foremen compared to journeymen and apprentices suggest that further hierarchical classifications within a single role, such as foremen, general foremen, and senior general foremen, could enhance specificity.

Additionally, multi-skilled foremen can step in to fulfill the roles of journeymen if needed, providing flexibility in workforce management. For certain trades, such as electrical work, the division of labor might be more complex. Electrical unions, for instance, have established additional classifications beyond journeymen and apprentices, such as Construction Wireman and Construction Electrician. These classifications allow electricians with some experience but not at the full journeyman level to become union members and work at a lower rate while receiving training.

When examining worker time distribution across various levels of a building, I initially presumed uniformity across all levels due to similar floor plans and workloads (Section 6.2.2). However, distinct variations on the first floor and the roof, which have unique floor plans and significantly more work, necessitated adjusted calculations. Instead, future data collection should try to collect this data with the detail of specific locations such that the assumption of time distribution by location is not made.

There are additional factors to be considered, such as the learning curve and disruptions, that can affect the amount of time needed to complete the same work with the same inputs.

Overall, understanding these dynamics and incorporating them into data collection and analysis can significantly improve the accuracy of work density predictions and workforce management in construction projects.

6.4.3.2 Classification Problem

In tackling the prediction of work density, I employed multi-class classification-based prediction techniques (Section 6.3.4.2.3). These techniques aimed to categorize work density into five ordinal classes, each spanning 40 hours, which corresponds to one standard working week. I designed this classification scheme to transform the regression problem into a more manageable categorical framework. By doing so, it allowed for a practical class size that maintained a balance between having enough classes to capture variability and ensuring that each class had a sufficient number of samples.

However, this approach was not without its limitations. One significant issue was the large class size, which, while somewhat practical, did not offer the granularity that might be desired for more precise predictions. Ideally, classes should represent a single day of work or less, providing a finer resolution of work density predictions. Unfortunately, such an approach would require creating approximately 200 classes, which is computationally prohibitive. Moreover, having a large number of classes would have increased the risk of overfitting and demand a much larger dataset to ensure each class is adequately represented. This level of complexity and data requirement made it challenging to implement in with the current dataset and hardware implementation.

In summary, while the multi-class classification approach facilitated a more structured and manageable framework for predicting work density, it was constrained by the need to balance class size and computational feasibility. Future research could explore ways to refine this approach, possibly by leveraging larger datasets or more advanced computational techniques to achieve the desired granularity without overfitting.

6.4.3.3 Future Models

6.4.3.3.1 Correlation and PCA Analysis

In the current analysis, I assumed that the PCC and PCA for correlation analysis would be sufficient to capture the relationships between variables. These methods were effective for the study's scope but limited in capturing the sequential impacts of time on work progression. Consequently, time-series analysis was not employed, as the data did not align with the necessary conditions of long-term and frequent data capture. Features such as "Original Detection Date", "Start Date" and "End Date" were excluded due to this limitation.

However, the limited frequency and duration of data collection hindered the ability to capture the sequential impacts of time on work progression. Future applications could benefit from more frequent or extended data collection periods, enabling the use of time-series analysis to discern trends and assess the effects of external disruptions on production performance. Advanced ML models, such as RNNs (Che et al. 2018), Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber 1997), and Gated Recurrent Unit (GRU) (Cho et al. 2014) are particularly suited for this type of analysis due to their proficiency in managing data with sequential dependencies.

6.4.3.3.2 Deep Learning with Larger Datasets

Recent studies by Gorishniy et al. (2021) and Shwartz-Ziv and Armon (2022) have highlighted the challenges and limitations of deep learning models, especially when dealing with structured (or tabular) datasets. Despite their efficacy with unstructured data, deep learning models do not necessarily outperform tree-based models such as Gradient Boosting and Random Forest for structured data, as observed in the model evaluation results in Section 6.3.4.2. Although Ensemble models performed the best on the data collected on Project O, the deep learning models can be re-visited when larger sets of data are collected.

6.4.3.3.3 Reproducibility and Generalizability

Ensuring reproducibility and generalizability of results is crucial in data science. Yu and Kumbier (2020) proposed the predictability, computability, and stability (PCS) framework for veridical data science. This framework aims to provide responsible, reliable, reproducible, and transparent results across the data science life cycle. The PCS framework uses predictability as a reality check, computability to ensure results are tractable, and stability to test the reproducibility of results relative to human decisions.

Among the three principles of this framework, future research should focus on stability, which is related to scientific reproducibility—a necessary condition for establishing scientific results. To achieve this, comprehensive documentation of considerations, identified alternatives, and decisions made at each step of the research process is recommended, including problem formulation, data cleaning, modeling decisions, and result interpretations.

6.4.3.4 More Features

In addition to the features considered in this research, several other contextual data points are essential for enhancing the accuracy and robustness of ML prediction models for work density. These include project characteristics, project schedules, sequential impacts of adjacent steps, means and methods used, and external factors such as weather conditions. Although the importance of these factors is recognized, they were not validated in this study due to limitations in data availability and scope.

The project schedule, for instance, is a critical factor that can significantly enhance the accuracy of work density measurements in empirical data. By aligning the frequency and location of data capture with the project schedule, data collection can be optimized to ensure that it occurs precisely when and where it is planned. This synchronization can improve the relevance and quality of the data gathered, leading to more accurate predictions of work density.

Weather conditions represent another vital external factor. Although no adverse weather or weather delay events were reported in the Project O case study, future research should include weather data to account for potential impacts on production. Other external factors, such as owner-caused delays, change orders, unavailability of materials or equipment, and work not being ready, also play a significant role in affecting production. These factors can introduce variability and delays that are critical to consider for accurate work density predictions. Incorporating these elements into the data collection process will provide a more comprehensive view of the factors influencing work density. Beyond traditional timesheets, detailed daily logs documenting these external factors can significantly contribute to the dataset's richness. This comprehensive data collection approach ensures that all relevant aspects affecting production are considered, leading to more robust and accurate predictive models.

6.4.3.5 Limitations of the Dataset

The dataset from Project O alone may not encapsulate the full spectrum of project conditions, limiting the generalizability of the results.

One major limitation observed is the high variability in duration hours per step, particularly among journeymen and apprentices (Sections 6.2.2 and 6.4.1.2). This variability can restrict the applicability of the findings to other datasets or projects. Additionally, there is significant variability in step duration hours across different location types, which challenges the accuracy of predictions that rely solely on location characteristics.

High pairwise correlations between certain features suggest potential redundancies within the dataset, which could complicate model training (Section 6.4.1.2). These redundancies necessitate careful feature selection to avoid overfitting and to improve the model's efficiency.

The dataset's high dimensionality, due to numerous one-hot encoded features, presents another limitation. This complexity can complicate correlation and PCA, potentially causing subtle yet significant correlations to be overlooked (Section 6.3.3.1). Furthermore, the dataset exhibits potent,ial bias, particularly due to the predominance of certain location types, such as room locations (Section 6.4.1.3). This bias may skew the analysis results, making them less representative of broader project scenarios.

Another limitation is the inadequate representation of specific trades and steps within the dataset. This lack of comprehensive data can impede the model's ability to provide a complete view of work density, thus affecting its accuracy. To mitigate this issue, future datasets need to encompass a wider range of worker-hours, location types, and areas to better capture the variability across different projects.

Additionally, the performance of DNN was found to be inferior to that of tree-based models when applied to medium-sized structured datasets (Section 6.4.2.2). This observation highlights the challenges associated with using DNNs for such datasets, including their extensive tuning needs and higher computational demands.

In conclusion, while the current study provides valuable insights into the application of ML models for predicting work density, these limitations indicate the need for more comprehensive data collection and refined feature selection processes in future research endeavors.

Chapter 7 Discussion

7.1 Takt Production System in DDPF

In this research, I have examined the takt production system, distinguishing it into two interconnected components: takt production planning and takt production control. The planning component structures and guides the production process, generating a takt production schedule. The control component ensures that production execution remains aligned with the plan, particularly when unexpected events occur or when circumstances arise that call for a shift in direction (Arbulu et al. 2016). I developed these components independently and then integrated them through the Data-Driven Production Framework (DDPF) (Section 4.3.1) which uses the work density construct to form a seamless project production system. The functionalities of these two components are detailed in the following sub-sections.

7.1.1 Takt Production Planning in DDPF

I initially developed the takt production planning component by introducing the Visual Workload Leveling and Zoning (ViWoLZo) tool (Section 3.2) using data I collected on the B33 case study. ViWoLZo served as a proof-of-concept for a system that enables planners to utilize work density for creating a takt production plan. This is achieved by zoning a work space and leveling workloads across various zones and steps. In ViWoLZo, successful production planning hinges on enhancing plan concurrency and strategic work structuring. Together these facilitate the reduction of project duration and enhance reliability by allowing simultaneous work across multiple zones while avoiding trade stacking, removing resource overburdening, and minimizing variability in workloads.

Work structuring within ViWoLZo plays an important role due to the process-specific nature of work density values, which vary according to the sequence of steps and their defined scopes. Users of the tool can modify work density to reflect changes in construction means and methods that impact crew sizes, equipment, and materials. Moreover, adjustments to process boundaries and the segmentation of processes into steps—including their sequence and scope—might necessitate restructuring of work, such as splitting a step into multiple steps or adding steps to create new ones. In such scenarios, ViWoLZo allows for straightforward updates to the work density maps of the steps. However, this assumes that work density maps allow arithmetic operations (maps are additive and subtractive), which may not always be the case. Therefore, planners must carefully evaluate each change's unique impact and, when significant changes are made, potentially develop new work density maps to accurately capture these changes.

Implementing ViWoLZo on the B33 case study validated the use of work density as an enabler for a data-driven approach to takt production planning and other non-takt location-based production methods. The data collection and processing procedure for ViWoLZo faced some challenges being predominantly manual, complex, and time-consuming, which made them prone to subjective biases and errors. To address the challenges in the original procedure, I introduced a novel data model within the DDPF, which adopts an automated and objective approach to data collection, analysis, and storage. This novel approach includes a work density calculation algorithm that leverages progress tracking data from construction sites. Subsequently, I used the work density data generated by the algorithm to train and test a machine learning (ML) model on real-world data (Section 6.3.4), moving away from traditional rule-based methods that rely on explicit formulation of any work density equation (e.g., Equation 3.1 in Section 3.1.1). Although, the predicted work density and ViWoLZo have not yet been integrated for use in real-world scenarios to plan future projects, they are validated individually and created with the foresight of connecting them using the DDPF (Section 4.3.1).

Furthermore, changes in the procedure also include shifting from a grid cell-based approach to a project-, process-, and location context-specific representation of work density and integrating production control with production planning. This integration not only enhances practical application by sharing common data, but also incentivizes the collection of real-world data during project execution. The nuances between the original and revised procedures and their implications for work density calculation are discussed in further detail in Section 7.1.3.

7.1.2 Takt Production Control in DDPF

In the development of the takt production control component, I found the existing literature on takt production control to be disproportionately less compared to its planning counterpart. A reason for this might be that researchers and practitioners alike implicitly include production control as part of the production planning or they assume that the traditional control methods are equally suitable to control work planned using takt, especially when only certain processes or phases of their project were takted. Additionally, one of the intended outcomes of using takt is to establish a consistent pace and define clear handoffs between steps, facilitating easier coordination and control (Alves and Formoso 2000). Similarly, although the Work Density Method (WDM) is a planning method, by creating detailed plans that include spatial and temporal aspects of processes steps, the resultant plan is easy for everyone involved to understand, execute, and control (Tommelein 2022).

I incorporated the desired outcomes supporting production control in ViWoLZo, however an explicit methodology to use the production data for control during execution was missing. Thus, in Chapter 5 I describe the production control component of the DDPF, which employs an end-to-end data processing procedure including data collection, analysis, and performance reporting. I implemented this component's user interface at Project O through a production performance dashboard for managing production which provided near real-time insights into production status. The data processing procedure included the following steps:

1. **Data Collection:** This step involved capturing real-time data on production activities using 360° camera-based tracking and their contexts through other sources of data (Section 5.2).
2. **Data Processing and Analysis:** Post-data-collection, the data cleaning and transformation steps ensured reliability of the collected data, which the resulting data then informed production planning and control decisions (Section 5.3).
3. **Performance Reporting:** The processed data updated the production performance dashboard, which is divided into three components: situational awareness, production parameters, and production metrics. These components collectively enhanced the control over ongoing projects by allowing for a clear communication of the production status (Section 5.4).

The production control using the performance dashboard was designed as a one-time setup and maintained throughout the execution of the study. The project team used the dashboard to ensure that production adhered to the planned schedule or was adjusted back on track when deviations occurred. I implemented the dashboard with visual graphics to communicate and surface problems helpful for production control. I tested the utility of the dashboard in various meetings—from daily check-ins to weekly coordination meetings—to synchronize activities and update all stakeholders on project progress (Section 5.5.2). Project superintendent, foremen, and field engineers were involved in the methodology used for tool development (Section 4.4.2) and their expert opinion was involved in defining dashboard's use case (Sections 5.4.1 and 5.5.2).

The situational awareness component (Section 5.4.2.2) provided updates to allow for a mutual understanding of production progress for all the stakeholders. To support control, the dashboard leveraged the same set of production-system throttles or adjustment mechanisms (Binninger et al. 2017b) that were used in ViWoLZo for takt planning (Section 5.4.2.3).

The implementation of the dashboard on Project O did not incorporate certain takt-specific features, as the project did not use a takt plan (Section 5.5.3.4). Project O's project team planned and controlled the production at a higher level than required for a takt plan, e.g., scheduling trades by multiple floor levels for durations varying from a day to multiple weeks long. In projects with a takt plan, the dashboard would allow the project team to do more, such as compare the step cycle times to the estimated workloads (by step or by zone), re-assess the sizing and position of used buffers by comparing step cycle times against takt, and use other takt-specific production parameters and metrics suggested in Section 3.3. When a project team identifies a performance deviation, planners can take corrective measures. However, the granularity of the dashboard's updates is limited to the duration of each process step as the underlying tracking technology used in this research can only detect work in process (WIP) or work completion, which is not enough if the user needs a more detailed progress reporting (e.g., 20 ft of drywall hung instead of simply detecting drywall present). This limitation could be addressed in number of ways, including by using more detailed data collection methods and by planning with smaller batches. To implement more detailed data collection methods planners can use technology solutions with more frequent data capture including continuous surveillance cameras and positioning systems or use daily manual progress report forms as implemented by Frandson and Tommelein (2014a). To reduce batch size, planners can use shorter takt or break down processes into steps with smaller scopes of work, while matching the detection capabilities of the technology.

The approach to production control presented here marks a shift toward a more dynamic and transparent system of real-time decision-making based on data visualization. The production performance dashboard and the supporting data processing procedure facilitate easier interpretation of data and enhances the project team's responsiveness to issues, thereby improving operational efficiency. By reducing error rates and fostering a culture of continuous learning, this method helps transform the project team into a learning organization.

7.1.3 Different Ways of Calculating Work Density

A major contribution of this research in advancing a data-driven production system is the refinement of methodologies for calculating work density. Based on an extensive review of the literature and previous methodologies, I have introduced two approaches for this purpose. Figure 4.1 in Section 4.1 juxtaposes the data models for these two approaches, as the change impacts the complete process including data collection, analysis, storage, and subsequent utilization in production planning and control. These approaches are evaluated against the existing ones using Choosing By Advantages (CBA) analysis, presented in Tables 7.1 and 7.2. CBA is a decision-making system (Suhr 1999) that is explained along with its steps in Section 2.4.2.5.

Table 7.1: Choosing By Advantages (CBA) analysis of different approaches to calculating work density (1/2).

Factor (Criterion)	Alternative 1: Color-Ups	Alternative 2: Uniform Grid-Based Maps
Source of Data	Att.: Requires tradespeople to generate work density data by marking floor plans to outline spatial and timing needs. This data is then translated into a work density grid.	Att.: Uses uniformly spaced grid lines for generating work density maps, utilizing Quantity Take Off (QTO) and production rates for estimation.
Preferably a uses more objective sources of data.		Adv.: Uses objective data from QTO to calculate work density.
Data Collection Process	Att.: Relies on getting trade commitment to provide data (entirely manual process).	Att.: Relies on manual input of QTO and trades to provide production rates to estimate work density.
Preferably easy to collect data with lesser human intervention.		Adv: Data collection involves some semi-automated steps including QTO.
Reusability of Data	Att.: Data is not transferable or scalable across different projects or takt.	Att.: Utilizes a standardized method to measure work density, enhancing consistency across projects.
Preferably the work density data generated should be re-usable on future projects.		Adv: Components like process maps and production rates are designed to be reusable across projects.
Flexibility in Zoning	Att.: Data is dependent on how much work a trade can do in a given amount of time (e.g., 1 day or 2 days), limiting flexibility in zoning to the predefined data.	Att: Provides cell level of detail to define zoning. Gets restrictive for complex or irregular floor plans. Finer grid cells are required to deal with irregular shapes.
More flexible is better in providing more alternatives and ability to change takt to meet demand or match with capacity.		Adv.: Allows for the precise calculation of work density at a cellular level.
Time and Effort Required for Application	Att: Requires obtaining data from individual trades fresh on every project, and converting them into work density maps.	Att: Requires manual data collection of QTO and production rates to create work density maps.
Preferably requires less time and effort to setup and use on the project.		Adv.: Reduced time and effort for data collection and setup with some components being reusable. Setup involves the QTO preparation and is independent of floor plan complexity.
Suitable for Type of Project or Work	Att: Well-suited for work that is not confined to predefined grid cells, ideal for scattered or area-specific tasks within a larger space requirement. E.g., overhead mechanical work.	Att: Well-suited for work that fit well within a structured orthogonal grid system.
Preferably usable on more types of projects or work.	Adv.: Provides flexibility in managing work across diverse and irregularly shaped locations, accommodating a wide range of project types and scopes of work.	Adv.: Provides flexibility for work confined to single rooms or spanning across multiple connected locations.
Inclusion of Trade Input	Att: Engages trades directly in the data generation process, fostering ownership, trust, and detail in the data provided.	Att: Utilizes trade insights during pull planning and production rate data collection, fostering ownership, trust, and detail in the data provided.
Preferably allows for professionals to add project specific and personal input.	Adv.: Encourages trades to actively consider their workflow, sequence of operations, and process improvement opportunities. Promotes detailed planning and foresight.	Adv.: Provides a comprehensive understanding of site-specific production issues through hands-on trade insights.
Initial Setup Before Project	Att: Each project requires a fresh setup with minimal dependence on past setup.	Att: Projects are set up independently but allow for the reuse of existing production rate data.
Less initial setup before project is better.	Adv.: Every project setup is tailored with no initial setup.	Adv.: Initial setup can include pre-defined process maps and production data form past projects.
Matching to Commitments	Att.: Relies on getting trade commitment to determine production and duration.	Att.: Relies on getting trade commitment on production rates.
Getting commitment from trades to perform the work as per the duration determined by the data is necessary.	Adv.: Allows trades to share their expectations on scope, duration, sequence, and batching, and make commitments accordingly.	Adv.: Allows trades to share their expectations on production rates and make commitments accordingly.

Table 7.2: Choosing By Advantages (CBA) analysis of different approaches to calculating work density (2/2).

Factor (Criterion)	**Alternative 3: Non-Uniform Grid-Based Maps**	**Alternative 4: Location-Based (by Rooms or Zones)**
Source of Data	Att: Uses non-uniformly spaced grid lines for generating work density maps, leveraging QTO and production rates for estimation.	Att.: Uses a historical database containing empirically measured work durations, along with related project-, process-, and location contextual data.
Preferably a uses more objective sources of data.	Adv.: Uses objective data from QTO to calculate work density, and aligns grid lines with actual floor plan features.	Adv.: Uses objective historical performance data to predict work density.. Incorporates a set of features to enhance contributing factors to work density, with the ability to include more features.
Data Collection Process	Att.: Relies on manual input of QTO, trades to provide production rates to estimate work density, and to setup a custom grid system per floor plan.	Att.: Relies on setting up basic contextual data regarding the project, process, and locations..
Preferably easy to collect data with lesser human intervention.	Adv: Data collection involves some semi-automated steps including QTO.	Adv: Data collection involves minimal manual inputs, with no need to collect QTO or production rates.
Reusability of Data	Att.: Utilizes a standardized method to measure work density, but the customized gid approach limits data transferability between projects.	Att: Employs a standardized library of historical data to train ML models. Assumes data is generalizable and reusable.
Preferably the work density data generated should be re-usable on future projects.	Adv: Components like process maps and production rates are designed to be reusable across projects.	Adv: All collected data is reused in the historical database, as a historical benchmark and to train ML models.
Flexibility in Zoning	Att.: Provides cell level of detail to define zoning and adaptable to any feature of a floor plan. Finer grid cells are required to deal with irregular shapes.	Att.: Provides room- or zone level of detail to define zoning. Adaptable to floor plans and rooms of any shapes.
More flexible is better in providing more alternatives and ability to change takt to meet demand or match with capacity.	Adv.: Allows the calculation of work density at a cellular level with added flexibility to zones according to floor plan features (such as along walls).	Adv.: Allows the calculation of work density at a room or zone level, that can be used individually or combined to create new zones.
Time and Effort Required for Application	Att: Requires manual data collection of QTO and production rates, and the setup of a grid system to create work density maps.	Att: Requires minimal data entry for setup.
Preferably requires less time and effort to setup and use on the project.	Adv.: Reduced time and effort for data collection and setup with some components being reusable. Setup involves the QTO and grid system preparation.	Adv.: Minimal collection and setup with reusable historical data. Setup is independent of floor plan complexity and grid system configurations.
Suitable for Type of Project or Work	Att: Well-suited for work that fit well within a structured orthogonal grid system, with flexibility of irregular shapes.	Att: Best for projects focused on standard or repeating rooms and zones (e.g., interior buildout) that have been captured in historical data. Independent of geometric shape of the space.
Preferably usable on more types of projects or work.	Adv.: Provides flexibility for work confined to single rooms or spanning across multiple connected locations. Adds flexibility to accommodate work specific requirements in the grid lines configuration.	
Inclusion of Trade Input	Att: Utilizes trade insights during pull planning, production rate data collection, and the customization of grid lines to align with project specifics.	Att: Utilizes trade insights during pull planning. ML model generates work density using pre-defined rooms and zones.
Preferably allows for professionals to add project specific and personal input.	Adv.: Provides a comprehensive understanding of site-specific production issues through hands-on trade insights.	
Initial Setup Before Project	Att: Projects are set up independently but allow for the reuse of existing production rate data.	Att: Requires a significant initial setup that accommodates data collection across multiple projects for ML training before deployment.
Less initial setup before project is better.	Adv.: Initial setup can include pre-defined process maps and production data form past projects.	
Matching to Commitments	Att.: Relies on getting trade commitment on production rates.	Att.: Relies on actual performance in the past with no trade-specific input on production or duration.
Getting commitment from trades to perform the work as per the duration determined by the data is necessary.	Adv.: Allows trades to share their expectations on production rates and make commitments accordingly.	

This analysis for selecting the optimal approach to use in the DDPF and the assessment of beneficial differences between attributes of alternatives reflect my personal view at this time, lacking additional context specificity (in any case, all decision-making is subjective). I am therefore also leaving out my assessment of importance of advantages.

The analysis involves four alternatives: (1) color-ups (2) uniform grid-based maps, (3) non-uniform grid-based maps, and (4) location-based (by rooms or zones). Each approach abstracts work density differently, suited to various scenarios such as source of data, project specifics, data availability, level of effort required, and desired planning detail. These alternatives are assessed across nine factors, with criteria that determine the suitability of each approach. The attributes for each alternative corresponding to each factor are marked as "Att.", with least favorable attribute underlined. The advantages of each alternative with respect to the attributes, marked as "Adv.", are evaluated relative to these least favored attributes. The paramount advantage for each criterion is circled to visually guide the selection process. A visual analysis of the table presents the fourth alternative (location-based approach by rooms or zones) with the highest number of paramount advantages (circled advantage). However, this approach has its drawbacks, ranking second in terms of the number of least favored attributes (underlined attributes), following the first alternative, color-ups. The second and third alternatives—uniform grid-based and non-uniform grid-based maps, respectively—rank between the extremes, with the third alternative ranking better than the first and second but not as well as the fourth.

The initial approaches, developed by Linnik et al. (2013) and Frandson et al. (2013), involved trades in generating work density data through color-ups (alternative 1 in Table 7.1) to delineate space needs and time requirements. Later, Bardaweel (2018) enhanced this by introducing a quantity take-off (QTO) method that used uniformly spaced grid lines (alternative 2 in Table 7.1). In contrast, my first approach, developed for the ViWoLZo tool (Section 3.2), improved upon the QTO method by adopting a non-uniform grid (alternative 3 in Table 7.1) that can be adjusted to fit any floor plan features relevant to work density and planning. During the development of ViWoLZo, I automated part of the data collection process by using take-off program—On-Screen Takeoff—to measure QTO by cells (Section 3.2.4.3). However, the QTO still requires a manual effort and can be improved in future with automation in quantity extraction from Building Information Model (BIM) data. This approach also required manual data entry by trades that fostered collaborative planning but also created a dependence on subjective production rates. The work density data, calculated using Equation 3.1 and stored in a site plan-specific grid system (Section 3.2.4.5), cannot be transferred directly from one plan to another due to its bespoke nature.

In my second approach, implemented for the DDPF, moves from a cell-based to a location-based system for storing work density, with a shift from estimated to empirically measured values. This location-based work density is specific to a room or zone (alternative 4 in Table 7.1). The location-based system limits the use of this approach in project situations specific to rooms and zones, such as interior buildout phase, and cannot be generalized to all phases without testing. For example, overhead work such as mechanical duct work that span in long runs across multiple rooms, is not a good fit for both location-based systems, but color-up-based systems are useful in this case. This is because of the generalization of work with work type (such as by product) and abstraction of distribution of density in space.

The location-based approach utilizes an algorithm to automatically measure the time needed for a step in a specific location using the work detection data, storing this data alongside contextual features of the process, human resources used for the steps, and the location of work (Sections 5.3.3 and 6.2.5). This data is used to train an Ensemble ML model that predicts work density using these contextual features as input. Future enhancement recommendations include additional contextual features such as project specifics, weather conditions, means and methods used, and the sequential impacts of adjacent steps. Analytical results, such as those from correlation, feature importance, and clustering analyses discussed in Section 6.4.1, offer a qualitative and comparative insight into how various features influence work density. Future research aimed at enhancing and understanding these algorithms will necessitate a deeper exploration of feature behaviors and innovative methods for encoding this information. For instance, different measurement units—such as measuring drywall in linear feet for stick-built projects versus counting prefab wall panels per piece—pose challenges for model training. The precise impact of these measurement variations on the model remains to be clarified, indicating a need for further study.

The location-based approach uses mathematical and statistical algorithms to learn from the knowledge embedded in the collected data, moving away from calculations that rely on quantity of work and production rates, and the need for storing work density as a map dependent on the two inputs. This new approach offers improvements in data utility and efficiency by using actual performance data that is automatically calculated, as compared to an estimated value that is measured using manual QTO and work density map generation. However, this approach makes several assumptions, such as related to sequential finality and duration of steps to be work density, as described in Section 5.5.3.1. It also introduces complexities such as higher initial setup costs, training requirements, technological dependence, and the need for accurate real-world production data for model training and application. Moreover, it presupposes that future work will mirror historical practices in terms of process capability and scope of work. To broaden the application and improve model robustness, it is essential to integrate diverse historical observations and corresponding features into the dataset. Past performances that reflect undesirable practices, if used for model training, may influence future predictions negatively, perpetuating suboptimal practices.

All four approaches offer work density values that facilitate manual adjustments to balance workloads, employing production-system throttles as discussed in Section 5.4.2.3. These adjustments, however, are executed differently across the methods and provide varying levels of detail. For instance, in ViWoLZo, altering crew sizes adjusts the total number of workers per step. Conversely, the DDPF modifies the number of workers according to specific roles—foremen, journeymen, and apprentices—per step. ViWoLZo demands manual inputs to determine the relationship between crew sizes and production rates, while the DDPF's Ensemble ML model employs a combination of linear and non-linear algorithms to model these dynamics, although the relationships are not transparently displayed within the model's architecture.

The location-based approach used in the DDPF incorporates room area as an input but overlooks other factors such as room shape, location, and access, which may influence work density. Projects with standard repetitive layouts that repeat within a project and across multiple projects stand to benefit more from this approach, as standardization simplifies the application of the ML model, aiding both in generalizing learning and in predictive planning. Future research should explore the model's sensitivity to such factors to enhance the balance between model complexity and practical usability in real-world scenarios.

Additionally, relying solely on ML model-based predictions for work density can diminish the critical steps of human collaboration and participation inherent in the color-up approach. Although the color-up approach is labor-intensive, it fosters significant engagement from trades, prompting them to deeply consider their workflow, sequence of operations, and potential improvements. This human involvement in pull planning, or for providing production rate data or color-ups, not only fosters detailed planning and foresight but also builds trust and commitment, as stakeholders are less likely to rely solely on data without seeing the actual source. In contrast, while ML models in the DDPF can leverage historical data for benchmarks, they often function as a "black box," combining numerous input features and their interactions in ways that are not transparent. Human participation also injects creativity into the planning process, enabling stakeholders to conceive new methods and apply innovative production techniques beyond the limitations of past data. Therefore, maintaining a balance between automated efficiency and the richness of human input is crucial for optimizing both the development and application of production planning methods.

There exists a spectrum of trade-offs among the four alternatives concerning the balance between human involvement and automation. The first alternative, color-ups, is the most manually intensive and requires significant human participation, fostering collaboration and creativity. The fourth alternative, location-based, is the most automated and requires minimal human interaction, emphasizing efficiency. The second and third alternatives, using uniformly-spaced and non-uniformly spaced grid respectively, strike a balance, blending human input with automated processes to optimize both engagement and implementation efficiency.

7.2 Type of Project Matters

Despite both case studies focusing on mixed-use biomedical- and office spaces, they exhibited notable differences in their processes and levels of planning and control, influenced by the scope of the project and regulatory variations. For instance, Project O's scope included structure and building envelope along with basic utilities (called warm shell construction), allowing future tenants to customize improvements as per their needs, which limited the level of detail for interior finishes processes and facilitated a higher level of planning and control. Conversely, the B33 project, owned and constructed for immediate occupancy, included comprehensive interior finishing, which demanded intricate planning.

Regulatory requirements also varied significantly. The B33 project, an institutional building with healthcare facilities in California, fell under the stringent Office of Statewide Health Planning and Development (OSHPD) jurisdiction. OSHPD (2023) required continuous oversight from third party Inspectors of Record and OSHPD field personnel throughout the construction phase, introducing additional layers of tests and inspections that influenced the project's workflow. Recognizing inspections as critical customers of the construction processes necessitated highly detailed planning and control. For example, in the development of ViWoLZo, the placement of grid lines for the work density maps were based on the in-wall inspection requirements (Section 3.2.4.2). Furthermore, in takt planning, processes are ideally pull-planned, starting from the end boundary of a process, which serves as the handoff to the "customer" of the process (Section 3.2.4.1). To ensure zones are handed off smoothly and without downstream disruptions, a heightened level of planning and control was implemented. This was particularly evident in the much higher spatial and temporal precision of the scheduling for the B33 project compared to Project O.

These differences underscore the importance of tailoring planning and control methods to the project type and the phase of delivery. With high level planning, the spatial and temporal resolution is large, leading to more variation in the workloads that are challenging to manage and plan to a common takt. For a successful implementation of the DDPF, certain types of projects and planning methods are a better fit, such as projects planned with takt production. These methods are best suited for environments where spatial and temporal details are defined to the scale of individual rooms or zones and timed to weekly or daily tasks.

Furthermore, the success of these methods hinges on the project delivery systems in use and the contractual and payment arrangements among stakeholders—including owners, general contractors, trades, suppliers, and permitting agencies. As discussed in Section 3.5.3.4, aligning the contractual terms with project goals from the outset is vital for successful implementation of these methods. It incentivizes stakeholders to effectively engage with the DDPF, enhancing data collection, schedule management, and responsiveness to control decisions.

7.3 All About Trade-offs

In this research, I developed several resources to support production planning and control practices. These resources include: (1) a data processing procedure that utilizes real-time work detection to support production control using a performance dashboard, (2) a standardized schema for storing past performance in a historical production database, (3) a work density prediction model that uses data from the historical production database, (4) a work density-based tool for production planning (ViWoLZo), and (5) the DDPF with its accompanying data processing procedures, which collectively integrate the planning and control components into a cohesive system. However, for these resources to be truly effective, project teams must adopt appropriate production methods and make informed decisions.

As I have highlighted throughout this dissertation, decisions in production planning and control often involve navigating trade-offs to balance various desired outcomes. An example of such an application is the use of ViWoLZo for workload leveling and zoning, which is theoretically detailed in Sections 3.1.2 and 3.1.3, with its practical implementation described in the B33 case study in Section 3.2.6.5.

Below, I summarize the key trade-offs discussed in the dissertation:

1. **Process step cycle time (workload) variability and capacity utilization:** There is a trade-off between adjusting workload levels across zones and steps of a process to ensure all trades can work efficiently without long waits or idle time (impacting capacity utilization), and the need to meet customer deadlines with certainty (Sections 3.1.2 and 3.2.6.5). To manage this, the dissertation suggests underloading crews to provide a capacity buffer that accounts for variability, ensuring that all zones are handed off on-time, according to the takt. This underloading strategy aligns with the takt production approach outlined in the dissertation, contrasting with other location-based planning methods such as line-of-balance planning, where the focus is not on moving through areas at a standardized rate but on maintaining constant crew sizes for continuous work (Frandson et al. 2015). Takt production seeks not only to optimize resource utilization but also to achieve a globally balanced solution for the entire production system.

2. **Crew size and capacity utilization:** Altering crew sizes (or production rates) to manage the workload across zones involves a trade-off between varying crew size per zone for higher capacity utilization and maintaining a constant crew for simpler team management, which can lead to lower capacity utilization (Sections 2.1.3 and 2.2.2). In a production system with workload variability, planners can use capacity buffer to absorb the variability keep constant crew size. They can also keep standby capacity to absorb this variability.

3. **Cost and production planning:** The cost modeling discussions in Sections 3.4 indicate trade-offs between production planning and cost. Decisions related to production system design (production planning) are based on deciding production parameters, such as the

number of zones, steps, operable takt, and amount and type of buffer used, impacting the project cost. In addition, there is a cost-benefit trade-off in managing the system using takt or other location-based production planning methods or not. Planners need to balance the outcomes to align with financial targets and project deadlines.

4. **Process duration and zoning:** Dividing the work space into zones affects the process duration, as discussed in Section 3.1.1 using Equation 3.4. The trade-off between having more zones to allow multiple crews to work in parallel and reducing process duration is challenged by the sensitivity of the duration to the number of zones. Increasing the number of zones usually decreases the workload peak, which may reduce the overall process duration, however, if zones are increased beyond a certain point, the duration can stabilize or even increase (Jabbari et al. 2020a, b), which is undesirable. The sensitivity of duration to zoning is illustrated through an example in Section 3.4.4.
5. **Spatial- and temporal continuity:** When deciding the batch size for a process in terms of the zone boundaries (spatial batch size) and the takt (temporal batch size), the planner might need to make a trade-off. This trade-off includes balancing spatial continuity, by creating zones that are well defined and logically sequenced for a repeatable and smoother trade flow, with temporal continuity, by sizing scope of work and production capacity to have continuous work from the perspective of process- and trade flow. Making this balance can reduce time wasted on movement, improve space utilization, and improve overall workflow efficiency.
6. **Process flow and trade flow:** Trade-off between process- and trade flow presents a common challenge for planners. Optimizing for process flow focuses on the overall quicker progression of steps through a zone, maximizing space utilization. This outcome can conflict when optimized for trade flow, which focuses on the progression of a step through the zones, maximizing trade utilization. This trade-off can lead to decisions that either reduce the process duration at the expense of individual trade utilization or enhance trade utilization but extend the overall process duration. Even within various trades and spaces, trade-offs can be made to prioritize smooth flow of work for a critical trade or space, as desired. The various types of flows are described in Section 2.1.5 and different desired flows based on the planning method are described in Section 2.2.2.
7. **Accuracy and data collection detail:** In general, increasing accuracy of work detection data requires higher level of detail in data collection. Higher accuracy of data ensures reliable production planning and control. However, higher level of detail, measured as resolution of the data in time, space, and scope of work, requires more effort and resources (technology and skilled personnel) to collect. Hence, planners need to balance the level of detail of data needed for the desired accuracy, against the practical constraints of project budgets and schedule. I made such trade-offs in selecting tracking technology for work detection (Section 2.4.2.5), defining the cell grid for ViWoLZo (Section 3.2.4.2), data collection for production control performance dashboard (Section 5.2), and data analysis using unsupervised-learning models to optimize future data collection efforts (Section 6.4.1).

The above listed trade-offs reflect the complexity of production planning and control in construction. They highlight the need for tools and methods that help planners in finding a globally favorable outcome instead of various locally optimal, but conflicting outcomes. Local optimization for production systems can create unfavorable or even redundant solutions, as priorities and capabilities change from project to project or stakeholder to stakeholder.

For some of these trade-offs, there exists guidance on what outcomes are desirable and non-desirable from the perspective of different stakeholders, which planners can use in making their decisions. For example, when implementing takt production planning with the computing and display support provided by ViWoLZo, determining appropriate capacity buffers (with resource utilization less than 100%) is essential to counteract any variability in process times and ensure smooth execution. In operations science, this has been empirically proven to be a useful strategy for production systems with variability, as shown by Hopp and Spearman (2008) through the law of capacity, the law of utilization, and the law of variability (Section 2.1.3). The law of capacity suggests that the workloads must be lower than the average capacity, as workloads going beyond capacity result in instability of the system. The law of utilization highlights that increasing resource utilization without other changes leads to nonlinear increases in work in process (WIP) and cycle time (CT), which suggests that variability in the system must be reduced, or utilization must be kept under control to deal with the variability. Finally, the law of variability emphasizes that increased variability within a production system negatively impacts performance.

There also exists specific guidance for some of the desirable production metrics values from the list of metrics selected in Section 3.3.2. For example, in takt production, Frandson et al. (2015) suggests keeping production units operating at 70 to 80% of their capacity, allowing for workload leveling across process steps (mura), absorbing cycle time variations, and helping mitigate potential bottlenecks. This strategy ensures that trades are not overburdened (muri) and provides flexibility for workers to engage in additional activities during less intense periods, such as skill enhancement or process improvement, thereby balancing both productivity and worker engagement, while making judicious trade-offs.

Analysis of trade-offs as pairs is helpful as working with two dependent variables makes the analysis simpler when finding a balanced solution. However in the real world, most of these trade-offs exist together and need to be made simultaneously.

7.4 Production Metrics

Metrics are pivotal in production planning and control, serving as tools to align diverse objectives and optimize performance outcomes. In real-world scenarios where multiple parties with conflicting objectives collaborate, understanding and employing the appropriate metrics can help planners make trade-offs based on objective data. For example, metrics such as the operable takt and variations in workload across process steps or zones help planners manage crew sizes and process- or trade flow. These metrics facilitate strategic decisions such as buffering for variation to meet customer deadlines, maintaining workloads under set takt, and optimizing space- and worker utilization to reduce idle times and variability in workloads.

Optimization of production decisions requires further development and application of specific algorithms that use these metrics as objective functions. For example, the WoLZo algorithm by Jabbari et al. (2020a, b) is programmed to minimize workload peaks, potentially reducing the overall process duration. This allows for the identification of the best solution without reliance on trial and error or extensive human intervention. Future research on computational tools to support decision-making in such complex multi-objective scenarios can use solutions such as Pareto optimization or weighted objectives to balance various project goals. These solutions can allow project planners to make informed decisions through a combination of algorithms, user input, and performance metrics to achieve optimal workload distribution and project outcomes.

7.5 Decision-Making Through Visualizations

The analytics and visualizations provided by the ViWoLZo tool, and the production control performance dashboard, provided shared information for the decision-making processes. Visual representations of work density and zoning allowed project managers to understand complex data more intuitively, making it easier to identify trends, patterns, and anomalies. For instance, workload histograms (Section 3.2.6.5) and real-time dashboards (Section 5.4) offered insights into which zones or steps were over- or under-loaded, guiding managers in redistributing tasks more evenly.

These visual tools also supported communication among stakeholders by providing a common platform that all parties could refer to during discussions. The transparency of production status by location (Section 5.5.1.2) and trades (Section 5.5.1.3), helped in aligning the objectives and expectations of different teams, facilitating consensus and quicker decision-making.

7.6 Improving the Machine Learning Models

In this research, I critically evaluated the application and performance of ML models for work density prediction. The evaluation suggests a potential for improving the performance of these models by refining data handling, feature engineering, and model validation processes (Section 6.3.1). Additionally, integrating domain-specific knowledge into the modeling process can improve the predictive accuracy and operational relevance of the ML models. I included the project-, process-, and location specific contextual features for this. Some of the identified areas for improvement and the incorporation of prior knowledge into the ML model development include:

1. **Improving Data Quality and Quantity:** The quality and quantity of data representing a breadth of sample data points are key for the training of robust ML models, especially the deep learning models (Gorishniy et al. 2021). I trained the models only on data from Project O, which, despite providing a valuable initial dataset, did not encapsulate the diversity of scenarios that will be encountered in other project environments. To address this, expanding the datasets to include a variety of projects can mitigate model bias and enhance generalization capabilities. It is also important to be cautious of training models on field-collected data that reflect undesirable performance, as this may perpetuate suboptimal practices and embed inefficiencies that could otherwise be eliminated. With a larger quantity of data, the application of techniques such as gradient boosting or deep learning could be explored again. Additionally, rigorous tuning of model parameters through cross-validation could further optimize performance.
2. **Advanced Feature Engineering:** The approach presented in Section 6.3.1 could be enriched by integrating more complex features that capture the dynamic nature of production environments. For example, features that model the time-dependent aspects of production could unveil patterns that static features might obscure (Che et al. 2018, Hochreiter and Schmidhuber 1997) such as time actually spent on work, or time spent on supporting activities such as cleaning and material setup, or time spent not working including waiting.

3. **Integration of Prior Knowledge:** The integration of domain-specific knowledge into the ML models can be used to enhance their functionality by further refining the feature set, refining the data preprocessing steps, and guiding the selection of more suitable ML models. For instance, knowledge of typical workflow patterns, key constraints in production environments, and success factors from different perspectives can inform a more targeted approach in data preprocessing and model training. Additionally, incorporating rules and constraints that govern production practices can help in aligning the model outputs with practical realities, thus enhancing the model's applicability and reliability.
4. **Implementation of Feedback Mechanisms:** Establishing mechanisms for ongoing feedback based on model predictions versus actual outcomes can create a continuous improvement loop. Such feedback, through application of semi-supervised- or reinforcement learning (Mohammadi et al. 2018), can provide empirical evidence to refine models iteratively, enhancing their accuracy and adaptability to changing conditions. These models can be incorporated as part of the ML workflow (Figure 6.7 step 8) described in Section 6.3.2). This approach can align not only with the agile development principles (as used in Section 4.4.2) but also ensure that the models remain relevant over time and across different project contexts.

The data processing procedure and implementation of the ML models in this research proved the concept to be viable, but still require extensive improvements in data collection to model training and learning. Incorporating these improvements into the development of ML models within the DDPF promises not only improved accuracy and efficiency in production planning but also a deeper integration of data-driven insights into strategic decision-making.

7.7 Success Beyond Data

The primary focus of this research was on enhancing production planning and control through data-driven methods and technological integration, but the research also considered the broader context of construction projects. Section 2.3.7.4 included the exploration of social systems, production systems, contractual obligations, payment terms, subcontracting dynamics, labor hiring practices, and the associated challenges and incentives.

Moreover, the research investigated the human aspects of production processes. It emphasized how visual management, simplicity, and repetition in work tasks contribute to better performance by increasing productivity, reducing communication errors, and simplifying control mechanisms.

This research also highlights the importance of collaboration, especially in the context of pull planning and problem-solving within the ViWoLZo framework. The research illustrated how aligning stakeholder interests and fostering collaborative relationships not only enhances project execution but also facilitates the resolution of conflicts and challenges that arise during production. By implementing contractual and financial incentives that reflect the benefits of takt production, stakeholders can gain a clearer understanding of its time-cost implications and benefits. This alignment and transparency are crucial for building a solid foundation for cooperation and achieving mutual gains among the project stakeholders (mainly project owners, GCs, and trades) across the project execution.

7.8 Integrated Data-Driven Approach to Production

This research has developed all the components of the DDPF, setting the stage for future enhancements, particularly through the integrated use of the ViWoLZo for production planning and the production performance dashboard for production control. This integration promises to significantly enhance the efficiency of production systems by creating learning cycles. The DDPF allows efficiency to be measured in various ways, tailored to the specific objectives of a project or an organization, often requiring a balance among multiple objectives. The core advantage of an integrated data-driven approach is its capability to enable project teams to plan production, execute work, measure performance for immediate corrections, and facilitate both short- and long-term learning cycles. The cycles range from daily learning for daily planning, moving up toward higher levels of planning, and finally learning from one project to the next.

By employing workload leveling and zoning strategies, planners can optimize the allocation and sequencing of workloads across different zones. This helps achieve a more balanced workload, thereby minimizing wasteful resource usage (muda), unevenness in workloads (mura), and overburdening of resources (muri). The production control dashboard's real-time updating feature is critical for continuous monitoring and adjustment of workloads, essential for maintaining an even flow of work across zones and steps. The DDPF equips teams to plan, measure, and control these flows effectively; however, the decisions involved in balancing these objectives often rely on heuristic judgments by the user.

Additionally, the shift towards data-driven methods creates a proactive control environment, moving away from reactive measures. By predicting potential delays and resource clashes before they materialize, teams can take preemptive corrective actions. This proactive approach helps keep projects on their planned trajectory, improving adherence to schedules and enhancing overall project management effectiveness.

The DDPF along with the methods and tools discussed in this research mark significant progress toward an integrated, data-driven approach to construction production planning and control. This discussion has highlighted the complex interaction between takt production, work structuring, performance measurement, and predictive modeling within the DDPF.

The trade-offs discussed highlight the necessity for flexibility and adaptability when implementing this framework in real world. Each project presents unique challenges and constraints, requiring a tailored approach that leverages the strengths of the proposed methods. The insights from these discussions set the stage for outlining future research directions and the potential scaling and adaptation of the framework in the subsequent conclusions chapter.

Chapter 8
Conclusions

8.1 Research Findings

In this research I took an integrated data-driven approach to production planning and control for on-site building construction. Moving away from traditional deterministic and transformation-focused methods, this approach employed the concept of work density to create a location-based production plan that emphasizes probabilistic and flow-focused methods, such as takt production. Based on this approach, I developed a prototype framework named the Data-Driven Production Framework (DDPF). This framework integrated the use of sensing technologies for data collection with the data-driven models to support human decision-making. The key findings of this research are summarized in the sub-sections that follow.

8.1.1 Findings from Theoretical Background

In Chapter 2, I reviewed the theoretical background necessary for understanding project-based production in construction industry, outlining the limitations of traditional construction planning methods. These methods often focus too narrowly on the transformations at the individual activity-level, neglecting the interactions within activities at the production-level, and their interaction at the process- or project-level. This review underscored the benefits of integrating lean principles, project production theory, and flow-based methods to improve workflow reliability, reduce waste, and increase overall efficiency. Location-based management systems such as takt production, supported by the Workload Density Method (WDM), offer a more balanced and reliable production system that addresses the limitations of traditional methods. I also explored the complexities of cost modeling in takt production and the advantages of stochastic models in capturing the dynamic nature of construction production.

To develop a data-driven approach that can overcome these limitations, I examined relevant literature and evaluated technologies and methods, highlighting the recent advancements and increasing importance of data-driven strategies. These strategies, especially the use of machine learning (ML) algorithms and tracking technologies such as 360° cameras, are crucial for enhancing real-time decision-making in production control. Despite these advancements, significant gaps remain in the collection of reliable real-world data and its integration into a framework that unifies production planning and control. The insights from the review helped to define the direction and objectives of this research.

8.1.2 Location-Based Project Production with ViWoLZo

In Chapter 3, I presented ViWoLZo, a novel computing tool to facilitate construction process planning using the WDM. I provided an example of ViWoLZo's use in practice based on the B33 case study. Developing this tool required creativity to move beyond traditional Critical Path Method (CPM) and other transformation focused planning methods. The process of gathering the necessary data from trades and project field personnel proved to be laborious.

The key findings from this development are detailed below.

- **Effectiveness of Work Density in ViWoLZo:** The development and application of ViWoLZo demonstrated the effectiveness of using work density for data-driven production planning. This tool facilitates objective decision-making and what-if analyses by offering interactive visualization and computing support, enhancing the planning process. Although initially developed to support takt planning, ViWoLZo is versatile and supports a broader range of location-based methods. The tool supports systematic and data-driven decision-making concerning construction process definition, work space zoning, and workload leveling, aligning effectively with the objectives of various location-based planning methods.
- **Data Collection and Input:** I enhanced the process of collecting and calculating work density, which is essential for utilizing the WDM, by making the collection of subjective data more collaborative and the collection of objective data more automated. The application of ViWoLZo involved gathering detailed input process and production data from the B33 case study project team. Trades participating in collaborative pull planning sessions created a shared understanding of the process flows. This collaboration ensured accurate data input for generating work density maps. With the semi-automated collection of quantity and spatial data, and increased flexibility for users during work structuring, the overall procedure for using work density improved significantly.
- **Non-uniformly Spaced Grid Work Density Maps:** In ViWoLZo, a work density map is a grid of cells where each cell represents the workload, i.e., time a crew will need to complete their work. These grids are composed of orthogonally arranged cells with non-uniformly spaced grid lines that can be placed as per the user's need during setup, such as along with a floor plan's architectural features. Such maps are vital for storing, visualizing, and managing work density data, to facilitate effective workload leveling and zoning decisions. Despite improvements I made in data collection and enhancing the functionality of work density map generation, I encountered challenges due to the bespoke grid system setup for each site plan. Work density is calculated and stored in cells specific to these grids, complicating the transferability of work density maps from one plan to another. Different spaces often require grid cell boundaries that align with specific architectural features, such as walls for interior finishes. While orthogonal grids generally align well with plan features, exploring other tessellations could improve flexibility and accuracy across various projects. I address some of these challenges with a new approach to storing work density as part of the DDPF, which is detailed in subsequent sections.
- **Dashboard Interface:** The ViWoLZo dashboard enables users to visually select a work space and its various steps, facilitating the exploration of alternative zoning scenarios that utilize underlying work density data while considering metrics related to the quality of the resulting process plan. With its user-friendly interface, users can methodically create a takt plan that achieves desired outcomes. The visual interface and production metrics guide users through the decision-making process step by step.
- **Production Parameters and Metrics:** I identified several metrics to evaluate the quality of production plans and subsequently used them to measure performance through the development of a production control dashboard. These metrics are instrumental in balancing performance across individual trades, locations, and the overall system to align

with customer demands. Utilizing ViWoLZo for what-if analyses, users can leverage data to determine if workloads and the process plan adequately meet desired outcomes, such as achieving schedule milestones and satisfying downstream customer demands.

- **Work Structuring and Trade-offs:** ViWoLZo enables users to structure work effectively by defining work spaces, selecting process steps, determining crew sizes, and zoning the work space. This flexibility facilitates iterative what-if analyses to find the best possible work structuring solution that aligns with the planner's objectives. For instance, process duration can be minimized by creating concurrency in work through reducing batch size. Planners can achieve this by decreasing zone size (spatial batch) or reducing takt (temporal batch), which typically, though not always, go hand-in-hand (Jabbari et al. 2020a, b). Alternatively, having multiple takted processes operating in parallel (by deploying multiple crews of the same trade) can achieve similar results without reducing batch size, thus providing crews with a larger laydown area within the zone and increasing space utilization. ViWoLZo enables planners to make such decisions with the functionality to divide a floor plan into multiple work spaces, enabling the creation of different takt plans using the same set of data.
- **Impact on Project Costs:** In my review of production systems in construction, I identified a significant gap: the impact on cost was almost entirely overlooked. To address this, I developed a framework for cost modeling that provides a structure to link production system design—including production parameters and decisions—with project costs. This framework is designed to support future research in creating cost models that aid in production system design decision-making and continuous cost monitoring and control. It accommodates the specific needs of location-based production methods, which traditional methods often fail to address due to their inability to fully capture the complexities and dynamic nature of production systems. This framework ensures that production characteristics, such as idle time, operational inefficiencies, and necessary buffers, are considered to avoid inaccuracies in estimating the true costs of production. Furthermore, I highlight the importance of aligning payment terms and subcontracting strategies with takt production objectives to ensure financial feasibility and secure stakeholder commitment.

The ViWoLZo tool along with the WDM offers a data-driven approach to enhance production planning in construction projects. The findings highlight the benefits of employing structured and standardized data collection and analysis methods to improve decision-making and project outcomes in the construction industry.

8.1.3 Data-Driven Production Framework (DDPF)

ViWoLZo offers a data-driven approach to production planning, which is part of the broader challenge of developing an integrated system for data-driven production planning and control. In Chapter 4, I introduced a novel framework called the DDPF, marking a shift from traditional reactive approach to a proactive, data-driven approach for production planning and control. Central to the DDPF's data-driven approach is the concept of work density, with rest of the framework being flexible by not being bound to specific technologies for data collection or to particular methods or tools for production planning and control.

In the DDPF, I developed a semi-automated and objective approach to data collection and analysis, creating an end-to-end data processing procedure that spans from initial data collection to the generation of reporting dashboards and tools. Importantly, I designed the DDPF to ensure that the collected data would support the production control component throughout the project's duration. I then utilized this data to enhance the production planning component. The outcomes from both the control and planning components are detailed in the subsequent sections.

8.1.4 Data-Driven Production Control

In Chapter 5, I developed the production control component of the DDPF and demonstrated its effectiveness through a proof-of-concept implementation on the Project O case study. This case study thoroughly examined data analysis techniques applied to a real-world scenario. I presented the data to the project team using the production performance dashboard that I developed, which utilizes a blend of time-based, location-based, process step-based, and work density analyses to enhance production control.

The key findings from Chapter 5 are:

- **Time-based Analysis:** This analysis focused on the impact of data collection frequency on the reliability of work detection. I segmented the dataset into various time intervals to examine fluctuations in work detection over time. The insights revealed that periods characterized by consistent data collection frequencies yielded more reliable detection of work. This highlighted the importance of implementing frequent data collection strategies to maintain data integrity.
- **Location-based Analysis:** This analysis focused on individual locations to examine the sequential progress of different steps and the interdependencies between them. I analyzed unit locations including specific rooms or zones, types of locations such as bathrooms, and aggregates including floor levels. Insights gained revealed process location flows and work durations, which were derived from location-based visualizations. For example, I effectively mapped the movement of trades across different floors and their progression in specific areas, underscoring the importance of spatial analysis in understanding project dynamics. Using the results from this analysis, project teams can better understand process flows, steps sequence, detect anomalies in sequencing and handoffs, and compare performance across multiple locations. These findings, presented through visualizations and metrics, provided performance measurements, illustrated how interdependencies affect workflows, and highlighted potential areas for process improvement.
- **Process Step-based Analysis:** This analysis focused on individual process steps, each associated with one or multiple trades, providing indirect insights into the workflows of both steps and trades. It highlights the sequential progression of a step through various locations, location types, and floor levels. The results from this analysis offer insights into trade location flow and workloads for each step. By generating detailed visualizations, such as time series and Gantt charts, this analysis aids in understanding the sequence and timing of steps, thereby facilitating strategic planning and effective monitoring of project progress.
- **Work Density Analysis:** This analysis combines location- and process step data to assess work density, specifically targeting steps with a defined start and end. It utilizes a variety of visual representations, such as histograms, bar charts, and Gantt charts, to illustrate workloads across locations and steps, highlighting average work durations. Visualizations that display workload distributions by process step and location provide insights into variations in work density. Additionally, two-dimensional heatmaps enhance this analysis

by offering a detailed view of how workloads are distributed and vary across different dimensions (time and locations). These insights are vital for refining production planning strategies and improving overall efficiency.

These data analyses significantly enhanced the dashboard users' understanding of work dynamics in Project O. The DDPF has demonstrated its effectiveness in capturing and utilizing production tracking data for production control by: (1) providing near real-time updates quick enough to support weekly production control efforts, (2) measuring performance with detailed granularity at individual location and step levels, and (3) accounting for crucial production parameters and flows vital for effective production planning and control. This approach not only facilitates more informed decision-making but also enables the frequent refinement of production strategies to enhance efficiency and minimize delays.

8.1.5 Data-Driven Production Planning

In Chapter 6, I developed the production planning component of the DDPF, with a focus on implementing a ML model trained on the data collected through the production control component. I trained this ML model to predict work density, using project-, process-, and location-specific features.

The key findings from Chapter 6 are:

- **Data Processing Efficacy:** I developed a specialized data processing procedure to support production planning predictions, enhancing data quality through wrangling, analysis, and storage. This process ensured that the data was robust and reliable for ML modeling. Additionally, I used a novel data schema for storing the processed data, setting a standard for future data collection and ML modelling efforts. With the prepared dataset, I prepared it for ML implementation through various preprocessing steps. These steps included normalizing to adjust feature scales, encoding categorical variables for ML compatibility, and handling missing values to complete the dataset. I also employed feature selection techniques to streamline the feature space by focusing on the most important features for effectively and accurately modeling system dynamics and variation in the data. Through exploratory data-, correlation-, feature importance-, and clustering analysis, I pinpointed the most important features, such as the physical area of locations and the worker-hour distribution across three worker roles (e.g., foreman, journeyman, and apprentice). By focusing on these key features, I was able to reduce computational complexity, enhance model performance by minimizing overfitting to redundant features, and simplify future data collection efforts by identifying the most important features to collect.

- **Integration of Machine Learning:** The ML model I developed uses processed data to predict work density based on certain input features, meant for supporting the production planning process for future projects. I implemented the training as both a regression and a multi-class classification problem. The best-performing models in both implementations were the corresponding Ensemble models (Tables 6.8 and 6.9). Among the individual models that I used in this Ensemble model, the Gradient Boosting Regressor model showed the best performance, consistent with the results from dimensionality reduction and clustering methods that showed structured data with branched, tree-like separation. A comparative analysis of all models using a set of evaluation metrics identified the most accurate ML model as regression-based, with a Root Mean Square Error (RMSE) of 3.7

days. The top classification model also performed well, with an RMSE of 4.7 days. These low RMSE values indicate a strong fit to the data, enabling the model to predict work density with an expected error of 3.7 days. Although these are positive results as a proof-of-concept, the model's performance was constrained due to the limited amount of data collected and higher variability in the higher range of values of measured workloads. The distribution of measured workloads in the dataset has a mean of 20.44 days with a standard deviation of 19.03. To use the model on takt plans requiring smaller workloads, the ML model will have to be exposed to empirical data from processes with similar workloads.

- **Beyond Work Density:** In addition to predicting work density, data analysis techniques such as correlation-, feature importance-, and clustering analysis provided valuable insights to enhance future data collection and planning efforts. For example, as is to be expected within the three different worker roles analyzed in the data, journeymen and apprentices accounted for a significantly larger share of worker-hours and, consequently, had a higher correlation with work density compared to foremen. Despite logging fewer hours, foremen exhibited a comparable impact on work density, underscoring their critical role on-site. This significance may also be influenced by labor union regulations that mandate the presence of a foreman for every crew. Moreover, results from the principal component analysis (Table 6.2) indicated that the "Foreman Hours" feature was the most important on the first principal component, contributing the most variance to the dataset. This observation, as expected, suggests that areas where foremen are actively working or supporting the crew typically exhibit higher work density. This observation raises a question about the activities of workers who are operating independently in other areas.
- **Practical Application:** The practical application of the ML model using data from Project O demonstrates its effectiveness in predicting work density, showcasing the advantages of a data-driven approach to production planning. The model processed the transformed data to generate accurate predictions that, in the future, can guide production planning decisions and can be further improved by re-training on larger dataset. WDM-based tools such as ViWoLZo can leverage these predictions for planning precision.

By leveraging ML to analyze and predict work density, the framework offers the potential for a more informed, efficient, and precise production planning process. This data-driven approach not only enhances operational efficiency but also paves the way for further advancements in the construction industry's adoption of structured and standardized data collection and storage practices for production data.

8.2 Response to Research Questions

The responses to the research questions, grouped by the five research objectives and ordered as presented in Section 1.4, are as follows:

First Objective: Delineating the principles and theoretical constructs that are foundational to the DDPF to enhance my comprehension of production planning and control (covered in Chapter 2)

a. **What are the foundational principles and theoretical constructs of a data-driven production system in the context of on-site building construction?**
The foundational principles for this research are grounded in the integration of lean principles and production theory. From Liker's (2004) fourteen lean principles, I have

selected five that are particularly relevant to this study (listed in Section 2.1.2). These principles emphasize key theoretical constructs such as continuous improvement and the reduction of unevenness (mura), waste (muda), and overburden (muri), which are critical to shaping the desired outcomes of the production system.

Hopp and Spearman's (2008) seminal work on production theory in "Factory Physics" provides essential principles and constructs in the form of production laws and parameters (listed in Section 2.1.3). These principles and constructs, along with location-based production planning and control methods such as takt production, the WDM, and the capabilities of data collection technologies, data analytics, and ML models (described in Section 2.4), collectively form the basis of the data-driven production system.

b. **How do the principles and constructs influence production planning and control?**
The identified principles and constructs influence production planning and control by identifying the desired outcomes and guiding the development of this research towards achieving them. The desired outcomes for takt production—such as optimizing project duration, increasing plan reliability by reducing variability, early problem identification, and fostering process standardization—are detailed in Section 2.2.2. These outcomes have directed the development of methods and tools throughout this research, enhancing decision-making for end-users and ensuring that each component contributes effectively to the overall efficiency and effectiveness of the production system.

Second Objective: To develop the DDPF with supporting method(s) and tool(s) for production planning and control using the work density construct (covered in Chapters 3, 5, and 6).

a. **Is it possible to develop a data-driven approach to production planning and control?**
The research presented in this dissertation successfully demonstrates a proof-of-concept for a data-driven approach to production planning and control, as evidenced by the implementation and validation of the DDPF in a real-world scenario—the Project O case study, detailed across Chapters 4, 5, and 6.

b. **What existing methods can be used, or new ones developed for effective data-driven production planning in building construction?**
I found existing methods such as takt production, the WDM, and various data-driven methods for work detection and predictive modeling in the review of existing literature and industry practice (Chapter 2). Additionally, I built on top of existing data collection-, transformation-, and analysis methods for developing new methods for visual workload leveling and zoning (Section 3.2) and automated work density calculations (Section 5.3). To create a novel data-driven production system capable of measuring and predicting work density, I utilized commonly available data wrangling and analysis methods (Sections 5.3 and 6.2), data preprocessing methods (Section 6.3.1), and ML methods (Sections 6.3.2, 6.3.3, and 6.3.4).

c. **What tools can be developed for enhancing data-driven production control in building construction?**
The tools I developed include ViWoLZo (Chapter 3) for production planning using data visualization for workload leveling and zoning, a customized dashboard for real-time production performance monitoring and production control (Chapter 5), and a predictive analytics tool that uses ML models to predict work density (Chapter 6).

d. **What metrics and visualizations are effective in supporting production planning decisions?**

The metrics selected for supporting production planning decisions, as listed in Sections 3.1.3 and 3.3.2, include workload (cumulative work density by step and zone), workload variation (measured in standard deviation, variance, and coefficient of workload variation), operable takt (workload peak of a process), process duration, average of workloads for all steps and all zones in a process, and workload-peak-to-average ratio. I also suggest considering total cost impact as a metric that represents the cumulative impact on various elements of cost (Section 3.4.3).

Interactive dashboards with visualizations such as workload histograms (Yamazumi chart), zoning maps, work density maps, takt plans, and process maps. These visualizations have proven effective in facilitating knowledge gathering and decision-making through their implementation and validation during the B33 case study project (Sections 3.2).

e. **What metrics and visualizations are effective in supporting production performance measurement and control decisions?**

The metrics selected for supporting performance measurement and production control decisions, as listed in Sections 3.3.2 and 5.4.2.4, include a blend of those used for production planning and others specific to control. The production control metrics include step cycle time, comparison of operable takt versus customer takt, workload variation (measured in standard deviation or variance), process duration, work density to worker-hour ratio, Plan Percent Complete (PPC), Tasks Made Ready (TMR), cumulative lost capacity for each step, service level, handoffs, and returns.

Interactive dashboards with real-time data visualizations, such as workload histograms, work density maps, and process maps, have proven effective for managing project progress, enhancing situational awareness, detecting anomalies, and facilitating decision-making though their implementation and validation during Project O case study (Section 5.4.2).

Third Objective: To use tracking technologies for capturing on-site production or progress data and support the production control component of the DDPF (covered in Chapter 5).

a. **What tracking technologies are most suited for real-time or near real-time monitoring of production progress by location in building construction?**

I conducted a comprehensive literature review and industry survey, followed by a Choosing by Advantages (CBA) analysis (Section 2.4.2), to select the most suitable tracking technology. Through this analysis, I identified vision-based tracking technologies, particularly 360° camera imaging solutions with Computer Vision (CV)-based work detection, as highly effective. However, I found positioning-based tracking technologies, especially Indoor Positioning Systems (IPS), to be equally suitable albeit less developed and not as readily available for construction site applications.

The technologies considered varied widely in their development stage, ranging from research applications to commercially available solutions. Although my evaluation included potential tracking technologies available on the market until the end of 2022, after which I chose to implement 360° cameras in a case study, this technology remains the best suited for the needs identified in my research by the end of this research in 2024.

b. **What data-driven methods can be used with tracking technology and contextual data to support DDPF?**

For the production control component of the DDPF, I integrated the work detection data from the 360° imaging solution to the manually collected contextual data from the project site (Section 5.1). The data-driven methods used to achieve this integration include the Extract, Transform, and Load (ETL) method to establish a data pipeline from the source to the output, and the use of cloud-based platforms for centralized data storage and access. Additionally, I developed a data transformation algorithm within the data processing procedure that calculates work density from the processed work detection data.

c. **What contextual data is essential for supporting production control and performance measurement?**
The proposed data schema (Section 4.2) encompasses project-, process-, and location-specific contextual data. This contextual data is essential for providing insights into who was performing the work, how the work was being done, when and where it was happening, and other relevant details not captured by the tracking technology. This includes data on the scope of planned work, location specifics, the trades involved and their corresponding process steps, and any schedule baselines for comparison (such as milestones or customer takt). For instance, details about the trades and associated process steps include the crew composition (including their skill levels and role) and their locations for each step, which were collected through daily logs (Sections 5.3.1 and 6.2.2).

d. **How can a data model interlink hardware, software, and processes to achieve the objectives of the DDPF?**
I developed a data model in this research (Section 4.1), interlinking hardware (sensors and trackers), software (data processing, storage, prediction, and visualization tools), and processes (takt production planning and control methods) by using work density as the entity interfacing between the digital measurements and the actual production parameters.

Fourth Objective: To use captured production data to calculate work density and support the production planning component of the DDPF (covered in Chapter 6).

a. **What contextual data is essential for supporting work density prediction?**
In the proposed data model for the DDPF, I included contextual data for work density prediction, similar to that outlined in research question 3.c. for production control. This includes project-, process-, and location-specific data. Specifically, I utilized data on the scopes of work planned, location details, and detailed logs of crew timesheets, which are segmented by location, by step, and by crew composition (Section 6.2). Additionally, there are other essential contextual data points that, while I recognized their importance, I was unable to capture data for and incorporate in this research. These include characteristics of the project, the project schedule, and other factors that impact production, such as weather conditions (Section 6.2.5). The project schedule can also be leveraged during data collection to enhance the accuracy of work density measurements in the empirical data used to train ML prediction models. By synchronizing tracking data frequency and location of capture with the project schedule, data can be collected precisely when and where it is planned, optimizing the relevance and quality of the data gathered, and improving work density prediction accuracy.

b. **How can actual production progress data be transformed into work density and stored in a historical production database for construction projects?**
I used structured data wrangling and integration techniques to transform production progress data into historical production database. These techniques, outlined in the data processing procedures for production control (Section 5.1) and production planning (Section 6.1), involve merging, cleaning, and transforming the actual production progress data with specific process- and location contextual data (Section 5.3.2). I developed a novel algorithm for the DDPF that uses this transformed data to calculate work density (Section 5.3.3). Subsequently, this data is merged with additional contextual data (Section 6.2.4), including daily log- and location dataset, before being stored in the historical production database (Section 6.2.5).

c. **How can historical production database be used to train ML models for work density prediction and production planning?**
Continuing with the data processing procedure outlined in research question 4.b., that calculates work density, merges it with additional contextual data, and stores it in a historical production database, I utilized this database (Section 6.2.5) for training ML models that predict work density. For the ML training phase, I employed various data processing methods, including data trimming, imputing, encoding, normalization, and a range of unsupervised learning methods including dimensionality reduction and clustering, as well as supervised learning methods (Section 6.3). To apply the trained ML model's work density predictions for production planning, I recommend using any planning tool that supports the WDM. This includes visual tools such as ViWoLZo, which I developed on B33 case study (Section 3.2), or mathematical optimization tools such as WoLZo by Jabbari et al. (2020a).

Fifth Objective: To develop a framework for cost modeling to facilitate location-based production planning and control (covered in Chapters 2 and 3).

a. **What are the strengths and weaknesses of current cost models, estimation, and management practices in location-based production planning and control?**
Current cost models have structured cost reporting through standardized systems such as the Work Breakdown Structure (WBS) and Construction Specifications Institute (CSI) MasterFormat that are product focused. They incorporate historical data and industry standards to aid in budgeting and forecasting (Section 2.3), again limited to the perspective of costing the product. However, these models rely on assumptions that overlook critical factors affecting production such as capacity utilization, idle time, waste, and buffer. Additionally, their fixed input and output limits their flexibility, and they struggle to adapt to dynamic production variables such as zones, batch sizes, or takt. This limited flexibility can impair their effectiveness in managing real-world production scenarios.

b. **How can the cost impacts of production system design decisions, in a location-based methods such as takt production, be identified and modeled?**
A shift toward an adaptive framework that incorporates stochastic cost models is crucial for accurately reflecting production dynamics and variability (Sections 3.4 and 3.5.3.1). This framework would integrate cost metrics directly with the production system and decisions made for production management, enhancing cost predictability and control. The adoption of advanced data methods such as parametric modeling and simulation can improve accuracy, even under data availability constraints

(Section 2.3.4). Implementing process-based cost modeling provides detailed insights into how changes in process design affect costs, facilitating rapid and informed decision-making during process design (Section 2.3.5). Additionally, incorporating Target Value Delivery principles aligns cost modeling with client-centric, value-driven outcomes, optimizing project efficiency and cost-effectiveness (Section 2.3.6).

c. **How can a cost modeling framework be used to guide production design decisions effectively within the DDPF?**
The cost modeling framework I developed in this research establishes detailed mappings between production parameters, decisions, and their associated cost impacts (Section 3.4.3). This is a starting point to facilitate a nuanced understanding of how specific production decisions, such as zoning in takt production, influence both project and production costs, as well as their financial impact on stakeholders including owners, general contractors, and trades. This understanding is crucial for managing the trade-offs between process and cost optimization from multiple stakeholders' perspectives, enabling planners to achieve more predictable and controlled project outcomes.

8.3 Summary of Research Contributions

In this dissertation, I aimed to advance the field of construction project management by developing and integrating data-driven methods. Specifically, I implemented the WDM and takt production within a comprehensive framework, named DDPF. The DDPF integrates production planning and control through a unified data collection, processing, and storage process. The research centered on enhancing the efficiency and effectiveness of on-site building construction by incorporating robust, evidence-based tools and practices. The key contributions are:

- **Integration of Takt Production:** I have operationalized the concepts of takt production in a construction context through a data-driven approach in this research. By applying takt production principles, this research has demonstrated that people can achieve improvements in process location flow, trade location flow, and resource allocation, thereby potentially enhancing overall project delivery timelines and potentially reducing costs. I developed ViWoLZo with a non-uniformly spaced grid system that uses WDM to support objective decision-making during planning, which allows for the adjustment of workloads, facilitating smoother workflow and reducing the variability that typically hinders construction production planning.

- **Advancement of Work Density Method (WDM):** In addition to developing ViWoLZo, I advanced the application of the WDM for production planning and control by incorporating an objective data collection and processing technique to calculate work density. This new technique transforms actual production data into historical work density data, expanding the use of work density beyond planning and into real-time production control. I used the historical data, along with contextual data from a case study project, to train ML models for predicting work density. These ML models can now be used for production planning in future projects using a WDM-based tool, such as ViWoLZo.

- **Development of the Data-Driven Production Framework (DDPF):** I developed the DDPF, a major theoretical and practical contribution of this research, to support production planning and control decisions through data-driven insights. This framework integrates various components such as near real-time data capture, data processing, and analytical tools to production parameters and metrics, offering a holistic approach to managing construction project production systems.

- **Utilization of Tracking Technologies for Real-time Production Progress Monitoring:** I investigated tracking technologies best suited for real-time or near real-time capture of production progress by location for on-site construction. I also developed the DDPF as a technology-agnostic framework to collect, analyze, and visualize progress data, which supports short-term (e.g., daily to weekly) production control. This contribution enhances the ability to monitor construction projects accurately and efficiently.
- **Development of a Proof-of-Concept Tools:** I developed proof-of-concept tools for both production planning and control that support what-if analysis during the takt planning phase and enable the performance measurement and progress monitoring during execution.
- **Empirical Validation through Case Studies:** I empirically validated the application and effectiveness of the proposed methods, tools, and framework through two case studies. These studies offered practical insights into the challenges and benefits of implementing data-driven approaches in real-world construction environments, thereby supporting iterative improvements, and confirming the applicability and functionality of this research's contributions.
- **Methodological Innovation in Construction Management:** I introduced a novel methodological approach to construction management by integrating lean principles, production theory from operations science, data analytics, and ML. This integration not only addresses some of the theoretical gaps in traditional construction project management, particularly at the production level, but also provides a semi-automated, scalable solution that can be adapted to various construction scenarios.
- **Integration of a Takt-Compatible Cost Model into Production Planning:** I presented a framework to implement a takt-compatible cost model, which involved identifying the strengths and shortcomings of existing cost models and cost estimation practices, modeling the cost impacts of takt production, and incorporating these elements into a broader production planning and control framework. Although these contributions are in the early stages of development, they provide a foundation for future research to build upon the DDPF and include cost impact in the decision-making process.

These contributions not only fill gaps in the existing literature and practice by linking data-driven practices with location-based production systems, but also pave the way for future research that can further refine and expand the use of technology in construction project production management. The findings from this research offer theoretical advancements for academic scholars and practical benefits for industry practitioners, highlighting the transformative potential of integrating data processing tools in construction production planning and control.

8.4 Literature and Professional Contributions

This dissertation contributes to production planning and control theory as it applies to the architecture, engineering, and construction (AEC) industry. With real-world impact as the primary goal, I designed this research using the principles of Design Science Research (DSR), implemented the research on case study construction projects, and worked with the project teams in an action-research setting. To disseminate the created knowledge and receive feedback from scholars and practitioners, I have published and presented the findings of the research.

The publications that I co-authored during my Ph. D. studies at UC Berkeley, which are also partially or entirely included in this dissertation, include:

- Formoso, C.T., I. D. Tommelein, T. A. Saurin, L. Koskela, M. C. T. Fireman, K. Barth, F. Bataglin, D. D. Viana, R. V. Coelho, V. Singh, C. Zani, N. Ransolin, and C. Disconzi. 2021. "Slack in Construction – Part 1: Core Concepts." In: *Alarcon, L.F. and González, V.A. (eds.). Proc. 29th Ann. Conf. Int. Group for Lean Constr.,* Lima, Peru. 14-16 Jul 2021. 187-196, https://www.iglc.net/Papers/Details/1883.
- Saurin, T.A., D. D. Viana, C. T. Formoso, I. D. Tommelein, L. Koskela, M. C. T. Fireman, K. Barth, F. Bataglin, R. V. Coelho, V. Singh, C. Zani, N. Ransolin, and C. Disconzi. 2021. "Slack in Construction - Part 2: Practical Applications." In: *Alarcon, L.F. and González, V.A. (eds.). Proc. 29th Ann. Conf. Int. Group for Lean Constr.*, Lima, Peru. 14-16 Jul 2021. 197-206, https://www.iglc.net/Papers/Details/1878.
- Singh, V. V. 2020. "Improvements in Workload Leveling and Work Structuring for Takt Planning Using Work Density Method." *Indep. Study Report* (unpublished), Engineering and Project Management Program, UC Berkeley, CA, 53.
- Singh, V. V., and I. D. Tommelein. 2023. "Visual Workload Leveling and Zoning Using Work Density Method for Construction Process Planning." *J. Constr. Eng. Manage*. 149 (10): 04023102. https://doi.org/10.1061/JCEMD4.COENG-13377.
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- Singh, V. V., M. Mittal, and J. Barrack. 2021. "Indoor Localization based on BLE Signal Strength." EDU 244 Data Mining and Analytics Final Project Report, UC Berkeley, CA.
- Tommelein, I. D., and V. V. Singh. 2019. "Knowledge Management for Data Center Delivery Progress Report." *Technical Report* (unpublished), Project Production Systems Laboratory (P2SL), UC Berkeley, CA, 51.
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The talks that I co-presented during my Ph. D. studies at UC Berkeley include:

- Martin, P., J. Leoncavallo, H. Nguyen, K. Tangirala, C. Moore, V. V. Singh, and R. Schoener. 2023. "Parametric Estimation and Artificial Intelligence." *Presentation to 8th Annual Advancing Preconstruction Conference*, Phoenix, AZ, USA, May 24.
- Martin, P., H. Nguyen, and V. V. Singh. 2023. "Maintaining Continuous Awareness of Cost & Time Predictions Throughout Maturity of Design." *Presentation to 8th Annual Advancing Preconstruction Conference*, Phoenix, AZ, USA, May 24.

- Singh, V. V. 2022. "Construction Production Planning and Control through Takt Production." *Presentation to The International Association for Automation and Robotics in Construction (IAARC) at IIT Madras. Building Technology & Construction Management (BTCM) Group*, Department of Civil Engineering, Indian Institute of Technology Madras, Chennai, India, November 29.
- Singh, V. V. 2023. "Onsite data capture and machine learning to support takt planning." *Presentation to CE298 Engineering and Project Management Industry Speaker Seminar*, University of California at Berkeley, CA, USA, September 7.
- Singh, V. V., and H. Nguyen. 2023. "Generative AI in Generative Design." *Presentation to Advancing Beyond the Basics Seminar Series*, The Institute for Construction Innovation (i4ci), Davis, CA, USA, November 1.

The dissemination of the research findings through publishing and presenting to academic and industry audiences indicates a potentially wide-reaching impact and recognition for contributions in data-driven construction production planning and control.

8.5 Limitations and Future Research

The examination of the assumptions, results, and limitations of this research has identified several challenges and opportunities for future study. The identified limitations and proposes strategies to address them in future research include:

- **WDM for Takt Production:** The current implementation of the WDM, including approaches developed in the past and the one suggested in this research, overlooks critical aspects of successful production planning such as logistics, including the delivery and storage of materials. Although the ViWoLZo tool is effective in implementing WDM for workload leveling and work space zoning, it is limited to supporting zoning of only a single work space at a time, limiting users to planning one process at a time. Observations from B33 and Project O indicate that multiple processes often occur simultaneously at different locations, each with unique process flows. Hence, future enhancement would be to develop an improved version of ViWoLZo that accommodates the time and space required for logistics and enables simultaneous multi-process management. This advancement would streamline the user experience and enhance the tool's utility in complex construction environments.
- **Cost Modeling for Takt Production:** The cost modeling framework introduced in this research is tailored to meet the specific needs of location-based production methods such as takt production. The framework enables users to link production system design parameters with project cost elements. However, to enhance usability and maintain flexibility, it simplifies many complex variables, leaving the intricate details of cost modeling for the user to implement as per their needs. Future research should focus on identifying and integrating the most important elements of the cost model into process planning tools such as ViWoLZo. This involves identifying key production parameters, production decisions, and their impacts on production, the project, and costs, as outlined in Section 3.4.3, including understanding their interrelationships. For example, including variability in the production system and the mechanisms used to deal with the variability, including slack (Formoso et al. 2021). Moreover, the current framework mirrors the project's perspective (which can be same as the project owner's), considering the project as a temporary independent organization, overlooking the potential impacts on other

stakeholders such as general contractors and trades. These stakeholders' fees and associated costs are typically linked directly to the project's timeline and overall budget, which the framework assumes to be fixed.

Future research should aim to develop a more comprehensive cost model that accurately reflects the dynamic nature of contractual relationships and encompasses the diverse perspectives of all stakeholders. This model should further detail the trade-offs involved in designing production systems, providing a balanced view that facilitates informed decision-making.

- **Quantification of Flow:** The importance of flow in production systems is widely recognized, yet this dissertation did not fully integrate flow metrics into the data-driven system. In the current implementation, the study of flow is qualitative, limited to process- and trade location flows. Existing research, including studies by Bashford et al. (2003), da Rocha et al. (2023), and Sacks et al. (2017) and others discussed in Section 3.5.2.3, mentioned the need for metrics to gauge and manage production flow. Future research should focus on investigating these suggested metrics and new metrics and incorporating appropriate ones into the DDPF to enable a detailed evaluation of flow efficiency from multiple perspectives.
- **DDPF Enhancements:** In the DDPF, the algorithm I developed for calculating work density currently assumes that work progresses sequentially from one step to the next without interruptions—a scenario that rarely occurs in practice. Given takt production's requirements for on-time, staggered, and evenly spaced handoffs between steps, it is recommended that planners introduce capacity buffers to absorb variability and ensure reliable workflow transitions (Frandson et al. 2015). However, the algorithm's assumption of sequential progression needs reevaluation to reflect the real-world complexities where multiple, parallel processes often occur with varying cycle time across steps and zones (Section 5.5.3). Future enhancements should focus on adapting the algorithm to recognize and manage these complexities. Additionally, improving the frequency and accuracy of data capture, possibly through continuous production tracking technologies, represents a vital research direction to enhance the predictive accuracy and reliability of the DDPF.
- **Data Collection:** This research has highlighted the types of data that are most beneficial for production control, work density prediction, and production planning. However, the proposed data schema outlined several contextual data fields that were not collected or utilized due to the constraints of the case studies. Notably, the data collection scope did not encompass the effects of ordering or sequencing of steps, the means and methods used (excluding workers), the project characteristics, and the quantity of work. These aspects should be included in future studies to enhance the comprehensiveness and applicability of the data-driven approach. Moreover, future research should expand data collection efforts to a broader range of project types and geographical locations and further automate the process of contextual data collection and analysis. A continuously operational intelligent system (24x7) that tracks work activities and supports automated and decentralized decision-making would greatly diminish the need for human intervention in routine and time-consuming tasks such as data collection and anomaly detection. By incorporating these enhancements, future research can provide a more comprehensive dataset for ML models, standardize data-driven practices, and deliver more detailed and real-time insights into construction production management.

- **Frequency of Data Capture:** The frequency of data capture in this study was determined by the tracking technology used—360° camera-based tracking—which currently requires manual site walks to document progress. The consistency of data capture aligned with the weekly planning routines, necessitating at least one site walk per week. However, I found the impact of data capture frequency on the accuracy of work density calculations to be substantial (Section 5.5.3.2). Discrepancies between captured and actual work durations increased significantly with less frequent data capture, highlighting the need for more frequent data collection (Section 5.5.1.1). For systems operating on an n-day takt schedule, synchronizing the data capture frequency with the takt schedule is essential for effective implementation. For detailed tracking and non-takt processes with variable step durations, daily—or even more frequent—data captures are recommended to ensure accuracy in tracking ongoing work. Generally, a takt plan facilitates more accurate data capture with simpler, consistent, and less frequent control efforts that can be synchronized with the takt. In contrast, for non-takt plans, daily or more frequent control efforts are necessary to achieve similar levels of control accuracy. From a lean perspective, the aim is to maximize the frequency of data capture, striving for a continuous monitoring system. This system would allow for immediate detection of anomalies and issues, facilitating timely corrections, akin to activating an Andon cord in a manufacturing line. This level of data capture serves a dual purpose: ensuring activities are completed as planned and that handoffs between activities are smoothly executed.
- **Tracking Technologies:** In this research I used 360° camera-based tracking, which proved adequate for documenting visible (in line of sight) work but was limited in capturing work obscured by physical obstructions. This limitation necessitated adjustments to the data capture route to ensure comprehensive coverage of all necessary locations. The requirement for human effort to traverse all locations also constrained the frequency and timing of data captures. Although ongoing research and industry efforts are exploring automation of this data capture by employing robots and drones with mounted cameras (e.g., Golparvar-Fard et al. 2023), the challenge of continuous monitoring—with frequency of data captures every few minutes or less—remains unresolved. A review of tracking technologies highlighted the potential of using alternative technologies including IPS, which do not depend on line of sight and can continuously capture data every few seconds or less. This suggests that a move toward more versatile and less intrusive tracking solutions could improve data accuracy and reduce labor requirements. However, IPS technologies also have limitations, as detailed in Section 2.4.2, and require further development and integration for effective use in construction applications.
- **Other Forms of Prediction Models:** The data-driven methods used in this research primarily relied on a mix of continuous and categorical inputs to predict work density. However, the limited frequency and duration of data collection hindered the ability to capture the sequential impacts of time on work progression. Future applications could benefit from more frequent or extended data collection periods, enabling the use of time-series analysis to discern trends and assess the effects of external disruptions on production performance. With larger and more frequent dataset, I would try advanced ML models, such as Recurrent Neural Networks (RNNs) (Che et al. 2018), Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber 1997), and Gated Recurrent Unit (GRU) (Cho et al. 2014). These models are particularly suited for this type of analysis due to their proficiency in managing data with sequential dependencies.

- **Prediction in Production Control:** In addition to using ML models for time-series data, developing predictive algorithms that can extrapolate from production data to forecast future performance based on real-time conditions at construction sites presents a promising path data-driven production control. These algorithms can work beyond the limitations of this research by not only making predictions based on historical data but also adapting to real-time changes, thereby enhancing decision-making during production control. This approach shifts the focus from merely planning production to establishing a dynamic, responsive control system within the DDPF. While traditional supervised learning models excel at interpreting complex patterns within their training data, they often struggle when extrapolating beyond the boundaries of the data (Ebert et al. 2014, Webb et al. 2020). This challenge is particularly acute in construction project management, where variability specific to projects and their geography affects performance. It necessitates the development of models that continuously update and adapt to maintain accuracy and relevance.
- **Limitations for Generalization and Reproduction:** The generalizability of the findings from this research is somewhat limited due to the case studies being specific to the North American construction sector, involving particular project types and contractual relationships. This specificity may affect the applicability of the results across different geographical, regulatory, and operational environments. Future research should strive to diversify case study selections and assess the adaptability of the developed tools in various global construction contexts to enhance the generalizability of the data-driven approach. In case of poor generalizable performance, multiple models specific to a set of contexts can also be explored.

  Additionally, the reproducibility of the results is constrained by a lack of standardization in data processing and model development across studies. Previous research in this area has often been opaque in modeling procedures and inconsistent in making code and detailed methodologies accessible, presenting challenges in replicating studies. Establishing unified guidelines for developing and documenting data-driven models in production planning and control could significantly improve the reliability and reproducibility of future research. To ensure reproducibility, I recommend following the stability principle in the Predictability, Computability, and Stability (PCS) framework proposed by Yu and Kumbier (2020). Their stability principle, as implemented in this research, emphasizes comprehensive documentation of considerations, identified alternatives, and decisions made at each step of the research, including problem formulation, data cleaning, modeling decisions, and result interpretations.

8.6 Final Remarks

This research was motivated by the need to improve outcomes and reduce variability of construction project delivery using location-based production planning and control methods such as takt production. Initial findings showed a strong alignment between the challenges of adopting and implementing these methods, and the recent advancements in sensor-based data collection technologies and data-driven computation methods. This study combines construction project management, lean philosophy, operations science, and data science to address current industry challenges.

The dissertation presents a data-driven approach to location-based production planning and control, embodied in the DDPF, which places the work density construct at its core. The DDPF offers an objective, data-driven methodology for addressing production management challenges and includes a novel process-based data model and schema for collecting, storing, and analyzing production data. Additionally, the dissertation demonstrates proof-of-concept methods and tools for production control and empirical work density measurement. Within this framework, data from production control integrates with proof-of-concept methods and tools for production planning, including a ML-based work density prediction model that enhances the ViWoLZo tool for production planning through workload leveling and work space zoning. The efficacy of these methods and tools was substantiated through two case studies, validating the use of work density and the DDPF in enabling a data-driven approach to takt production and other non-takt location-based production methods.

The rapid development of sensor technology, alongside advancements in data-driven methods, particularly in artificial intelligence and ML, continues to expand capabilities for data collection, processing, and decision-making support. Coupled with increasing complexities including labor market dynamics, these technological advancements are steering the construction industry toward more efficient and precise outcomes. This research highlights the potential of adopting sophisticated data-driven approaches to meet the contemporary demands of construction project management, setting a promising direction for future research and technological innovations in the field.

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Appendix A: Construction Technology Survey Results

Table A.1 lists 106 software and hardware technologies actively deployed in preconstruction and construction, as surveyed by Tommelein and Singh (2019). These technologies are evaluated through a comparative analysis in Section 2.4.2.

Table A.1: Construction Technology Survey Results

Technology Name	**Type**	**Form**	**Use Case Category**							
			Planning	**Execution**	**Cost**	**Schedule**	**Project Management**	**Quality**	**Safety**	**Others**
3DR SiteScan	Drone - Register	Software		✓			✓	✓		
ArcGIS	GPS/Total station	Software		✓				✓		
ArcGIS	Laser Scanner - Register	Software		✓			✓	✓		
Arvizio	AR - Software	Software	✓					✓		
Assemble	BIM Model	Software	✓	✓	✓		✓	✓		
Autodesk Recap and decap	Laser Scanner - Register	Software		✓			✓	✓		
Avvir	Laser Scanner - Register	Software		✓			✓	✓		
BIM 360 Design	BIM Model	Software	✓	✓			✓	✓		
BIM 360 Glue	BIM - Tracking	Software		✓			✓	✓		
BIM 360 Glue	Laser Scanner - Register	Software		✓			✓	✓		

BIM 360 Plan	Planning	Software	✓				✓	✓		
BIM Box	BIM - Tracking	Software		✓			✓	✓		
BIM Collab	BIM - Tracking	Software		✓			✓	✓		
BIM Track	BIM - Tracking	Software		✓			✓	✓		
BIM360 Field/Build	Project Tracker	Software		✓			✓	✓	✓	
Blender Game Engine	3D	Software	✓							✓
Bloom Cloud Engine	Laser Scanner - Register	Software		✓			✓	✓		
CamDo	Timelapse	Hardware		✓			✓			✓
Civil 3D	BIM Model	Software	✓	✓			✓	✓		
Cloud Compare	Laser Scanner - Register	Software		✓			✓	✓		
Control Targets--Building Control Stickers	Control Point	Hardware		✓			✓	✓		
Control Targets--Primary and Secondary Monuments	Control Point	Hardware		✓			✓	✓		
Control Website	Control Point Information	Software		✓			✓	✓		
Cupix	360° Camera	Hardware		✓			✓	✓	✓	
Dalux	AR - Software	Software	✓					✓		
Data Scope	Logistics	Software	✓				✓	✓		
Data Touch	Display	Hardware	✓	✓			✓	✓	✓	
Dewalt Wi-Fi WAPs	Wi-Fi	Hardware								✓

DJI Phantom 4 Pro/Mavic 2 Pro	Drone - Capture	Hardware	✓	✓			✓	✓	✓	
Doghouse Computer	BIM - Tracking	Software		✓			✓	✓		
Drone Deploy	Drone - Capture	Hardware	✓	✓			✓	✓	✓	
Drones (generic)	Drone - Capture	Hardware	✓	✓			✓	✓	✓	
Dynamo	BIM - Addons	Software	✓					✓		
Excel	Laser Scanner - Register	Software		✓			✓	✓		
Faro 330X	Laser Scanner - Capture	Hardware		✓			✓	✓		
Faro Focus S	Laser Scanner - Capture	Hardware		✓			✓	✓		
Faro S350	Laser Scanner - Capture	Hardware		✓			✓	✓		
Faro Scanbot	Laser Scanner - Capture	Hardware		✓			✓	✓		
Faro Scanbot	Robot	Hardware		✓			✓	✓		
Faro Scene	Laser Scanner - Register	Software		✓			✓	✓		
FARO X330 Laser Scanner	Laser Scanner - Capture	Hardware		✓			✓	✓		
FME Workbench (Python scripting)	Laser Scanner - Register	Software		✓			✓	✓		
FUZOR Ultimate	VR - Software	Software	✓				✓	✓		
Geoslam Horizon	Laser Scanner - Capture	Hardware		✓			✓	✓		
Heavy Duty Drone	Drone - Others	Hardware		✓						✓
Holo Lens	AR - Hardware	Hardware	✓					✓		

Hololive	AR - Software	Software	✓					✓		
HTC Vive	VR - Hardware	Hardware	✓				✓	✓		
iConstruct	BIM - Tracking	Software		✓			✓	✓		
Indus AI	AI/ML	Software	✓		✓	✓				
Insite VR	VR - Software	Software	✓				✓	✓		
Insta360 Camera	360° Camera	Hardware		✓			✓	✓	✓	
Laser Scanning (generic)	Laser Scanner - Capture	Hardware		✓			✓	✓		
LAStools	Laser Scanner - Register	Software		✓			✓	✓		
Leica BLK360	Laser Scanner - Capture	Hardware		✓			✓	✓		
Leica Cyclone Register 360	Laser Scanner - Register	Software		✓			✓	✓		
Leica GS✓4 GPS Unit	GPS/Total station	Hardware		✓				✓		
Leica GS✓8 GPS Unit	GPS/Total station	Hardware		✓				✓		
Leica P30 Laser Scanner	Laser Scanner - Capture	Hardware		✓			✓	✓		
Leica P40 Laser Scanner	Laser Scanner - Capture	Hardware		✓			✓	✓		
Leica P50 Laser Scanner	Laser Scanner - Capture	Hardware		✓			✓	✓		
Leica Pegasus	Laser Scanner - Capture	Hardware		✓			✓	✓		
Leica RTC360 Laser Scanner	Laser Scanner - Capture	Hardware		✓			✓	✓		

Leica TS✓6i Robotic Total Station (3" instrument)	GPS/Total station	Hardware		✓				✓		
Lieca Cloudworks	Laser Scanner - Register	Software		✓			✓	✓		
Lieca Cyclone Register	Laser Scanner - Register	Software		✓			✓	✓		
Lulzbot Taz	3D Printer	Hardware		✓						✓
Lumion	3D	Software	✓							✓
Matterport	360° Camera	Hardware		✓			✓	✓	✓	
Matterport	Laser Scanner - Capture	Hardware		✓			✓	✓		
Maya	3D	Software	✓							✓
MOBILIVE	AR - Software	Software	✓					✓		
NuDesign	VR - Software	Software	✓				✓	✓		
Nureva Spanwall	Display	Hardware	✓	✓			✓	✓	✓	
Nvidia Holodeck	VR - Software	Software	✓				✓	✓		
Oculus (Quest/Rift/Go)	VR - Hardware	Hardware	✓				✓	✓		
Oculus Quest	VR - Hardware	Hardware	✓				✓	✓		
OpenSpace	Camera	Hardware		✓			✓		✓	
Photo Sentinel	Timelapse	Hardware		✓			✓			✓
Photoshop	Photo Editing	Software			✓					✓
Pix4d	Drone - Register	Software		✓			✓	✓		
Pixor VR	VR - Software	Software	✓				✓	✓		

Power BI	Dashboard	Software		✓			✓	✓		
Pype	PDF	Software		✓	✓					✓
Recap	Laser Scanner - Register	Software		✓			✓	✓		
Reconstruct	Laser Scanner - Register	Software		✓			✓	✓		
Revizto	BIM - Tracking	Software		✓			✓	✓		
Ricoh Theta Camera	360° Camera	Hardware		✓			✓	✓	✓	
Rithm	Laser Scanner - Register	Software		✓			✓	✓		
RocketBook	Tablet	Hardware		✓			✓			✓
Senseware	IoT Sensor	Hardware		✓				✓		
Sherlock	BIM - Tracking	Software		✓			✓	✓		
Signiant	Data/File Handling	Software		✓			✓			✓
Skycatch	Drone - Capture	Hardware	✓	✓			✓	✓	✓	
Skycatch Explorer✓ (DJI M✓00)	Drone - Capture	Hardware	✓	✓			✓	✓	✓	
Smartvid	Computer Vision	Software		✓			✓		✓	
StructionSite	360° Camera	Hardware		✓			✓	✓	✓	
Synchro	4D	Software	✓			✓				
Time Lapse Camera (generic)	Timelapse	Hardware		✓			✓			✓
Topcon GT-503 Robotic Total Station	GPS/Total station	Hardware		✓				✓		

Total Commander	Data/File Handling	Software		✓			✓			✓
VDC Station	Display	Hardware	✓	✓			✓	✓	✓	
Verity	Laser Scanner - Register	Software		✓			✓	✓		
VisiLean	Planning	Software	✓				✓	✓		
VR Laptop	VR - Hardware	Hardware	✓				✓	✓		
Vuforia	AR - Software	Software	✓					✓		
YouBIM	BIM - FM	Software	✓	✓						✓

Appendix B: Positioning-Based Tracking Technology Solutions

Table B.1 lists positioning-based tracking technology solution providers. These technologies are evaluated through a comparative analysis in Section 2.4.2.

Table B.1: Positioning-Based Tracking Technology Solution Providers

Name	Short Description	Mode of Data Collection	Use-Case
Rhumbix	Streamline Field Operations	Computer Entry, Mobile APP	Daily Construction Report, Payroll, Production Tracking, T&M tracking, Timecard, Timekeeping
Fieldwire	Field Management Software	Computer Entry, Mobile APP	As-built, Communication, Daily Construction Report, Drawing Viewer, Inspection, Markups, Punch-list, Schedule, Taks
Ynomia	Harness real-time data to build faster and safer.	BLE	Equipment Tracking, Location Data, People Tracking, Production Tracking, Supply Chain Tracking, T&M tracking, Tool Tracking
Data 61 CSIRO - BLEAT (Bluetooth Low Energy Asset Tracking)	Tracking tech for Ynomia	BLE, Cloud, LoRaWAN	Equipment Tracking, People Tracking, Supply Chain Tracking
Roambee	Asset Monitory Solution	BLE, Ethernet, Wi-Fi	Equipment Tracking, Supply Chain Tracking
Innovative Construction Technology (ICT)	Real-Time Progress Tracking	AR, Mobile APP	Production Tracking, Progress Tracking
Pillar Technologies	Sensor	Mobile APP	Operational Insights, Quality Control, Risk Management
Indus.ai	Artificial intelligence and computer vision on construction sites	Camera, Computer Vision	Equipment Tracking, Progress Tracking, Safety
Autodesk Infraworks	The software's multi-modal 'Mobility Simulation' engine can be used to simulate pedestrian mobility in indoor environments, such as a large retail space, an airport terminal, or a shared office space	Simulation	Distancing, Motion Simulation
iTWOsafe	iTWOsafe supports construction companies by smartly monitoring and tracking physical distancing onsite. Once the iTWOsafe app is downloaded to a user's smartphone and connected with our light-weighted Bluetooth Low Energy (BLE) devices attached on the working outfit, working distances are then ready to be measured.	BLE, Wearable	Location Data, People Tracking, Safety
Smartvid.io	Minimize risk across all of your projects with safety observations, safety monitoring and predictive analytics while aggregating all sources of photo and video content into one system powered by AI.	Camera, Computer Vision	People Tracking, Safety
Spacewell	Spacewell's unique technology layer – combining IWMS software, Building Information Modeling (BIM), and Internet of Things (IoT) – brings buildings to life and makes them smart.	IoT	Indoor Comfort, Real Estate, Space Utilization

Triax Proximity Trace	Better manage your safety, risk, and efficiency with our wearable technology and IoT platform.	BLE	Distancing, Equipment Tracking, People Tracking, Production Tracking, Supply Chain Tracking, Timekeeping, Tool Tracking
Cozie	Cozie is an iOS App for human comfort data collection. Developed by Prof. Stefano	Mobile APP, Wearable	Indoor Comfort, People Tracking, Survey
Built Robotics	Green field projects, excavator, dozer and loader	Robots	Machine
Cloud Leaf	Securely monitor the condition and location of high-value machinery, tools and other operational assets to protect your investment.	IoT	Equipment Tracking, Supply Chain Tracking
IPSUM Proplanner	franco@ipsumapp.co ProPlanner is built under the Last Planner ™ work methodology, it allows planning, monitoring progress, managing tasks, resources and much more.	Computer Entry, Mobile APP, Scheduling	Schedule, Takt
Basking	-occupancy trends, mobility patterns, space utilization rates and real estate opportunities. Using WIFI as the primary source of data, the Basking software securely connects to the existing wireless network consisting mainly of Wi-Fi access points distributed within the space. These access points see the Wi-Fi-enabled devices connected to the network or within its vicinity.	Wi-Fi	Real Estate, Space Utilization
Open Space	Turn the 360° camera on, tap go, and just walk your site. The OpenSpace Vision Engine maps photos to your plans automatically.	Camera, Computer Vision, Mobile APP	As-built, Production Tracking, Progress Tracking
OpenSpace (Space planning) UK	UK startup OpenSpace has developed a platform that uses IoT and AI to detect and visualize the distance between pedestrians in real-time. The technology uses cameras with computer vision to measure pedestrian flow rate, travel patterns and social distancing. The resulting data can then be used to compare historical weekly and daily information for trend analysis.	Camera, Computer Vision, IoT	Motion Simulation, People Tracking
Raken	Raken's construction project management software is the easiest solution for creating daily reports, time cards, toolbox talks, and insights.	Mobile APP	Daily Construction Report, Production Tracking, Timecard, Timekeeping
Holo Builder	Easily capture, view, and control project progress with 360° photos, enabling teams to stay on schedule and on budget.	Camera, Computer Vision	As-built, Punch-list
StructionSite	Site documentation platform built for construction.	Camera, Computer Vision, Mobile APP	As-built, Progress Tracking
Wakecap	WakeCap is an IoT-based product and service that provides construction site safety, productivity, and especially, in enabling a workable environment in unprecedented situations such as those set forth by strict COVID-19 guidelines.	IoT	Location Data, People Tracking, Safety
Opal	Opal is an integrated RTLS system that provides tailored insights to optimize your workplace.	Camera, IoT, RTLS	People Tracking
SolePower	Work boots become a technology platform that improves situational awareness by monitoring real-time location, status and environmental factors. Low power sensors including GPS, RFID and IMUs are embedded in OSHA approved work boots. Data is sent to the cloud and projected on a dashboard.	GPS, RFID	People Tracking, Safety

Proxxi	Protects workers with social distancing alerts, reduce disruptions to business with contact tracing reports.	Wearable	Distancing
VergeSense	VergeSense gathers the highest fidelity of occupancy data that helps you better understand how to maximize your workspace.	Software	Real Estate, Space Utilization
Estimote	Popular and reliable proximity beacon that supports many microlocation use cases	BLE, IoT, Wearable	Distancing, Indoor Comfort, People Tracking, Space Utilization
ZiaNar	ZaiNar tracks the location of phones, vehicles, drones, IoT, and physical assets.	5G, BLE, GPS, IoT, LTE, Wi-Fi	Asset Tracking, People Tracking, Safety, Supply Chain Tracking
Proximi	Proximi.io's uniqueness lies in its capability of utilizing a multitude of technologies through a single system.	BLE, GPS, Software, Wi-Fi	Asset Tracking, Geofencing, Indoor Navigation, Location Data, People Tracking, Push Marketing, Real Estate
Kontak	Our technology runs the backbone of IoT and extends to solve use cases for healthcare and other smart buildings.	BLE, RTLS, Software, Wi-Fi	Location Data, People Tracking, Safety, Supply Chain Tracking, Tool Tracking
Sensoro	Simple, efficient and practical multi-purpose sensors for smart buildings, municipalities, and fire protection. Ultra-low power consumption, ultra-long coverage and long battery life.	BLE, IoT	Indoor Comfort, People Tracking
GIMBAL	Power your omnichannel marketing with the industry's leading geofencing and proximity-aware location stack built on a privacy-first foundation.	BLE	Geofencing, Push Marketing
Autodesk Forge IoT toolkit	The Forge Viewer team at Autodesk is excited to announce the new Data Visualization extensions as an IoT toolkit to integrate sensor data from your preferred database service (Azure, AWS, others) into your BIM models.	BIM, Software	Dashboard, Digital Twin
Project Dasher	Project Dasher is an Autodesk research project using a BIM-based platform to provide building owners with greater insight into real-time building performance throughout the life-cycle of the building.	BIM, Software	Dashboard, Digital Twin
Sewio	With Sewio RTLS for precise indoor tracking, you can transform your business into a highly efficient, powerful and streamlined operation. Using technology based on ultrawideband TDoA, only Sewio gives you the RTLS hardware and software you need to gain accurate and actionable data and be more productive, cost-effective and safe.	RTLS, Software, Ultrawideband	Asset Tracking, Equipment Tracking, Indoor Navigation, People Tracking, Production Tracking, Safety, Supply Chain Tracking
Kinexon	KINEXON gathers localization data in real time and translates it simultaneously into powerful actions for industries, sports and entertainment entities. Generate previously inaccessible insights with our technology — and use them to your advantage!	Ultrawideband	Asset Tracking, Equipment Tracking, Safety, Supply Chain Tracking
Pozyx	Improve safety, speed, and efficiency. By turning accurate real-time location data into valuable insights. With the power of ultra-wideband (UWB) technology.	Software, Ultrawideband	Asset Tracking, Equipment Tracking, People Tracking, Supply Chain Tracking
Sensolus	Sensolus provides three types of asset trackers to monitor your fleet of assets.	BLE	Asset Tracking, Equipment Tracking, Production Tracking, Supply Chain Tracking
Atoll Solutions	Offer range of standard and customizable wireless modules and embedded modems that are the ideal building blocks for your product development	BLE, LTE, Ultrawideband, Wi-Fi	Asset Tracking, Equipment Tracking
Clean Slate Technologies	Precisely track the movement of assets or people indoors and outdoors Reduce operating costs and boost	RTLS	Asset Tracking, Equipment Tracking, Indoor Navigation, People Tracking, Supply Chain Tracking

	productivity with location intelligence from our proprietary real time location systems RTLS Asset Tracking, Equipment Tracking, Indoor Navigation, People Tracking, Supply Chain Tracking		
Tagvance	Tagvance manpower & asset tracking solutions for real-time workforce tracking and environmental monitoring are tested with several customers worldwide.	BLE, LoRaWAN	Asset Tracking, People Tracking
SenseGiz	SenseGiz makes enterprise and industrial IoT products for sensor based condition monitoring, security and real time asset/people tracking applications using a combination of proprietary mesh connected hardware, cloud, analytics and apps.	BLE	Asset Tracking, Geofencing, People Tracking, Supply Chain Tracking
Navigene	Navigine is a global provider of integrated positioning mobile technologies that enable advanced indoor and outdoor navigation and proximity solutions	BLE, Software, Ultrawideband, Wi-Fi	Asset Tracking, Equipment Tracking, Indoor Navigation, People Tracking, Production Tracking, Push Marketing, Supply Chain Tracking
Decawave	Decawave is the pioneer in UWB wireless semiconductor technology for precision indoor navigation and tracking applications in Smartphones, Access Points and RTLS systems.	Ultrawideband	Asset Tracking, Equipment Tracking, People Tracking, Supply Chain Tracking

Appendix C: Project O Tracking Datasets

Tables C.1 through C.5 present the entries for various tracking datasets collected from StructionSite during the Project O case study, as explained in Section 5.3.2. These datasets, represented as individual entities of the entity relationship diagram in Figure 5.9, were merged into a single source of information. Specifically, Table C.1 includes the project data, Table C.2 includes the drawings data, Table C.3 includes the location data, Table C.4 includes the work detection CSI MasterFormat data, and Table C.5 includes the process step data.

Table C.1: Project O Tracking Data - Project Dataset

Project ID	Project Name	Company Name	Project Type	Build Type	Project Location Type	Project GSF	Levels
62342	1450 Owens	Truebeck Construction	Commercial	Core and Shell (warm)	Urban	210,000	8

Table C.2: Project O Tracking Data - Drawings Dataset

Drawing Name	Drawing ID	Project ID
Level 5	****-9aa8	62342
Level 6	****-93d0	62342
Level 7	****-ea9c	62342

Table C.3: Project O Tracking Data - Location Dataset

Project ID	Location ID	Drawing ID	Location Name	Location Number	Location Type
62342	****-1261	****-9aa8	FSAE Lobby	500	Lobby
62342	****-ceba	****-9aa8	STAIR 1 VEST.	501	Vestibule
62342	****-14c9	****-9aa8	STAIR 2 VEST.	502	Vestibule
62342	****-ba6d	****-9aa8	JAN	503	Storage
62342	****-e121	****-9aa8	Men	504	Restroom
62342	****-b00f	****-9aa8	Women	505	Restroom
62342	****-b00g	****-9aa9	SERV ELEV VEST.	506	Vestibule
62342	****-9376	****-9aa8	Electrical	507	Utility Room
62342	****-0fc4	****-9aa8	NE	581	Open Area
62342	****-776a	****-9aa8	SE	582	Open Area

62342	****-7358	****-9aa8	S		583	Open Area
62342	****-e936	****-9aa8	SW		584	Open Area
62342	****-640c	****-9aa8	W		585	Open Area
62342	****-907e	****-9aa8	NW		586	Open Area
62342	****-d9a3	****-9aa8	N		587	Open Area
62342	****-19ca	****-93d0	FSAE Lobby		600	Lobby
62342	****-8fd1	****-93d0	STAIR 1 VEST.		601	Vestibule
62342	****-a71b	****-93d0	STAIR 2 VEST.		602	Vestibule
62342	****-da29	****-93d0	JAN		603	Storage
62342	****-e75c	****-93d0	Men		604	Restroom
62342	****-6adc	****-93d0	Women		605	Restroom
62342	****-db00	****-93d0	SERV ELEV VEST.		606	Vestibule
62342	****-dbe3	****-93d0	Electrical		607	Utility Room
62342	****-04a6	****-93d0	NE		681	Open Area
62342	****-47b6	****-93d0	SE		682	Open Area
62342	****-2cfc	****-93d0	S		683	Open Area
62342	****-a477	****-93d0	SW		684	Open Area
62342	****-39e9	****-93d0	W		685	Open Area
62342	****-a1ae	****-93d0	NW		686	Open Area
62342	****-362a	****-93d0	N		687	Open Area
62342	****-3b41	****-ea9c	FSAE Lobby		700	Lobby
62342	****-9371	****-ea9c	STAIR 1 VEST.		701	Vestibule
62342	****-d893	****-ea9c	STAIR 2 VEST.		702	Vestibule
62342	****-501e	****-ea9c	JAN		703	Storage
62342	****-4c9c	****-ea9c	Men		704	Restroom
62342	****-cb86	****-ea9c	Women		705	Restroom
62342	****-6d47	****-ea9c	SERV ELEV VEST.		706	Vestibule
62342	****-1aec	****-ea9c	ELECT.		707	Utility Room
62342	****-6037	****-ea9c	NE		781	Open Area
62342	****-bd09	****-ea9c	SE		782	Open Area
62342	****-2527	****-ea9c	S		783	Open Area
62342	****-d687	****-ea9c	SW		784	Open Area
62342	****-cab5	****-ea9c	W		785	Open Area
62342	****-354d	****-ea9c	NW		786	Open Area
62342	****-bb20	****-ea9c	N		787	Open Area
62342	****-b00h	****-9aa8	STAIR 1	5-ST1		Stairwell
62342	****-d138	****-9aa8	STAIR 2	5-ST2		Stairwell
62342	****-ca2f	****-93d0	STAIR 1	6-ST1		Stairwell
62342	****-9ee6	****-93d0	STAIR 2	6-ST2		Stairwell

62342	****-1b24	****-ea9c	STAIR 1	7-ST1	Stairwell
62342	****-b508	****-ea9c	STAIR 2	7-ST2	Stairwell
62342	****-b00i	****-93d0	FSAE ELEV	EL - 1	Elevator Shaft
62342	****-b00j	****-9aa9	FSAE ELEV	EL - 1	Elevator Shaft
62342	****-b00k	****-ea9c	FSAE ELEV	EL - 1	Elevator Shaft
62342	****-b00l	****-93d0	ELEV	EL - 2	Elevator Shaft
62342	****-b00m	****-aa10	ELEV	EL - 2	Elevator Shaft
62342	****-b00n	****-ea9c	ELEV	EL - 2	Elevator Shaft
62342	****-b00o	****-93d0	FSAE ELEV	EL - 3	Elevator Shaft
62342	****-b00h	****-aa11	FSAE ELEV	EL - 3	Elevator Shaft

Table C.4: Project O Tracking Data – StructionSite Work Detection CSI MasterFormat Dataset

Section No	**Title**
31000	Concrete Forming and Accessories
32000	Concrete Reinforcing
33000	Cast-In-Place Concrete
34100	Precast Structural Concrete
34713	Tilt-Up Concrete
42200	Concrete Unit Masonry
51200	Structural Steel Framing
53100	Steel Decking
54000	Cold-Formed Metal Framing
55113	Metal Pan Stairs
61000	Rough Carpentry
61600	Sheathing
62023	Interior Finish Carpentry
64023	Interior Architectural Woodwork
72100	Thermal Insulation
75419	Polyvinyl-Chloride (PVC) Roofing
81113	Hollow Metal Doors and Frames
83323	Overhead Coiling Doors
88000	Glazing
92216	Non-Structural Metal Framing

92900	Gypsum Board
93013	Ceramic Tiling
95123	Acoustical Tile Ceilings
96340	Stone Flooring
96400	Wood Flooring
96513	Resilient Base and Accessories
96813	Tile Carpeting
99113	Exterior Painting
99123	Interior Painting
102800	Toilet, Bath, and Laundry Accessories
104413	Fire Protection Cabinets
104416	Fire Extinguishers
210700	Fire-Suppression Systems Insulation
211200	Fire-Suppression Standpipes
211313	Wet-Pipe Sprinkler Systems
220719	Plumbing Piping Insulation
221113	Facility Water Distribution Piping
221116	Domestic Water Piping
221316	Sanitary Waste and Vent Piping
221413	Facility Storm Drainage Piping
224213	Commercial Water Closets
224213	Commercial Urinals
224216	Commercial Sinks
230713	Duct Insulation
230719	HVAC Piping Insulation
232113	Hydronic Piping
233346	Flexible Ducts
260519	Low-Voltage Electrical Power Conductors and Cables
260533	Raceway and Boxes for Electrical Systems
260536	Cable Trays for Electrical Systems
263213	Diesel-Engine-Driven Generator Sets
265119	Led Interior Lighting
265613	Lighting Poles and Standards
265619	Led Exterior Lighting
312000	Earth Moving
312319	Dewatering
315000	Excavation Support and Protection
321216	Asphalt Paving
321313	Concrete Paving

Table C.5: Project O Tracking Data – Process Step Dataset

Process Step (Work Detected)	Trade
Acoustical Tile Ceilings	Drywall
Ceramic Tiling	Tile Installer
Cold-Formed Metal Framing	Drywall
Domestic Water Piping	Plumbing
Duct Insulation	Mechanical Dry
Facility Storm Drainage Piping	Plumbing
Facility Water Distribution Piping	Plumbing
Fire-Suppression Standpipes	Fire Protection
Flexible Ducts	Mechanical Dry
Glazing	Glazing
Glazing	Misc. Specialties
Gypsum Board	Drywall
Hollow Metal Doors and Frames	Doors/Frames/Hardware
Hollow Metal Doors and Frames	Door - waterproofing
HVAC Piping Insulation	Mechanical Wet
Hydronic Piping	Mechanical Wet
Interior Painting	Painter
Led Interior Lighting	Electrical
Low-Voltage Electrical Power Conductors and Cables	Electrical
Metal Pan Stairs	Structural Steel (Iron Work)
Non-Structural Metal Framing	Drywall
Plumbing Piping Insulation	Plumbing
Raceway and Boxes for Electrical Systems	Electrical
Resilient Base and Accessories	Tile Installer
Sanitary Waste and Vent Piping	Plumbing
Steel Decking	Structural Steel (Iron Work)
Structural Steel Framing	Structural Steel (Iron Work)
Thermal Insulation	Drywall - Fireproofing
Wet-Pipe Sprinkler Systems	Fire Protection