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On Proactive Activity Management with Demand-Responsive Mobility Systems

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On Proactive Activity Management with Demand-Responsive Mobility Systems

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Kotaro Yamada

Dissertation Committee:
Professor R. Jayakrishnan, Chair
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2026

DEDICATION

To

my colleagues at JR East.

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ABSTRACT OF THE DISSERTATION

On Proactive Activity Management with Demand-Responsive Mobility Systems
by
Kotaro Yamada
Doctor of Philosophy in Civil and Environmental Engineering
University of California, Irvine, 2026
Professor R. Jayakrishnan, Chair

This dissertation investigates the potential of proactive activity management for demand-responsive mobility (DRM) services by incorporating travel-activity patterns (TAPs) into a vehicle routing model, focusing on the temporal flexibility of activities. Based on a literature review on operational strategies, service quality, and evaluation methodologies for DRM systems, Chapter 2 identifies research gaps as well as three research questions, namely, how to consider activities in planning and operating a DRM system, how to manage activities for efficient DRM operation, and how to acquire and use information on activities.

To answer the identified questions, Chapter 3 first formulates the activity-based pick-up and drop-off problem (ABPDP) that is sensitive to passengers' activity durations. It also develops a heuristic solution algorithm to handle inter-route constraints. Computational experiments with simulated TAPs verify the solution algorithm and suggest an activity management strategy that uses passengers' activity duration.

Chapter 4 then develops an estimation methodology to infer the temporal flexibility of activities, based on chance-constrained programming (CCP) and statistical extreme value theory. Since the conventional estimation method for the generalized extreme value distribution requires a large sample, this chapter proposes an alternative method that can synthesize sample blocks from the population density distribution estimated on a given small sample. Through an experiment with the National Household Travel Survey (NHTS) dataset, this chapter finds that

Kernel Density Estimation (KDE) is more comparable to the conventional method than other parametric and empirical cumulative density function (ECDF) methods in estimating the population density distribution.

In Chapter 5, this research presents a case study that applies the CCP and KDE methodologies to evaluate proactive activity management strategies that exploit empirical information on the temporal flexibility of activities. The case study uses GPS trajectories to estimate the potential demand of train travelers in Japan. This chapter also presents a procedure to preprocess the GPS trajectories. The case study confirms the effectiveness of the proposed activity management strategies in improving the performance of DRM systems.

Chapter 6 concludes this dissertation by identifying the limitations as well as the necessary model extensions for supply and demand sides, considering real-world implementations. Realistic supply models should consider dynamic operation, stochasticity, and congestion effects, while demand modeling should include more market segments and be sensitive to service levels.

CHAPTER I: Introduction

1.1 Background

Transportation technologies are evolving; nevertheless, people are still captivated by private automobiles, which have long been criticized for their negative societal impacts: congestion, accidents, noise, and emissions. 86.9% of person trips in the 2022 National Household Travel Survey (NHTS) rely on conventional automobiles, including vans, SUV/crossover, pickup trucks, recreational vehicles, and motorcycles (Federal Highway Administration, 2022). However, fixed-route public transit (PT), their eco-friendly counterpart, is considered inconvenient, unreliable, unsafe, and accordingly prone to fail in areas with sparse travel demand. Transportation experts therefore say that we need a transportation system that is more flexible than fixed-route transit and more environmentally sustainable than private vehicles.

Demand Responsive Mobility (DRM) systems show promise in improving the efficiency of urban transportation systems. DRM services flexibly operate vehicles to serve users' trip requests and are expected to fill spatial-temporal transportation gaps in conventional fixed-route PT. While DRM may refer to various forms of transportation from conventional taxi to shared micromobility (Ortúzar and Willumsen, 2024), this research defines DRM as a non-fixed-route car- or shuttle-based service that a certain agency operates to offer either shared- or exclusive-ride transportation. In addition, this research does not include peer-to-peer options in DRM such as private individuals offering rides to peers while following their own itinerary.

Contrary to our expectations, DRM is not always successful in practice. It is costly and often fails to attract passengers. A large body of literature proposes strategies to keep DRM systems viable and attractive. Some of the strategies use information on users' travel behavior to prepare for future demand. Other strategies furthermore aim to improve the performance of DRM systems by shifting users' behavior. However, most of those strategies are trip-based, although our travel behavior is driven by activity participation, according to the activity-based approach (ABA) in travel demand modeling. In this dissertation, I therefore hypothesize that explicit consideration of activities can provide insights into DRM operation and aim to contribute to the literature on DRM strategies by expanding the consideration of activities underpinning the demand for DRM services.

1.2 Definition of Demand Responsive Mobility

First of all, I clarify the definition of DRM in the context of existing similar terms. We can regard DRM as a subcategory of 'shared mobility'. The Federal Transit Association (FTA) defines shared mobility as "transportation services that are shared among users, including public transit; taxis and limos; bikesharing; carsharing (round-trip, one-way, and personal vehicle sharing); ridesharing (carpooling, vanpooling); ridesourcing; scooter sharing; shuttle services; neighborhood jitneys; and commercial delivery vehicles providing flexible goods movement" (Murphy, 2016). FTA further classifies public transit into fixed-route and demand-responsive systems. Therefore, our DRM includes taxis, limos, and demand-responsive transit (DRT) out of shared mobility. Moreover, ridesharing and ridesourcing, both of which are sometimes called Transportation Network Company (TNC) service or ride-hailing in FTA's definition, may be DRM services because they sometimes work as a de facto taxi service, where drivers do not have their own itinerary. This research also regards such taxi-like ride-sharing services as a DRM service.

Mobility on Demand (MOD) is another broad term that refers to "an integrated and connected multi-modal network of safe, affordable, and reliable transportation options that are available and accessible to all travelers." (U.S. DOT Federal Transit Administration, 2023) Any shared mobility service can be MOD in this definition if it is integrated within a multimodal network. Shaheen et al. (2017) also define MOD as a mobility service in which "consumers can access mobility, goods, and services on-demand by dispatching or using shared mobility, courier services, unmanned aerial vehicles, and public transportation strategies." According to their definition, MOD may include courier services. Another term, 'On-demand mobility' (ODM), exists and appears to be interchangeable with MOD. Considering the definition of MOD by Shaheen et al. (2017), we differentiate DRM from MOD/ODM in the sense that DRM excludes courier services.

Mobility as a Service (MaaS) is another more recent term that first appeared in Helsinki, Finland (Heikkilä, 2014). MaaS is often characterized by a unified app-based interface to bundle multiple transportation services, although its definition still varies in literature. Moreover, subscription to the bundles is supposed to strengthen the connection between users and the transportation services and promote shifts from private vehicles. MaaS can include DRM in addition to other shared mobility services.

1.3 Motivation of DRM Implementation

It is expected that DRM's flexibility will help transform existing urban transportation systems. We can consider three possibly compatible transformation scenarios. The first scenario expects DRM to replace existing fixed-route PT systems. This replacement aims to improve operational efficiency and service quality of the current transportation systems. Its demandresponsiveness is supposed to reduce empty vehicle trips of PT. DRM can save passengers' travel times with fewer stops between their origin and destination. On-demand scheduling in conjunction with these travel time savings may decrease door-to-door travel time and help in more effective time-use of passengers.

The second scenario expects DRM to enhance existing PT systems by covering larger areas that the PT systems do not serve. DRM can complement the geographic coverage of PT services and may work as a first/last-mile feeder service. This scenario expects that DRM will improve accessibility and transportation equity in the area and moreover attract more ridership to the new PT system.

The third scenario uses DRM to capture travel demand from private vehicles to the DRM service. The objective of this scenario aligns with the goal of shared mobility implementations. The two previous scenarios can extend to this situation if the service quality of DRM, possibly integrated with other shared mobility, is comparable to that of private vehicles. High service quality will encourage private auto-dependent travelers toward shared mobility systems. Reductions in private car use and ownership will bring environmental benefits, such as decreases in total vehicle miles traveled (VMT) and vehicle emissions. Reductions in private vehicle use will also ease parking space requirements and trigger more effective land use.

1.4 Operational Issue

Contrary to the expectations above, empirical studies show that DRM introduction may result in negative consequences. Common concerns about DRM operation include financial viability, negative externalities, and low ridership. This section discusses these issues.

1.4.1 Financial Viability

DRM can still be financially unviable although it is supposed to be more cost-effective than conventional PT. Currie and Fournier (2020) point out the high failure rate of past DRT services and attribute the failures to high operational costs.

DRM can be more costly than conventional PT when it uses a larger fleet of small vehicles and thus requires more drivers. The advanced technologies for DRM, such as payment, reservation, and routing cause not only operational benefits but also extra costs. The use of these technologies does not necessarily mean a cost-effective operation. A survey conducted with transit agencies by Palmer et al. (2008) finds no effect of Paratransit Computer Aided Dispatching systems on operational costs, although they improve productivity. A more recent study by Currie and Fournier (2020) comes to a similar conclusion that it is still unclear that advanced technologies lower overall operational costs.

1.4.2 Negative Externality

Undesirable externalities from DRM systems are possible. Increases in VMT and emissions due to deadheading and detours are observed in the context of TNC. In San Francisco, TNC vehicles are 15 times more than taxi vehicles during peak hours, and TNC trips comprise 20.3% of the trips in the congested areas (San Francisco County Transportation Authority, 2017). Moreover, Erhardt et al. (2019) indicate that TNCs contribute to weekday vehicle delay in San Francisco. According to Qian et al. (2020), TNCs reduced the average speed in New York by 22.5% on weekdays from 2017 to 2019. Effective vehicle routing schemes are important for reducing unnecessary VMT. The next chapter reviews several vehicle dispatchment and routing strategies.

DRM can deplete demand from existing, more efficient transportation modes, making the use of the whole transportation system less efficient. Chicago Transit Authority reports that TNCs partly caused declines in PT ridership, including that of students, despite the free travel pass program, in two consecutive years (Chicago Transit Authority, 2018, 2019). The integration of DRM with conventional PT systems is a potential remedy for this cannibalization among shared mobility modes.

1.4.3 Low Ridership

DRM systems sometimes suffer from low ridership regardless of their improved service quality. External factors that PT operators cannot control have greater effects on PT ridership than internal factors (Taylor and Fink, 2013). Wang et al. (2014) identify influential external factors on ridership, such as car ownership, population density, race, income level, education level.

However, some research still supports the effectiveness of service design on DRM ridership. An experience in Denver shows that simpler operational strategies, such as checkpoint service, may create a base market with consistent ridership (Denver Regional Transportation District, 2008). Pan and Shaheen (2025) moreover show point-deviation strategy and service area are more influential on the ridership of US microtransit services than external factors.

1.5 Dissertation Outline

The goal of this dissertation is to propose and verify operational strategies that realize the expectations for DRM systems, while addressing viability issues. For this goal, the dissertation carries out four interrelated research tasks. Chapter 2 first identifies research gaps and research questions for this dissertation to answer by reviewing literature on operational strategies for

DRM systems and tools for strategy evaluation. Chapter 3 then formulates a vehicle routing problem that considers passengers' activity participation. It also presents a solution algorithm for this problem. This chapter is based on a presentation by Yamada and Jayakrishnan (2026). Chapter 4 proposes a framework that estimates temporal flexibility of activities based on the chance-constrained programming and the extreme value theory. Chapter 5 demonstrates the feasibility of the methodologies proposed in the previous chapters on real-world data of travel-activity patterns and evaluates some operational strategies that incorporate passengers' activities. Chapter 6 concludes the dissertation, discussing the limitations of the research and future research directions. It moreover suggests ideas for the implementation of the methodologies.

CHAPTER II: Literature Review

2.1 Operational Strategies

This chapter first reviews literature regarding strategies to improve DRM operational performance.

2.1.1 Ridepooling

Ridepooling or shared ride is the most common operational strategy for DRM systems. Ridepooling allows different passenger groups to share the same vehicle to utilize operational resources. The effectiveness of ride pooling service is clear in comparison to taxi-like service that only offers exclusive rides. Santi et al. (2014) examined the shareability of New York City (NYC) taxi trips by using the shareability network of the trips. They showed that ridepooling of up to 2 trips could save substantial vehicle travel time with limited increases in passenger travel time. Alonso-Mora et al. (2017) developed an optimization-based matching and routing algorithm for vehicles with higher capacity. Their result indicates that 2,000 ten-passenger vans, which are equivalent to 15% of the taxis, can serve 98% of the existing taxi trips in NYC and reduce VMT with waiting times and trip delays slightly increasing. Inturri et al. (2021) used agent-based simulation to compare taxi and demand responsive shared transport (DRST) in Ragusa, Italy, and showed that DRST can be effective when travel demand and available vehicles are sufficient.

2.1.2 Meeting Point

A door-to-door DRM service, where passengers can request rides between almost any two desired locations, may involve many detours and decrease operational efficiency. DRM operators may therefore restrict locations available for boarding and alighting vehicles. This type of system is called point-to-point service. In a point-to-point service, passengers must walk or use other modes to designated locations to use DRM service. Those places are called meeting points, or collection points (Korompay and Földes, 2025). Point-to-point services can have some advantages, such as safety and convenience, identification, service time, privacy, health, and designation, over door-to-door services (Czioska et al., 2019). Meeting points secure boarding and alighting by avoiding dangerous traffic conditions. They make it easy for both drivers and passengers to identify with each other. They save travel and service times by reducing stops and detours. They eliminate passengers' need to disclose the exact locations of private places (e.g. home and workplace). They may encourage walking and clarify where to board/alight the vehicle.

Some research shows that using meeting points improves the operational efficiency and the service reliability of DRM systems. For example, Nishida et al. (2022) showed that introducing meeting points can reduce vehicle travel distance as well as passenger travel time.

Effective allocation of meeting points is crucial. The number of points being too limited may harm DRM service quality, leading to a failure to attract passengers, whereas too dense allocation does not differentiate point-to-point service from door-to-door service and decreases operational efficiency. A common approach to allocating meeting points at meaningful locations uses the distribution of trip requests for DRM. Some research applies clustering techniques to trip endpoints to identify meeting point locations. Martínez et al. (2015) cluster trips based on their origin, destination, and arrival time and use the centroids of the trip ODs in each cluster as meeting points. Korompay and Földes (2025) present a clustering method to select meeting point locations that minimize total walking distance considering acceptable walking distance, given demand points. Czioska et al. (2019)'s VRP finds the assignment of meeting points to passenger clusters in addition to optimal vehicle routes. They conduct a simulation experiment to compare a system with meeting points to a door-to-door service and show reductions in operational costs, while average passenger travel time increases due to more walking and waiting times. Other allocation methodologies do not rely on clustering. Qu et al. (2019) use taxi GPS data and kernel density estimation (KDE) to identify taxi travel hotspots. To find optimal meeting point locations, they solve an optimization problem that minimizes the total cost, including passengers' access cost to candidate points generated along both sides of the road plus the taxi stand construction costs. Zhang et al. (2020) formulates and solves a two-stage analytical point allocation model for flex-route transit systems. Their model, assuming uniform demand distribution, maximizes the number of requests served and minimizes the total travel time of the accepted requests.

2.1.3 Flex-route Strategies

Flex-route or semi-flexible strategies compromise the benefits of DRM and conventional PT systems, considering the demand density distribution of the service area. PT is effective in high-demand areas but provides lower service quality, while DRM is suitable for low-demand areas but more costly per vehicle. Flex-route strategies include point- and route-deviation systems. The vehicles of the former systems are scheduled to stop at a limited number of checkpoints, whereas the latter systems partly follow fixed routes and may deviate from those routes upon request. Pan and Shaheen (2025) survey microtransit systems in the US and find point-deviation systems are associated with high ridership. Koffman (2004) and Potts et al. (2010) survey the implementations of flex-route systems. Errico et al. (2013) and Shahin et al. (2024) furthermore offer comprehensive surveys on evaluation methods for flex-route strategies.

2.1.4 Predictive Vehicle Routing and Prebooking

The time frame of ride requests affects DRM operation. Dynamic or online DRM service takes immediate ride requests and offers flexibility to users, while static or offline service accepts ride requests before the start of operation and can enable operators to arrange more efficient routes.

Existing literature shows that information on future requests helps matching and routing decisions improve the performance and the service quality of dynamic DRM services. Alonso-Mora et al. (2017) showed that predicting future requests based on samples from the distribution of past requests reduces wait and detour times but increases VMT and single rides perhaps due to predicted but unrealized demand. Miller and How (2017) apply a predictive positioning method that computes passenger arrival rates at each node to a campus-scale ridesharing problem. They demonstrate the effectiveness of the method in reducing passenger waiting time. Iglesias et al. (2018) devised a model predictive control (MPC) that supports rebalancing strategies by forecasting short-term demand based on past data. Tsao et al. (2019) showed that MPC-based ride-pooling algorithm decreases wait and travel times with a slight increase in VMT, compared to a system without MPC.

Other research supports the advantages of prebooking systems. A simulation study by Scholtes and de Almeida Correia (2017) concludes that prebooking a feeder service can reduce average waiting time. Ma et al. (2017) use a linear programming model and show that shared autonomous vehicle with reservation can increase vehicle utilization and reduce vehicle ownership without a substantial increase in VMT compared to conventional taxis. An analytical study by Bilali et al. (2019) shows that introducing a reservation time improves the shareability of trips, especially when trip density and waiting time or detour time are low. Duan et al. (2020)

confirm that a hybrid request mode that takes either immediate or in-advance ride requests for autonomous taxis improves service quality and economic efficiency. Higher reservation rates enhance operational robustness to errors in predicted requests. Furthermore, early reservations with enough vehicles available improve the completion rate of requests and the revenue. Ma and Koutsopoulos (2022) showed that even "near-on-demand" operations with short planning horizons in conjunction with an increased willingness in passengers to share are beneficial for all users, operators, and cities. Lu et al. (2023) suggest that prebooking makes vehicle routing more efficient than online systems. Additionally, Ghimire et al. (2024) claim that, in contrast to unpredictable ride availability in dynamic operation, the prebooking system is more reliable for time-sensitive and patterned users, such as commuters, patients with medical appointments, and daycare attendants.

2.1.5 Request Prioritization and Pricing

Operators may strategically prioritize which requests to serve, depending on their objective such as profit maximization or equity, particularly when resources are limited. Existing research proposes prioritization strategies that control demand to achieve the objective of DRM system.

Simple prioritization approach rejects undesirable requests. Schuller et al. (2021) propose prioritization techniques to equalize service rates among different zones within a services area. Other prioritization strategies offer 'better' alternatives than the original request. Lu et al. (2024) and Tiwari et al. (2025) moreover propose the active request rejection method that assigns any alternative PT mode available to rejected requests. This strategy can reserve the capacity of the DRT fleet for passengers without alternative travel options and encourage PT use. More advanced strategies are pricing schemes that offer users alternatives with different prices and nudge them to choose more operationally desirable options by controlling the prices. Fleckenstein et al. (2023) and Anzenhofer et al. (2025) overview recent demand control and pricing schemes.

2.2 Service Quality

Literature reveals several important service qualities for service adoption. Ride time or in-vehicle time is a common service quality indicator for transportation services. Ride time is usually associated with disutility and may be longer for DRM services because of detour time and additional stops for the pick-ups and drop-offs of other passengers. This is why Dial-a-ride problem (DARP) and its variants commonly impose constraints on ride time (Jaw et al., 1986). As with the case of PT, the presence of other passengers may also be an additional concern. However, this effect may be limited in DRM services. The users of the Kutsuplus pilot project in Helsinki point out riding comfort and amenities in the vehicle, including real-time information, as the positive features of the service (Weckström et al., 2018). Krauss et al. (2022) estimate a lower (but statistically insignificant) value of in-vehicle time for ridepooling service than for other modes, implying that in-vehicle time might be more acceptable and that the smaller on-demand vehicles could increase attractiveness. Avermann and Schlüter (2019) showed that the presence of others in the vehicle is insignificant for user satisfaction. Lavieri and Bhat (2019) find that passengers feel greater inconvenience about detour time than pooling with strangers. Although some estimate positive willingness-to-pay for avoiding pooling with strangers (Kang et al., 2021; Vij et al., 2020), these estimates perhaps include that for avoiding prolonged travel time.

Due to its shared and demand-responsive nature, people tend to be more concerned about the punctuality of their trips (Li et al., 2019). Morsche et al. (2019) point out that uncertainty in departure and arrival times negatively affects preferences for DRT services. Bansal et al. (2020) use a discrete choice model to show that the pick-up time reliability (i.e., the difference between displayed and actual pick-up times) affects passengers' intention to choose DRM services. Although most research agrees that temporal reliability is a key service quality factor, departure time delay appears insignificant on the preference for the on-demand alternative in the choice model of Bronsvoort et al. (2021). In addition, Alonso-González et al. (2020) point out inconsistency in reliability representation among research works.

Ridepooling also makes waiting time for DRM uncertain. Waiting time is one of the determinants of DRT customer satisfaction (Avermann and Schlüter, 2019). Xing et al. (2022) report that the users of SmaRT Ride in Sacramento find waiting time discouraging for service use.

The ride availability of DRM can be less reliable than conventional PT because DRM systems typically provide smaller passenger capacity than fixed-route PT due to their smaller vehicles. The evaluation of Kutsuplus indicates that ride availability is a key performance metric for the success of DRT service (Weckström et al., 2018).

Point-based services require access and egress trips as well as PT systems. Early experiences of DRT show that the dispersion level of meeting points affects user satisfaction (Mageean and Nelson, 2003). Other research agrees that access and egress to meeting points can be the barriers to the adoption of DRM services (Morsche et al., 2019; Miah et al., 2020; Bronsvoort et al., 2021)

DRM services' user interface is another important factor for service acceptance. Avermann and Schlüter (2019) find that the ease of entry determines customer satisfaction. Miah et al. (2020) claim that difficulty in using the service is a barrier to adoption. Since most DRM' use advanced ICT for booking and payment, those who feel unfamiliar with such technologies may find it as a barrier to the use of the service.

It is crucial for successful DRM implementations to address the issues above. However, enhancing service quality often contradicts improving operational efficiency. Some operational strategies sacrifice service quality for performance improvements. To propose a balanced operational strategy, DRM planners need effective evaluation tools that can measure both service quality and operational performance.

2.3 Evaluation Tool

2.3.1 Supply Model

Vehicle routing is crucial for the supply side of DRM system. Agent-based modeling is commonly used to determine individual vehicle routes that serve given travel demand for a DRM system. A vehicle is an agent in the system. Moreover, agent-based vehicle routing is based on two different approaches: optimization and simulation (Mourad et al., 2019).

2.3.1.1 Optimization-based approach

The optimization-based approach aims to find an optimal set of routes to the given demand by solving vehicle routing problem (VRP), specifically, pick-up and delivery problem with time windows (PDPTW) or DARP. The difference between them is that DARP includes additional constraints to maintain service quality. For example, maximum ride time constraints prevent passengers from spending too much time inside a vehicle. Most optimization-based approaches assume deterministic demand; all demand is known before starting operation. Although this setting is valid for full prebooking systems, it cannot handle dynamic requests that arrive during operation. Some existing VRPs use the techniques of stochastic programming to deal with such dynamic demand as well as other stochasticity regarding travel time and service time. Readers may refer to Oyola et al., (2017, 2018) for a comprehensive review on stochastic VRP models and relevant solution methods.

While the optimization-based approach could provide the best routing, one drawback of this approach is scalability. Since PDPTW/DARP is an NP-hard problem, large problem instances are not exactly solvable within practical time. For this reason, many algorithms proposed so far are based on (meta)heuristics and can approximately but quickly solve large problem instances.

2.3.1.2 Simulation-based approach

Simulation-based evaluation can deal with more realistic and complicated settings. This approach simulates vehicle operation following certain vehicle dispatching and routing strategies while keeping track of the system status at each time step. The simulation-based approach is not intended to guarantee optimal vehicle routes but can efficiently handle dynamically arriving requests and time-dependent conditions such as traffic congestion.

Many recent studies employ the simulation-based approach to realistic DRM evaluation. Examples are found in review papers (e.g., Karolemeas et al., 2024; Ronald et al., 2015; Wang et al., 2023). Moreover, DRM operation modules are integrated into several agent-based traffic simulation models, such as MATSim (Maciejewski, 2016), SimMobility (Marczuk et al., 2015), and SUMO (Armellini, 2022). Another interesting example is FleetPy (Engelhardt et al., 2022).

FleetPy is an open-source fleet simulation framework written in Python and is able to offer a flexible testbed for algorithm developments.

2.3.2 Demand Model

The supply-side models require trip data that specify high-specificity origin and destination as well as departure and/or arrival times. For this reason, research often uses real-world taxi trip datasets to validate DRM supply-side models. Singapore (Government of Singapore, 2026), NYC (The New York City Taxi and Limousine Commission, 2026), and City of Chicago (2026), for example, provide detailed data on taxi trips. While the datasets of Singapore and NYC provide the coordinates and time stamps of trip origin and destination, the Chicago dataset is spatially and temporally aggregated. Some research uses datasets from TNCs; however, those datasets are not publicly available. The data of DiDi Chuxing is an open TNC dataset but no longer accessible on the official site (Didi Chuxing, 2024).

However, those real-world datasets are only available in limited metropolitan cities. Thus, synthesizing demand for DRM systems is necessary to evaluate DRM services in most areas. Alsaleh and Farooq (2021) develop four machine learning based models (random forest, bagging, artificial neural network, and deep neural network) of trip production and distribution at dissemination area level for on-demand transit (ODT) services in Belleville, Canada. The authors use the Bayesian hyperparameter optimization method to calibrate the models on the ODT operation data and the 2016 census data. Franco et al. (2020) use Mobile phone Network Data (MND) as input for MATSim to assess the viability of DRT in a suburban area in UK. Their MND includes a trip-chain dataset aggregated at zonal level. Although this trip-chain dataset yields a better result than a conventional trip-based dataset, the paper does not provide a clear explanation for the result.

Activity-based travel demand models (ABTDM) gain attention in practice these days due to their capability of simulating detailed travel behavior that is essential for DRM evaluation. Oke et al. (2020) uses SimMobility to evaluate the impacts of automated mobility on-demand (AMoD). SimMobility incorporates an activity-based model that generates Traffic Analysis Zone (TAZ)-level tours of individuals for an AMoD supply model. Mahmoudi et al. (2021) use OpenAMOS (Pendyala et al., 2012) to obtain more than 39 million trip requests in Phoenix.

2.4 Research Objective

2.4.1 Research Gap

DRM systems by nature operate in response to passengers' travel behavior. Some proactive strategies, such as predictive vehicle routing and prebooking, show the effectiveness of considering information about travel behavior in improving the efficiency of DRM operation. Prioritization and pricing strategies moreover expect passengers' behavioral shifts toward an operationally better option different from their original request or even another mode. In this context, information about passengers' travel behavior also helps offer more acceptable alternatives.

From the perspective of ABA, travel behavior is a result of activity participation. Literature on ABA argues that understanding the nature of activities is crucial for understanding travel behavior. Understanding activities should provide useful behavioral information for DRM operation. However, current literature on DRM has limited consideration on passengers' activities. First, few strategies focus on activity participation and the effects of activity changes on DRM performance. Second, most analyses of service quality are trip-based, although service quality requirements for travel time are concerned with on- or in-time arrival at destination (i.e., activity). Third, travel demand estimation uses ABTDMs, but current ABTDMs do not provide high-resolution demand data for agent-based vehicle routing models because the travel-activity patterns from ABTDMs are spatially and temporally aggregated into zones and periods. On the other hand, taxi or TNC datasets can provide massive and detailed information on trips. However, it is hard to extract activity information from those datasets. Finally, supply-side models seldom consider the interrelationships among trips of the same traveler. Even when supply-side models are combined with ABTDMs, they only take trips that are supposed to choose DRM service by decomposing output travel-activity patterns (TAPs).

2.4.2 Research Question

In the context above, this research hypothesizes that expanding behavioral consideration will provide additional insights into DRM operation. It specifically supposes that information on passengers' activities between trips will benefit DRM operation. However, the relationship between DRM operation and passengers' activity is still ambiguous. There is a lack of methodology that can translate activity information into operationally meaningful information. Therefore, this dissertation contributes to the literature by answering research questions about how to consider activities in DRM system planning and operation, how to manage activities to facilitate DRM operation, and how to obtain and use activity information.

2.4.3 Research Approach

This dissertation tackles the research questions in three steps. The next chapter first formulates a VRP that incorporates activity consideration into the prebooking strategy and develops a solution algorithm to deal with the activity consideration. The second step presented in Chapter 4 estimates the temporal flexibility of activities, supposing that such flexibility matters for DRM operation through controlling trip flexibility. This step is based on CCP as well as the extreme value theory in statistics. The last step develops an activity-based DRM evaluation framework that combines the two methodologies presented in the previous steps. The dissertation tests this framework in evaluating the efficacy of proactive activity management strategies that utilize activity information for DRM operation. This evaluation is based on a large GPS-based trajectory dataset on travelers' detailed TAPs.

CHAPTER III: Activity-based Pick-up and Drop-off Problem

3.1 Introduction

One of the goals of this dissertation is to incorporate consideration on passengers' activities into DRM system planning and operation. Chapter 2 indicated that modeling the supply side of DRM systems often ignores riders' activity participation that underlies ride requests for DRM systems. This ignorance makes DRM system planning less sensitive to changes in activities. I suppose that explicit consideration on passengers' activities in planning will enable planners to investigate further operational strategies.

This chapter answers research questions: "how do we consider activities in DRM system?"; "what factors are important for the viability of DRM?"; and "how does passengers' activity participation affect the performance of DRM?" For this purpose, the research proposes a methodology that can comprehensively evaluate DRM services in ABA. This proposed methodology is based on VRP that finds the minimal costs required to satisfy transportation demand. The VRP for DRM can be formulated as PDPTW or DARP. In PDPTW, vehicles are supposed to transport delivery/drop-off requests from their pick-up locations to their destinations. The pick-up and delivery times may be constrained within specified time windows. However, conventional PDPTW regards requests as standalone (independent) and ignores the behavioral aspect that people's trips are interrelated through activities. DRM routes should respect not only passengers' individual trips but also their activity participation. This research therefore modifies PDPTW to consider the interrelationships among trips. I call this problem the activity-based pick-up and drop-off problem (ABPDP). Furthermore, this modification requires us to develop a solution algorithm that handles the complexities of ABPDP.

This chapter is organized as follows. The next section overviews related literature. Then, the chapter introduces the problem setting and the formulation of ABPDP as well as an efficient algorithm for large-scale problems. It finally conducts computational experiments to test the proposed algorithm.

3.2 Literature Review

Transportation systems planning evaluates alternative solutions to improve existing transportation systems. This evaluation is based on estimating the performance metrics of the solutions and requires modeling both the supply and demand sides of transportation systems, and their interactions. The models should be as realistic as possible.

The ABA provides a theoretical background to current travel demand modeling. Based on a premise that "travel is a demand derived from the demand for activity participation" (McNally and Rindt, 2007), ABA is characterized by the reasonable and detailed representation of travel behavior. Among many ABTDMs in use (Rasouli and Timmermans, 2014), ActivitySim is a notable example of real-world ABTDM applications (Association of Metropolitan Planning Organizations, 2019). Many US metropolitan planning organizations contribute to the development of ActivitySim and use it in actual planning.

Supply-side models describe how transportation networks and vehicles perform in response to travel demand. Planning and operating a DRM system focus on vehicle routing that satisfies given travel demands. From the vehicle routes, planners can derive performance metrics, such as fleet size and VMT, for evaluation. Since DRM vehicles operate to serve passengers' trips, the spatial-temporal distribution of trips affects the performance of DRM services. From an ABA perspective, the spatial-temporal distribution of trips depends on the travelers' activity participation. In summary, DRM operates according to passengers' activity participation.

Solving VRP is a common way to find vehicle routes that best transport passenger trips. DRM operation can be modeled as the well-known PDPTW or dial-a-ride problem (DARP) (Doerner and Salazar-González, 2014). The solution to PDPTW represents optimal vehicle routes that passenger pick-ups and drop-offs are done within specified time windows. Since PDPTW is an NP-hard problem, many algorithms for efficient problem solving are developed. Those algorithms are categorized into exact algorithms and metaheuristics. The former intends to find an exactly optimal solution, while the latter searches for an approximate but good-quality solution within a shorter computational time. In both solution approaches, the column generation algorithm is commonly used to solve large problems. Dumas et al. (1991) first developed an exact column generation algorithm for PDPTW. Xu et al. (2003) also use the column generation algorithm in conjunction with two heuristics to solve subproblems. Cordeau and Laporte (2007), Battarra et al. (2014), Doerner and Salazar-González (2014), Molenbruch et al. (2017), and Ho et al. (2018) overview the characteristics of PDPTW/DARP and relevant solution algorithms. Sartori and Buriol (2020) provide a good summary of more recent solution approaches for PDPTW.

As reviewed in Chapter 2, prebooking DRM services are operationally advantageous to dynamic/immediate booking services. Prebooking DRM systems may take multiple trip requests of the same passenger at a time. Those trips make a trip chain, within which activities exist between consecutive trips. However, as Mahmoudi et al. (2021) point out, most PDPTW regard trips as independent from each other, though the trips of the same person are interrelated. Vehicle routes may be interrelated because different vehicles may serve the interrelated trips of the same individual. This situation imposes inter-route constraints on vehicle routing for passenger trips, while most existing solution algorithms for VRP only consider intra-route constraints and ignore the linkages among trips.

In the context above, this research introduces the activity-based approach to PDPTW for prebooking DRM operation and proposes ABPDP that considers activity duration between trips of the same passenger. Activity duration constraint is a dynamic time window constraint that imposes bounds on “the difference between the (two) points in time when the two operations are performed”(Gschwind and Irnich, 2015). While Gschwind and Irnich (2015) only consider intra-route dynamic time window constraints, ABPDP is a vehicle routing problem with multiple synchronization constraints (VRPMS), which is “a VRP in which more than one vehicle may or must be used to fulfill a task” (Drexl, 2012). As with other VRPMSs, solving ABPDP requires solution techniques that handle the inter-route constraint. Mahmoudi et al. (2021) do the most relevant study to this research. They use a time-discretized multi-commodity network flow model that can represent possible transportation states, such as congestion, at any given time. This model considers the linkage among trips through passengers’ space-time paths. The discretization of temporal attributes is advantageous in handling time-dependent attributes. However, it adds more dimensions of integer variables and imposes high computational complexity. High-resolution discretization, say, at minute level, that real-world DRM operation requires may be impractical in their approach. For this reason, this research refrains from discretizing temporal variables.

3.3 Method

3.3.1 Problem Setting

This section introduces our formulation. ABPDP considers TAPs, which are alternating sequences of trips and out-of-home activities, to make the vehicle routes that respect passengers' activity participation. The trips within a TAP are connected by activities in between, so they are spatially and temporally interrelated. In other words, the spatial-temporal attributes of activities determine trip attributes. The locations of activities determine the origin and destination of trips. Activity start times and duration determine the departure and arrival times of trips.

I assume that each passenger group has one TAP to begin and end within a specified timeframe. TAPs are also associated with specific origins and destinations. Although the origin and destination of a TAP are typically both at one place (i.e., home), they could also be at different places. Passenger groups may have more than one member, but all the members in the same group together execute an identical TAP. To complete activities, passengers have to arrive at their activities while the activities are available and early enough to stay there for a certain duration.

Another assumption is that passengers only use the DRM service for trips. They are supposed to have provided all their ride requests before they begin their TAPs (i.e., no new ride request is accepted during operation.). The ride request information includes a sequence of activity locations as well as the temporal restrictions on the activity participation, such as their out-of-home time windows and the minimum duration of activities.

DRM vehicles depart from their designated depots, move to pick up passengers at trip origins and drop them off at trip destinations, and return to the depots. The vehicles do not necessarily return to the depot that they depart from. ABPDP does not assume transfers between vehicles. So, the same vehicle must serve the origin and the destination of a trip.

3.3.2 Notation

ABPDP is a variant of the PDPTW. In ABPDP, passengers' origins and activity end points are pick-up nodes, and their destinations and activity start points are drop-off nodes. A vehicle route is then expressed as a sequence of the arcs between the nodes.

Table 3.1 summarizes the notation of model parameters and decision variables. Model parameters are exogenously specified and given to the problem.

Let $|G|$ be the number of traveler groups/TAPs. Passenger group $g \in \{1, \dots, |G|\}$ has s_g members and n_g trips. A TAP with n_g trips has $n_g - 1$ activities. The total number of trips is $n = \sum_{g=1}^{|G|} n_g$. The total number of pick-up and drop-off nodes is hence $2n$. Let $|V|$ be the number of dispatchable vehicles. Vehicle $v \in \{1, \dots, |V|\}$ has passenger capacity k_v as well as origin and destination nodes, not necessarily at the same location. For convenience, the indices for the origin and the destination nodes of vehicle v are denoted as $\varphi_v^+ := v - 1$ and $\varphi_v^- := \varphi_v^+ + |V| + 2n$, respectively. Using this notation, we define the origin node index of passenger group g as $\phi_g := \varphi_{|V|}^+ + \sum_{k=1}^{g-1} n_k + 1$. Index set $P_g^+ = \{\phi_g, \dots, \phi_g + i, \dots, \phi_g + n_g\}$ is for the pick-up nodes for passenger g. Since the drop-off node corresponding to pick-up node u is $u + n$, the index set for passenger g's drop-off nodes is $P_g^- = \{\phi_g + n, \dots, \phi_g + i + n, \dots, \phi_g + n_g + n\}$. Accordingly, passenger g passes through nodes $\phi_g, \phi_g + n, \phi_g + 1, \phi_g + 1 + n, \dots, \phi_g + n_g, \phi_g + n_g + n$. Note that an arc between node $\phi_g + n + i - 1$ and node $\phi_g + i$

$\forall i \in \{1, \dots, n_g\}\ \forall g \in \{1, \dots, |G|\}$ represents an activity that begins at node $\phi_g + n + i - 1$. We also call the activity that begins at node u activity u. Figure 3.1 illustrates the indexing system in the case that $|G| = 2$, $|V| = 2, n_1 = 2$, and $n_2 = 3$. Since $n = n_1 + n_2 = 5$, vehicles that originate from node $\varphi_1^+ = 0$ and $\varphi_2^+ = 1$ and destined to $\varphi_1^- = \varphi_1^+ + |V| + 2n = 12$ and $\varphi_2^- = \varphi_2^+ + |V| + n = 13$, respectively, after serving travelers.

Let arc uw be the arc with its tail at u and the head at w. Let X_{uw}^v be a binary variable that indicates whether vehicle v uses arc uw. Let t_{uw}^v and c_{uw}^v denote the travel time and the travel cost, respectively, of arc uw for vehicle v. Vehicle v's route is the set of arcs each of which has $X_{uw}^v = 1$. Thus, the total travel cost for vehicle v is $\sum_u \sum_w c_{uw}^v X_{uw}^v$.

Each node u is associated with its access time T_u that is constrained within a specified time window $[a_u, b_u]$. That is, $a_u \le T_u \le b_u$. An admissible vehicle route must satisfy the time window constraints at all the nodes on the route.

ABPDP allows multiple passengers to share a vehicle when traveling. To model shared rides, the problem considers passenger loads. Pick-up or drop-off node u has passenger load d_u. d_u is proportional to the size of traveler group to which node u belongs. If the node is a pick-up node, the load is the same as the group size. If the node is a drop-off node, the load is the negative of the group size. Otherwise, $d_u = 0$. Let Y_u^v be the cumulative load of vehicle v right after leaving node u. The cumulative load of an admissible vehicle route may not exceed the vehicle's capacity after visiting every u. That is, $Y_u^v \le k_v\ \forall u \in N\ \forall v \in V$.

Let Z denote the objective value of the problem. Z is an arbitrary linear combination of decision variables, each of which is associated with a weight to express its relative value in the objective. The components of Z can include, for example, the total travel cost $\sum_u \sum_w c_{uw}^v X_{uw}^v$ and the total vehicle service time $\sum_v (T_{\varphi_v + |V| + 2n} - T_{\varphi_v})$.

Table 3.1 Notations of Parameters and Variables

Notation	Meaning
Parameter	
$G = \{1, \dots, g, \dots, \lvert G\rvert\}$	Set of passenger groups.
$q_g \in \mathbb{N}$	Size of passenger group g.
$n_g \in \mathbb{N}$	Number of trips of passenger group g.
$n := \sum_{g=1}^{\lvert G\rvert} n_g$	Number of all the trips.
$V = \{1, \dots, v, \dots, \lvert V\rvert\}$	Set of vehicles.
$k_v \in \mathbb{N}$	Capacity of vehicle v.
$\varphi_v^+ := v - 1$	Index of the origin node for vehicle v.
$\varphi_v^- := \varphi_v^+ + \lvert V\rvert + 2n$	Index of the destination node for vehicle v.
$O = \{\varphi_1^+, \dots, \varphi_v^+, \dots, \varphi_{\lvert V\rvert}^+\}$	Set of vehicle origin nodes.
$D = \{\varphi_1^-, \dots, \varphi_v^-, \dots, \varphi_{\lvert V\rvert}^-\}$	Set of vehicle destination nodes.
$\phi_g := \varphi_{\lvert V\rvert}^+ + \sum_{k=1}^{g-1} n_k + 1$	Index of the origin node for passenger group g.
$P_g^+ = \{\phi_g, \dots, \phi_g + i, \dots, \phi_g + n_g\}$	Set of the pick-up nodes for traveler group g.
$P_g^- = \{\phi_g + n, \dots, \phi_g + i + n, \dots, \phi_g + n_g + n\}$	Set of drop-off nodes for traveler group g.
$P^+ = \bigcup_{g=1}^{\lvert G\rvert} P_g^+$	Set of all pick-up nodes.
$P^- = \bigcup_{g=1}^{\lvert G\rvert} P_g^-$	Set of all drop-off nodes.
$P = P^+ \cup P^-$	Set of all pick-up and drop-off nodes.
$N = P \cup O \cup D$	Set of all nodes.
$d_u = \begin{cases} q_g & \text{if } u \in P_g^+ \\ -q_g & \text{if } u \in P_g^- \\ 0 & \text{otherwise} \end{cases}$	Load at node u.
c_{uw}^v	Travel cost for vehicle v between node u and w.
t_{uw}^v	Travel time for vehicle v between node u and w.
s_u	Service time at node u.
$[a_u, b_u]$	Time window for access time to node u.
$[o_u, p_u]$	Time window for the availability of the activity at node u.
l_u	Minimum duration of the activity starting from node u.
Decision Variable	
$X_{uw}^v = \begin{cases} 1 & \text{if arc } uw \text{ is used by vehicle } v \\ 0 & \text{otherwise.} \end{cases}$	Indicator for arc usage by vehicle v.
T_u	Access time to node u.
Y_u^v	Passenger load of vehicle u right after leaving node u.
Z	Objective value

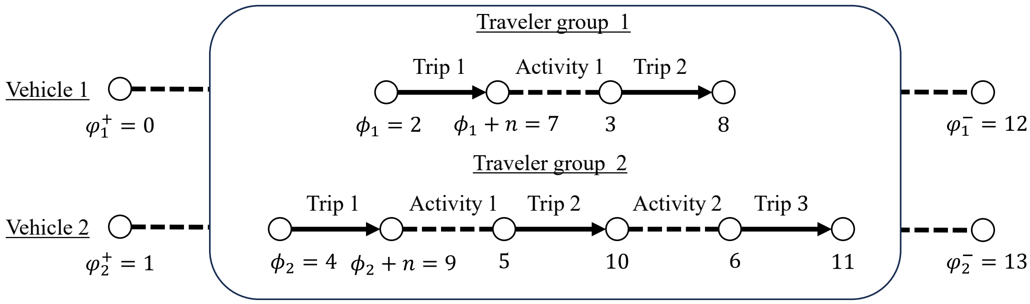

Figure 3.1 Example of Node Indexing

3.3.3 Mathematical Formulation

3.3.3.1 Basic Formulation

Based on the notation introduced in the previous subsection, the mathematical formulation for ABPDP is presented below:

$$\min Z \tag{3.1}$$

subject to

$$\sum_{v \in V} \sum_{w \in P} X_{uw}^{v} = 1 \ \forall u \in P^{+} \tag{3.2}$$

$$\sum_{w \in N} X_{uw}^{v} - \sum_{w \in N} X_{wu}^{v} = 0 \ \forall u \in P, \forall v \in V \tag{3.3}$$

$$\sum_{w \in P^{+}} X_{\varphi_v^+, w}^{v} \leq 1 \ \forall v \in V \tag{3.4}$$

$$\sum_{w \in P^{-}} X_{u, \varphi_v^-}^{v} \leq 1 \ \forall v \in V \tag{3.5}$$

$$\sum_{w \in P^{+}} X_{\varphi_v^+, w}^{v} = \sum_{u \in P^{-}} X_{u, \varphi_v^-}^{v} \ \ \forall v \in V \tag{3.6}$$

$$\sum_{w \in N} X_{uw}^{v} - \sum_{w \in N} X_{u+n, w}^{v} = 0 \ \forall u \in P^{+}, \forall v \in V \tag{3.7}$$

$$T_u + t_{u,u+n} + s_u \le T_{u+n} \; \forall u \in P^+ \tag{3.8}$$

$$X_{uw}^v = 1 \Rightarrow T_u + t_{uw}^v + s_u \le T_w \; \forall u, w \in N, \forall v \in V \tag{3.9}$$

$$a_u \le T_u \le b_u \tag{3.10}$$

$$l_u \le \min\{T_{u+1-n}, p_u\} - \max\{T_u, o_u\} \; \forall u \in P^- \setminus \bigcup_{g \in G} \{\phi_g + n_g + n\} \tag{3.11}$$

$$X_{uw}^v = 1 \Rightarrow Y_w^v = Y_u^v + d_u \; \forall u, w \in N, \forall v \in V \tag{3.12}$$

$$0 \le Y_u^v \le k_v \; \forall u \in P \tag{3.13}$$

$$Y_{\varphi_v^+}^v = Y_{\varphi_v^-}^v = 0 \; \forall v \in V \tag{3.14}$$

$$X_{uw}^v \in \{0,1\}. \tag{3.15}$$

Constraints (3.2) and (3.3) require that only one vehicle serve each pick-up and drop-off node. Constraints (3.4) and (3.5) claim that at most one vehicle can access each vehicle's origin and destination node. Constraint (3.6) requires that dispatched vehicles return to their depots. Constraint (3.7) ensures that the same vehicle serve pick-up and drop-off pairs. Constraint (3.8) states that pick-ups must precede their corresponding drop-off. Constraint (3.9) controls the temporal relationship between two connected nodes, considering the travel time between them, and Constraint (3.10) is the time window constraint. Constraints (3.12) to (3.14) are vehicle capacity constraints that restrict passenger loads not to exceed vehicle capacity.

This formulation is almost the same as the conventional PDPTW, except for Constraint (3.11) that ensures activity duration and consider the temporal availability of the activity. This constraint restricts the temporal relationship between the drop-off and pick-up at the same activity and adds complexity to the conventional PDPTW. Since the drop-off and pick-up at an activity may not be served by a single vehicle, the duration constraint may require coordination between two vehicles. Consequently, Constraint (3.11) is an inter-route constraint and complicates the problem structure.

3.3.3.2 Arc Elimination Constraint

Some pairs of nodes cannot be directly connected. Eliminating the arcs between such node pairs improves the efficiency of problem solving. This elimination is done by fixing the decision variables for such pairs to be zero. We therefore add constraint

$$X_{uw}^{v} = 0 \ \forall (u, w) \in Q_v \ \ \forall v \in V, \tag{3.16}$$

where Q_v is the set of unconnectable node pairs for vehicle v. Q_v includes the arcs that meet the arc elimination criteria (a)-(f) presented in Dumas et al. (1991). Appendix B summarizes the criteria.

In ABPDP, some pairs of the nodes in the same TAP cannot be connected since the nodes in the same TAP must be visited in the fixed order. For example, if a vehicle that picks up a traveler group cannot visit the same group's nodes other than the corresponding drop-off node before dropping them off. Therefore, Q_v additionally includes:

(g) arcs with its tail at a pick-up node and the head at the other pick-up nodes and irrelevant drop-off nodes of the same passenger group: $(u, w)\ \forall u \in P_g^+ \ \forall w \in P_g^+ \cup P_g^- \backslash u + n \ \ \forall g \in G$

(h) arcs with its tail at a drop-off node and the head at the drop-off nodes of the same passenger group: $(u, w)\ \forall u, w \in P_g^- \ \ \forall g \in G$

(i) arcs with its tail at a drop-off node and the head at the previous pick-up nodes of the same passenger group: $(u, w)\ \forall u \in P_g^- \ \forall w \in \{i \in P_g^+ \,|\, i \le u - n\}\ \forall g \in G$.

For the purpose of computational implementation, Q_v further includes:

(j) arcs between the same pick-up and delivery node: $(u, u)\ \forall u \in P$,

(k) arcs between the origin and destination nodes and those of the other vehicles: $(\varphi_v^+, \varphi_{\tilde{v}}^+)$, $(\varphi_v^+, \varphi_{\tilde{v}}^-)$, $(\varphi_v^-, \varphi_{\tilde{v}}^+)$, $(\varphi_v^-, \varphi_{\tilde{v}}^-)$, $(\varphi_{\tilde{v}}^+, \varphi_v^+)$, $(\varphi_{\tilde{v}}^-, \varphi_v^+)$, $(\varphi_{\tilde{v}}^+, \varphi_v^-)$, $(\varphi_{\tilde{v}}^-, \varphi_v^-)$ $\forall \tilde{v} \in V$.

3.3.3.3 Time Window Setting

This subsubsection describes how to derive time windows from the structure of TAPs. We can sequentially derive time windows based on these relationships between the time windows on the activities in the same TAP. We may know the temporal availability of activity u, namely $[o_u, p_u]$ $\forall u \in P^- \setminus \bigcup_{g \in G} \{\phi_g + n_g + n\}$, from the publicly available information on, for example, the business hours of the activity place. However, we furthermore need time window $[a_u, b_u]$ $\forall u \in N$ to constrain pick-up and delivery times. As activity u begins at node u and ends at $u + 1 - n$, $[a_u, b_u]$ stands for the earliest and latest arrival times at the activity, and $[a_{u+1-n}, b_{u+1-n}]$ stands for the earliest and latest departure times from the activity. These time windows may differ, even for the same activity, depending on the sequence of activities in a TAP and passenger's out-of-home time window $[a_{\phi_g}, b_{\phi_g+n_g+n}]$. The earliest arrival to the jth activity in TAP g is at

$$a_{\phi_g+j-1+n} = a_{\phi_g} + \min t^v_{\phi_g,\phi_g+n} + s_{\phi_g} + \sum_{i=1}^{j-1} \min t^v_{\phi_g+i,\phi_g+i+n} + \sum_{i=1}^{j-1} s_{\phi_g+i} + \sum_{i=0}^{j-1} l_{\phi_g+n+i}. \quad (3.17)$$

Below are the meanings of the terms:

- a_{ϕ_g}: the earliest departure time from g's origin
- $\min t^v_{\phi_g,\phi_g+n} + s_{\phi_g} + \sum_{i=1}^{j-1} \min t^v_{\phi_g+i,\phi_g+i+n} + \sum_{i=1}^{j-1} s_{\phi_g+i}$: the sum of the shortest travel time to the activity
- $\sum_{i=0}^{j-1} l_{\phi_g+n+i}$: the sum of the shortest duration of the activities prior to the jth in the TAP.

Also, the latest departure from the jth activity in TAP g is at

$$b_{\phi_g+j} = b_{\phi_g+n_g+n} - s_{\phi_g+n_g} - \sum_{i=j}^{n_g} \min t^v_{\phi_g+i,\phi_g+i+n} - \sum_{i=j+1}^{n_g-1} s_{\phi_g+i} - \sum_{i=j+1}^{n_g-1} l_{\phi_g+n+i}\,. \quad (3.18)$$

Below are the meanings of the terms:

- $b_{\phi_g+n_g+n}$: the latest arrival time at g's destination
- $s_{\phi_g+n_g} + \sum_{i=j}^{n_g} \min t^v_{\phi_g+i,\phi_g+i+n} + \sum_{i=j+1}^{n_g-1} s_{\phi_g+i}$: the sum of the shortest travel time from the activity to the destination
- $\sum_{i=j+1}^{n_g-1} l_{\phi_g+n+i}$: the sum of the shortest duration of the activities after the $(n_g - j)$th in the TAP.

Moreover, we can set $b_u := \min\{b_{u+1-n}, p_u\} - l_u$ because the latest possible arrival to activity u is at the latest time when it is possible to participate in u for its minimum duration. Also, the earliest possible departure from activity u is at the earliest time when a completion of u is possible. That is, $a_{u+1-n} := \max\{a_u, o_u\} + l_u$. We can thus modify time window constraints:

$$T_u \le b_u \Rightarrow T_u \le \min\{b_{u+1-n}, p_u\} - l_u \quad (3.19)$$

$$a_{u+1-n} \le T_{u+1-n} \Rightarrow \max\{a_u, o_u\} + l_u \le T_{u+1-n}. \quad (3.20)$$

This result indicates that T_u is always earlier than $p_u - l_u$ and that T_{u+1-n} is always later than $o_u + l_u$. Consequently, when $T_u < o_u$ or $p_u < T_{u+1-n}$, Constraint (3.11) is satisfied. We thus only need to consider the case that $o_u \le T_u$ and $T_{u+1-n} \le p_u$ or, equivalently, the case that $\max\{T_u, o_u\} = T_u$ and $\min\{T_{u+1-n}, p_u\} = T_{u+1-n}$ to guarantee sufficient activity duration and can replace Constraint (3.11) with

$$l_u \le T_{u+1-n} - T_u \;\forall u \in P^- \setminus \bigcup_{g \in G} \{\phi_g + n_g + n\}. \quad (3.11')$$

3.3.4 Solution Algorithm

3.3.4.1 Set Partitioning Formulation

Since PDPTW is in the class of NP-hard problems, commercial solvers cannot solve its large problem instances. Our problem is intended to be solved for multiple passengers and thus requires an efficient solution algorithm. In line with decomposition methods that are a major approach for large-scale optimization, this research specifically proposes the use of a column generation algorithm.

The column generation algorithm only considers a subset of the decision variables (or columns) of large optimization problems that involve almost an infinite number of decision variables. The column generation algorithm decomposes the problem into a master problem and subproblems. The master problem finds the best feasible linear combination of decision variables. The algorithm uses, rather than considering all the variables, the restricted master problem (RMP) that considers a subset of decision variables. RMP yields an incumbent solution that enables the algorithm to compute dual variables associated with each constraint. Subproblems then try to find unincluded decision variables with negative reduced cost that can be computed based on the dual variables, if the problem is a minimization problem. Since those variables will possibly improve the objective, the RMP includes them and again solves for a better solution. This process continues until it finds no additional variable with negative reduced cost.

To use a column generation algorithm for VRP, it is common to formulate the master problem as a set partitioning formulation. In this formulation, each integer decision variable corresponds to an admissible vehicle route, representing whether the route is used in the solution. The master problem finds a combination of admissible routes that best serve the requests, and the subproblem generates the admissible routes that respect the temporal, spatial, and capacity constraints. We formulate a set partitioning formulation for ABPDP in a similar manner to Dumas et al. (1991). To set up the formulation, we additionally introduce variables shown in Table 3.2. Based on this notation, we formulate the master problem as follows:

$$\min \sum_{r \in R} c_r x_r + \sum_{u \in N} \omega_u T_u \tag{3.21}$$

subject to

$$\sum_{r \in R} \alpha_{ru} x_r = 1 \forall u \in P^+ \tag{3.22}$$

$$\sum_{r \in R_v} x_r \leq 1 \forall v \in V \tag{3.23}$$

$$\sum_{r \in R} \beta_{ruw} x_r = 1 \Rightarrow\ T_u + \sum_{r \in R} t_{ruw} \beta_{ruw} x_r + s_u \leq T_w\ \forall (u, w) \in N \times N \tag{3.24}$$

$$l_u \leq T_{u+1+n} - T_u\ \forall u \in P^- \setminus \bigcup_{g \in G} \{\phi_g + n_g + n\} \tag{3.25}$$

$$a_u \leq T_u \leq b_u\ \forall u \in N \tag{3.26}$$

$$x \in \{0,1\}. \tag{3.27}$$

ABPDP adds temporal Constraints (3.24) through (3.26) to the original set partitioning formulation for PDPTW. Constraint (3.24) ensures that the access times of nodes on route r follow a temporally feasible order. Constraint (3.25) is the activity duration constraint and identical to Constraint (3.11') previously introduced.

For a large VRP, the number of admissible routes is almost infinite. So, we should consider solving RMP. Let $R' \subset R$ and $R'_v \subset R_v$ be subsets of R and of R_v, respectively. We can obtain the RMP of ABPDP by simply replacing R with R' and R_v with R'_v, respectively, in Objective Function (3.21) through Constraint (3.23).

Table 3.2 Notation of Parameters and Variables for the Set Partitioning Formulation

Notation	Meaning
Parameter	
$R_v = \{1, \dots, r, \dots, \lvert R_v \rvert\}$	Set of routes for vehicle v.
$R = \bigcup_{v \in U} R_v$	Set of all the vehicle routes.
c_r	Cost of route r.
ω_u	Relative weight of T_u to the route costs in the objective function.
$\alpha_{ru} = \begin{cases} 1 & \text{if node } u \text{ is in } r \\ 0 & \text{otherwise.} \end{cases}$	Node coverage indicator of route r.
$\beta_{ruw} = \begin{cases} 1 & \text{if arc } uw \text{ is on } r \\ 0 & \text{otherwise.} \end{cases}$	Arc coverage indicator of route r.
$v(r)$	Vehicle using route r.
Υ	Set of vehicle types.
Decision Variable	
$x_r = \begin{cases} 1 & \text{if route } r \text{ is used} \\ 0 & \text{otherwise.} \end{cases}$	Indicator for the usage of route r.

By solving a linear relaxation of the RMP (LRMP), we can obtain the dual variables associated with each constraint. Note that Constraint (3.22) is associated with each pick-up node, while Constraint (3.23) is associated with each arc. We can therefore transfer the dual variables of these constraints to pick-up nodes and arcs. This helps us easily compute the reduced costs of new columns (i.e., routes). Let λ_u and μ_{uw} be the dual variables associated with pick-up node u and arc uw, respectively. Without loss of generality, suppose $\lambda_u = 0\ \forall u \in N \backslash P^+$. The reduced cost of route r is its route cost minus the sum of the dual variables of the nodes and arcs that are included in the route and $\nu_{v(r)}$, a dual variable for the vehicle of the route. That is,

$$\tilde{c}_r = c_r - \sum_{u \in P^+} \alpha_{ru} \lambda_u - \sum_{(u,w) \in N \times N} \beta_{ruw} \mu_{uw} - \nu_{v(r)}. \tag{3.28}$$

If c_r is the sum of the arc costs in route r, $c_r = \sum_{(u,w) \in N \times N} \beta_{ruw} c_{uw}$. We have

$$\tilde{c}_r = \sum_{(u,w) \in N \times N} \beta_{ruw} c_{uw} - \sum_{u \in N} \sum_{w \in N} \beta_{ruw} \lambda_u - \sum_{(u,w) \in N \times N} \beta_{ruw} \mu_{uw} - \nu_{v(r)}$$

$$= \sum_{(u,w)\in N\times N} \beta_{ruw}\, \tilde{c}_{uw} - \nu_{v(r)} = \sum_{(u,w)\in L_r} \tilde{c}_{uw} - \nu_{v(r)}, \qquad (3.28')$$

where $\tilde{c}_{uw} = c_{uw} - \lambda_u - \mu_{uw}$, and L_r is the set of the arcs in route r. This result implies that we can decompose the reduced cost at arc level, except for ν_v.

3.3.4.2 Heuristic

The set partitioning formulation introduced above is only concerned with the master problem, and we moreover need a methodology to solve subproblems or, equivalently, to generate admissible vehicle routes.

Dumas et al. (1991) develop an exact dynamic programing algorithm to solve the subproblems for PDPTW. It is a shortest-path algorithm that extends routes from the origin toward the destination by labeling the nodes and eliminates routes that appear inadmissible or non-dominant during the process. However, the dynamic programing algorithm is time consuming for large problem instances because of the label enumeration procedure.

I instead apply a heuristic approach to solve the subproblems. I use two heuristics and their combination as well. The heuristics transform an initial feasible set of vehicle routes into a better route set. The rest of this subsection introduces the three heuristics.

Heuristic 1: MERGE heuristic

Among many heuristics that generate admissible routes for PTPDW, we first use the heuristic proposed by Xu et al. (2003). Among their two heuristics: MERGE and TWO-PHASE, we use MERGE because the logic of TWO-PHASE does not fit ABPDP. The MERGE algorithm generates a new route by merging a pair of the basis columns of RMP. The rationale of this operation is that merging the basis columns, if successful, will likely generate a new column with a negative reduced cost. Appendix D describes the MERGE algorithm as well as the GENERATE subroutine for MERGE.

Heuristic 2: Local search in the giant-tour representation

Heuristic 1 does not consider inter-route Constraint (3.25) and may be inefficient for ABPDP. To address this issue, we consider a Giant-Tour (GT) representation that handles inter-route constraints (Christofides and Eilon, 1967; Irnich, 2008) (Figure 3.2). This representation combines multiple routes into a single GT, so that we can interpret inter-route constraints as intra-route constraints for the GT. The GT representation works well with existing local search (LS) algorithms that improve incumbent solutions.

I tailor an LS algorithm for ABPDP. This algorithm tries to improve the current solution by applying several operations. A GT is just a sequence of subtours (i.e., vehicle routes), and, in most cases, the number of vehicles used relates to the total cost. Following this rational, this algorithm for prespecified times iterates attempting to reduce the number of subtours involved in the GT. The algorithm examines if repositioning the requests in the first subtour to the other subtour will lead to a better GT. If all the requests in a subtour can be moved to the other subtours, we can eliminate the subtour from the GT.

Given a GT, the algorithm begins with removing one request from the first subtour and tries to find its best possible position in the other subtours. If this repositioning can lead to a better feasible GT than the current one, the current solution will be replaced with the new GT. If repositioning all the requests of the first subtour into other routes fails to find a better GT, the algorithm modifies the current solution by reordering its subtours; specifically, it moves the first subtour to the end of the GT. In this way, the algorithm returns to the beginning of the repositioning process with a new GT, whether it is better than the previous one. Figure 3.3 summarizes the procedure of Heuristics 2.

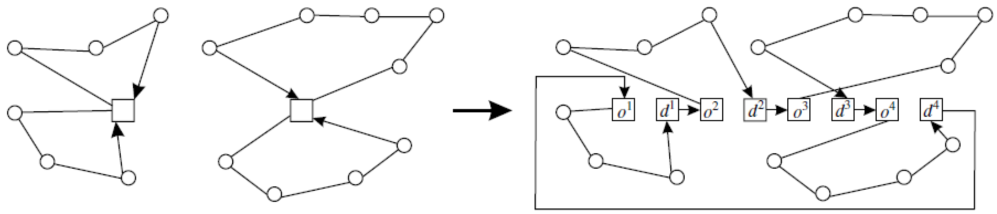

Figure 3.2 Giant-Tour Representation (Irnich, 2008)

GT may be temporally infeasible even if its subtours are individually feasible. The repositioning procedure checks the temporal feasibility of a GT by sequentially determining the node access times of each subtour. The feasibility check iterates over subtours until it confirms the feasibility of GT. For each subtour, this check computes earliest node access times until one of the three conditions is met; it reaches the end of the subtour, it reaches an activity end node whose start time has not yet been determined, or the time is infeasible with respect to its time window. In the first two cases, the check goes to check the next subtour or, if at the end of the GT, returns to the first subtour; otherwise, we determine that the GT in consideration is infeasible.

Heuristic 3: Combination of Heuristics 1 and 2

We find that combining the two heuristics above leads to a better solution. We discuss this in detail later.

3.3.4.3 Solution Algorithm

We develop a solution algorithm for ABPDP by using our heuristics that are based on the column generation algorithm. The basic procedure of the column generation algorithm includes finding an initial solution, iterating adding new columns as well as solving LRMP until no new columns improve the objective, and solving MP to find the best combination of columns

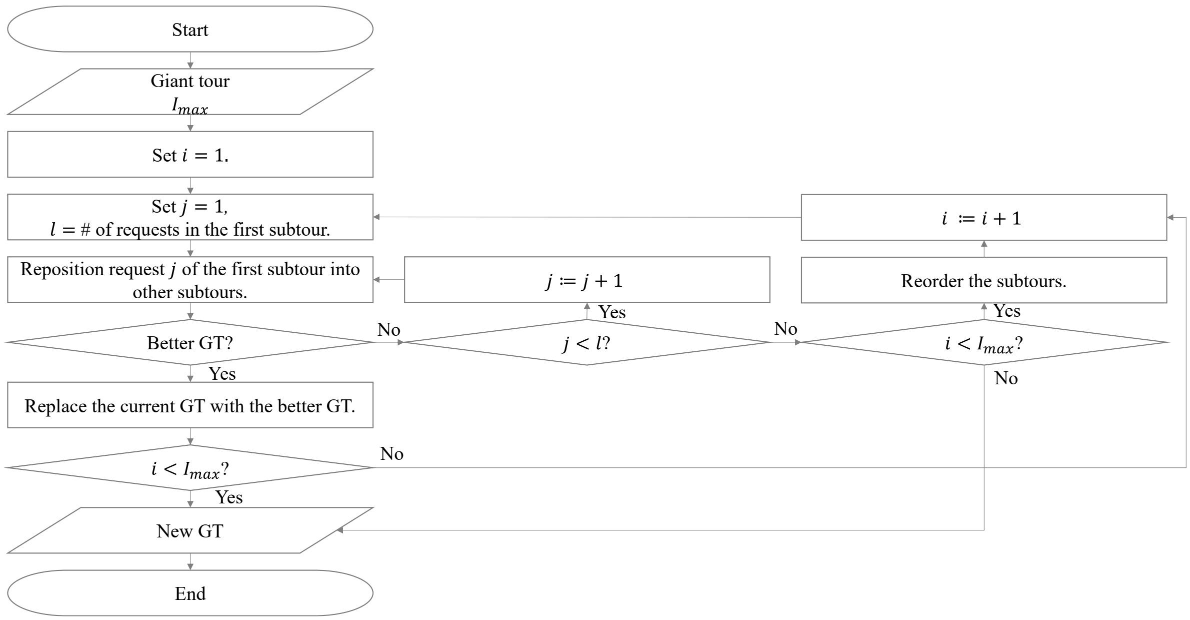

Figure 3.3 Heuristic 2 Flowchart

generated so far. To develop a solution algorithm, we make two modifications to this basic procedure.

First, I consider iterating problem solving with the heuristics because the heuristics produce different solutions depending on the initial solution. I obtain a pool of solutions by iterating problem solving and find the best route set from this pool.

I secondly implement steps to provide good initial feasible solutions that each iteration improves. For the first iteration, we try to reduce the number of routes involved in the initial solution because the number of vehicles in the initial solution affects the efficiency of the heuristics. An effortless way to find a feasible solution is to use the given TAPs, meaning that each vehicle serves only one passenger and trace its TAP as its route, but this way produces excessive vehicles. To provide a smaller initial solution, I add an initialization step that utilizes the MERGE heuristic because the MERGE heuristic does not take long to find inferior but smaller feasible solutions.

For the following iterations, the solution algorithm uses the solution of RMP in the previous iteration. Instead of directly using the solution of RMP, we use split routes as the initial solutions because a less optimal initial solution to the next iteration leads to a different solution. We randomly split each path into two feasible paths, while keeping the order of requests.

Figure 3.4 illustrates the flowchart of the solution algorithm. The algorithm first initializes vehicle routes, given TAPs to serve. Then, it solves the problem using a heuristic to yield a tentative solution, which is pooled. If the algorithm iterates fewer than I_A times, it goes to the next iteration with the tentative solution split as initial routes; otherwise, it ends up finding the best route set from the solution pool as the final solution.

3.4 Computational Experiment

3.4.1 Experimental Settings

3.4.1.1 Problem Instances

To demonstrate solving ABPDP with the solution algorithm we propose, this section conducts computational experiments that evaluate a DRM service in a hypothetical urban setting of a grid road network. The road network of the study area is a 10×10-square-mile Manhattan grid. Intersections are located every 0.5 miles, and, thus, there are 441 nodes in the network.

The vehicle depot of the DRM is located at the central node of the grid network. Out-of-depot time windows are set large enough for all passengers to participate in their activities within opening hours. All the vehicles allow shared rides and have 10-passenger capacity.

I simulate TAPs as travel demand for the DRM service. Travelers participate in activities that are randomly generated with their temporal availability, and minimum duration and location at a network node. They participate in from one to three activities out of 30 distinctive activities.

The order of the activities is determined to minimize the total travel distance of each TAP. The attributes of those activities are randomly drawn from prespecified distributions. Travelers' origin and destination are also at the same randomly selected node as if they depart from and return to the same home. The time horizon for this case study is from 6am to 11pm, but travelers must complete their TAP within their out-of-home time window that is also randomly assigned. I only assume single-passenger groups, meaning that every group size is one. Appendix E details this TAP generation process. I assume that service time for every pick-up and drop-off is 30 seconds (i.e., $s_u = 30\text{s}\ \forall u \in P$).

Finally, I select the hyperparameters of the heuristics and the solution algorithm, say, $M_M = 1000$, $I_G = 3$, $I_{H2} = 100$, and $I_A = 5$.

3.4.1.2 Objective Function

The problem for this experiment is to minimize the total operational cost of DRM: the sum of fixed operational costs, per-mile fuel costs and drivers' wages. The cost of route r is $c_r = \sum_{u\in N}\sum_{w\in N}\beta_{ruw}c_{uw}^{v(r)}$, where $c_{uw}^{v(r)}$ is vehicle $v(r)$'s cost to use arc uw. To decide on the parameter $c_{uw}^{v(r)}$, we assume that the DRM service uses 2025 Ford T350 Vans XL Wagon Medium Roof RWD 148 in California and refer to AAA Your Driving Costs calculator (Automobile Club of Southern California, 2025). Route costs consist of fixed costs and fuel costs that are proportional to route distance. The \$40/vehicle fixed cost is charged on any arcs originating from the vehicle origins. Any arcs with length are charged with \$0.5/mile fuel cost.

We assume that each vehicle has one driver, whose daily wage is proportional to how long the vehicle operates. Since the duration of vehicle v's operation is $T_{\varphi_v^-} - T_{\varphi_v^+}$, the total wage is $\sum_{v\in V}\omega_v\left(T_{\varphi_v^-} - T_{\varphi_v^+}\right)$ where ω_v is the hourly wage for vehicle v's driver. We assume

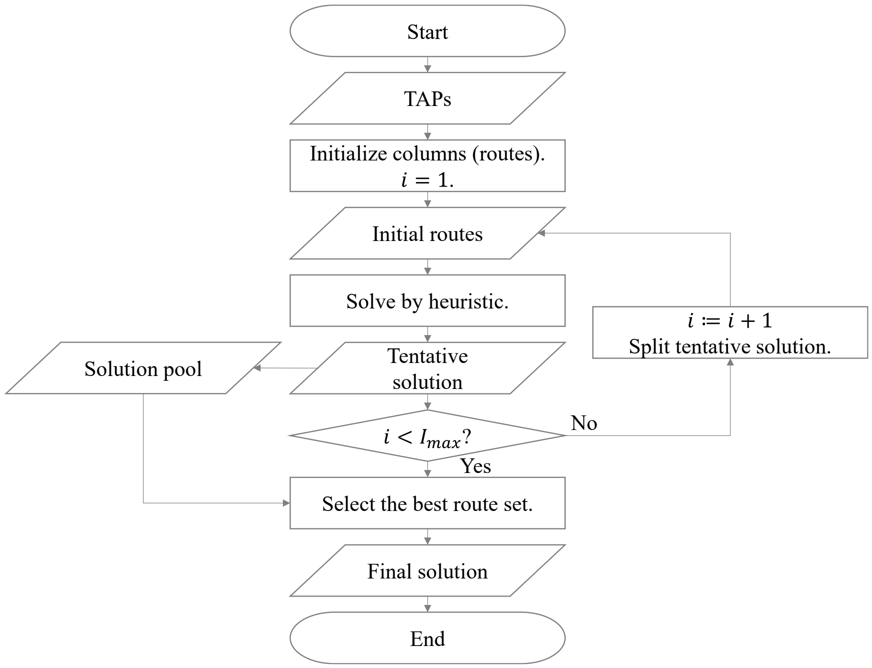

Figure 3.4 Solution Algorithm Flowchart

that drivers' hourly wage ω_v is \$25/hour, considering the driver wage of Orange County Transportation Authority (2025).

3.4.2 Experiment 1

The first experiment demonstrates the necessity of the activity duration constraint in the ABPDP by comparing the solutions with and without the constraint. Specifically, we solve the same problem instances with or without constraint (11) in the formulation introduced in **Error! Reference source not found.**. The latter formulation is equivalent to the conventional PDPTW. For this experiment, we exactly solve the instances by a commercial solver, IBM® Decision Optimization CPLEX® Modeling 22.1.1.0, concerted with Python 3.10. Since this solver cannot solve large problem instances, we limit the instance size to three passengers.

summarizes the results for ten instances. The PDPTW formulation always leads to better objectives; nevertheless, those better results are at the cost of activity duration. In fact, the

PDPTW formulation violates more than 50% of the duration constraints on average. The result of this experiment confirms that consideration on activity

Table 3.3 Comparison of ABPDP and PDPTW

Instance	n	ABPDP Obj. ($)	PDPTW Obj. ($)	# act.	# violated act.
A	6	262.1	241.7	3	3
B	7	316.8	250.2	4	4
C	7	265.7	249.6	4	2
D	8	364.2	335.2	5	3
E	6	268.5	224.9	3	2
F	7	470.6	465.5	4	3
G	8	433.4	412.4	5	2
H	10	446.6	387.6	7	3
I	7	337.1	321.2	4	1
J	7	303.2	295.9	4	1

duration is necessary in keeping the service quality of DRM services that take multiple prebooked requests from the same passenger.

3.4.3 Experiment 2

The second experiment compares the performance of the proposed algorithm with the three heuristics. With each heuristic, this experiment solves ten different problem instances of ten passengers. The performance metrics for this experiment are objective function values and computational time. The algorithm is coded in Cython 3.2.1 in conjunction with the Python-CPLEX combination. I run the code on Dell 16 Plus DB16250 with Intel(R) Core (TM) Ultra 9 288V CPU @ 3.30 GHz and 32 GB RAM. Table 3.4 summarizes the performance metrics of the three heuristics. Heuristic 1 is the fastest among the three in most instances; however, it always obtains a less optimal solution than others. This is perhaps because Heuristics 1 does not consider the inter-route constraint and generated ‘individually’ admissible routes that cannot improve the solution on their own. Heuristics 2 and 3 are comparable, but Heuristic 3 obtains better solutions in 8 out of 10 instances and is faster in 5 out of 10 instances. It is thus more likely that Heuristic 3 yields a better objective function value as fast as Heuristic 2. We only use

Table 3.4 Performance Comparison of the Three Heuristics

Instance	Heuristic 1		Heuristic 2		Heuristic 3	
	Obj. ($)	Time (s)	Obj. ($)	Time (s)	Obj. ($)	Time (s)
A	895.7	69.8	610.8	128.8	544.0	93.0
B	919.9	73.3	791.6	91.9	717.6	111.3
C	1103.3	43.6	831.8	74.8	818.4	79.2
D	1337.6	41.5	906.3	90.5	853.5	72.3
E	1107.2	105.4	890.0	75.1	754.1	77.0
F	1306.8	75.5	1179.1	57.5	1175.0	78.9
G	1266.0	34.6	992.9	83.1	892.1	73.1
H	1410.0	29.1	937.2	87.4	967.8	85.3
I	830.9	40.1	697.2	84.7	709.2	62.4
J	1121.2	27.2	963.1	69.8	948.8	77.4

Heuristic 3 for the following experiments. In Heuristic 3, Heuristic 1 provides a better initial solution to Heuristic 2. We interpret this result as meaning that Heuristic 2 works well if a relatively quality solution is given.

3.4.4 Experiment 3

To see the effect of demand density on the performance of the proposed algorithm as well as the DRM system, this experiment solves problem instances for different numbers of passengers. That is, $|G| = 10, 20, 30$. We accordingly add ten 20-passenger and ten 30-passenger problem instances that are labeled with 20A, 20B, …, 30J. Note that larger instances include smaller instances with the same alphabet label. For example, 30A includes all the travelers in 20A, and 20A includes 10A as well.

Table 3.5 summarizes the numbers of ride requests in the experiment instances. The performance metrics for this experiment consider computational time, empty VMT, operational costs, and VMT reduction. Figure 3.5 plots the metrics and approximate curves for their mean against instance size.

The upper left pane of Figure 3.5 shows that computational time exponentially increases as problem instance size increases. This is understandable because Heuristic 2 improves solutions in a greedy manner that examines every possible position of a request in other subtours. Improving algorithm efficiency as well as coding in other fast languages, such as C/C++, can reduce the computational time.

The upper right pane of Figure 3.5 plots operational costs per request, showing that the cost per request is lower in instances with larger demand density. Although DRM is preferred to fixed-route transit even in lower demand density, it may not be viable when the density is quite low. Figure 3.5 also indicates that the rate of decrease diminishes as the density increases, implying that more travel demand may not significantly improve operational efficiency. Nonetheless, none of the vehicles are fully occupied in all instances. The DRM service can improve efficiency by accepting more passengers with the same TAPs as those already served.

The lower left pane of Figure 3.5 plots the ratios of empty VMT to total VMT. The ratio shows a similar trend to the cost per request, but we do not see a significant reduction in empty VMT from $|G| = 20$ to 30. Additional demand contributes to the improvement in cost effectiveness by fulfilling empty vehicles when demand density is low. We may attribute the further improvement in operational costs to the increase in shared rides when the density is high.

Next, to estimate the potential reduction in VMT by the DRM system, we introduce metrics VMT-DRM and VMT-PV. VMT-DRM is based on the ABPDP solution, while VMT-PV is hypothetical VMT assuming that all TAPs use private vehicles for their trips. For each instance, the difference between VMT-DRM and VMT-PV represents the potential reduction in VMT when all the passengers shift from private vehicles to DRM. The lower right pane of Figure 3.5 plots the ratios of VMT-DRM to VMT-PV. Although the solutions obtained are probably suboptimal, some VMT- DRM/VMT-PV ratios of the 30-passenger instances are lower than one. The result implies that the ratio will likely decline as demand density increases. In other words, a

Table 3.5 Number of Ride Requests in Problem Instances

Instance	$\|G\|$		
	10	20	30
A	21	46	74
B	23	49	70
C	24	51	72
D	27	52	82
E	24	49	77
F	26	48	76
G	27	53	79
H	29	53	78
I	22	48	75
J	26	55	84

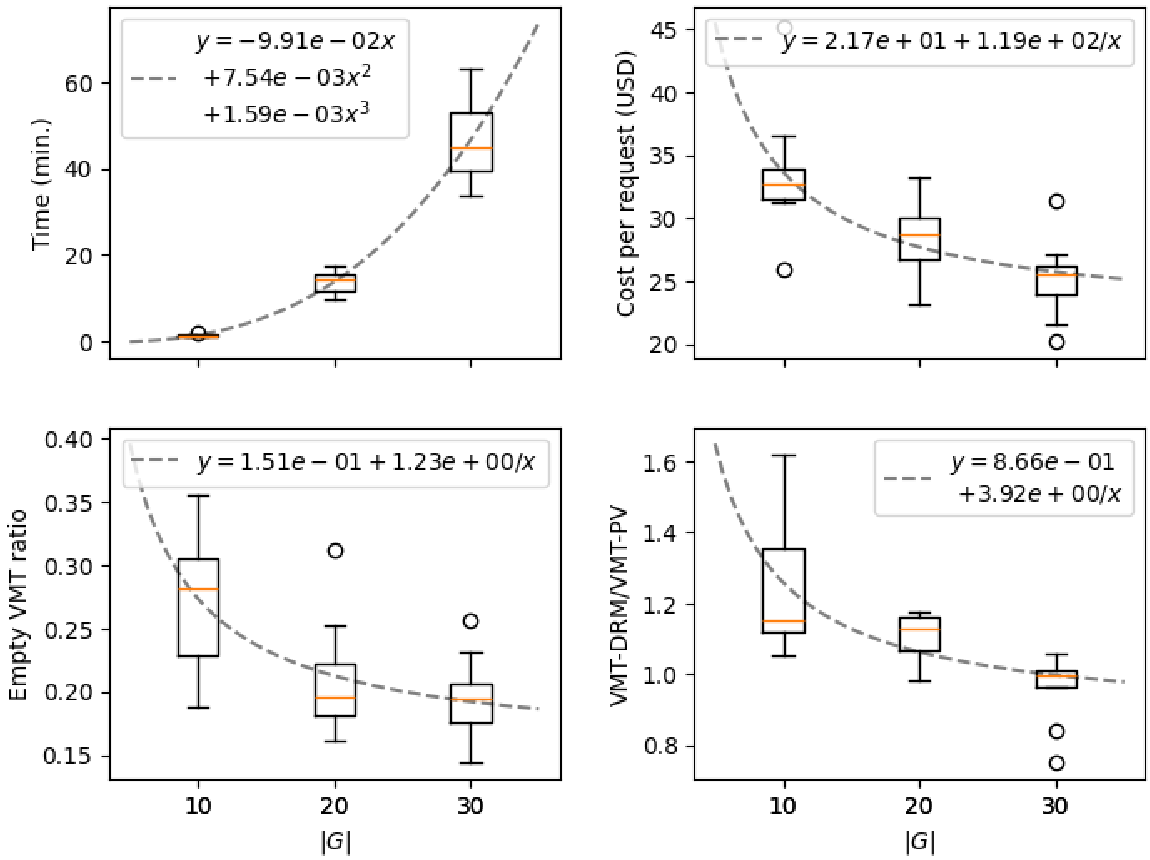

Figure 3.5 Box Plots of Performance Metrics

certain level of demand density is necessary to materialize DRM's VMT reduction effect because the effect of deadheading vehicle trips outweighs the effect of ride sharing when demand level is low.

3.4.5 Experiment 4

The last experiment of this chapter conducts a sensitivity analysis with respect to activity duration. Specifically, we reduce the minimum duration of activities in the synthesized TAPs used in Experiment 3 to 90% and compare the performance metrics, keeping other conditions the same. We use $|G| = 30$ for this experiment. Table 3.6 compares the objective function values and the VMT of the previous experiment (E3) to those of this experiment (E4). Overall, shorter minimum activity duration helps DRM reduce operational costs. Shorter passenger activities help reduce operational hours of DRM service. Additionally, reduction in activity duration increases the temporal flexibility of ride requests and accordingly operational efficiency, as seen in VMT reduction in most instances. Keeping the temporal availability of activities the same, shorter activity duration enables later arrival and/or earlier departure at each activity. These results imply that passenger activity duration can be a control variable for the management of activity-based prebooking DRM systems. To prevent passengers from requesting unnecessarily long activity duration, providing information on moderate activity duration at destination may help efficient such DRM operation.

3.5 Conclusion

3.5.1 Summary

This chapter formulates ABPDP that not only transports passengers' trips but also guarantees their successful activity participation. Since ABPDP adds inter-route activity duration constraints to PDPTW, the chapter also develops a special decomposition solution algorithm that utilizes two heuristics and their combination. To manage the inter-route constraints, one of the heuristics applies a Local Search (LS) algorithm with a Giant Tour (GT) representation. Our methodology can bridge the detailed TAPs forecast by ABTDMs to more reliable vehicle routes.

Table 3.6 Effects of Activity Duration Reduction ($|G| = 30$)

Instance	Obj. ($)			VMT		
	E3	E4	Ratio (E4/E3)	E3	E4	Ratio (E4/E3)
A	1807.9	1702.8	0.94	948	898	0.95
B	1412.5	1431.0	1.01	674	728	1.08
C	1834.8	1773.3	0.97	946	868	0.92
D	2156.7	1790.8	0.83	1040	926	0.89
E	1983.9	1698.6	0.86	1052	870	0.83
F	2382.8	1976.3	0.83	1170	1042	0.89
G	2142.8	1887.7	0.88	1140	1018	0.89
H	1849.8	1667.8	0.90	944	842	0.89
I	1616.3	1606.6	0.99	848	852	1.00

J	2142.4	2082.5	0.97	1162	1070	0.92

While ABTDMs can deal with travelers' complex choice behavior, ABPDP enables consistent vehicle routing by considering activity duration.

Computational experiments demonstrate the application of ABPDP with simulated travel demand on a hypothetical urban network. One experiment demonstrates the importance of activity duration constraint in DRM operation in supporting riders' activity participation. It is shown that combined heuristics work better than individual ones. The proposed methodology is useful in investigating DRM operators' best response to given TAPs. ABPDP can examine the effect of travel demand density on the performance of DRM systems. ABPDP moreover enables planners to evaluate the impact of activity duration on DRM performance, suggesting a potential management strategy regarding activity duration.

I finally remark that ABPDP can furthermore evaluate autonomous/driverless vehicles just by, say, assuming larger initial costs, including those for vehicles, special insurance, and necessary infrastructure, but no wage for drivers. Through computational experiments, I find that drivers' wage accounts for most of the operational cost, autonomous vehicles will improve the economic viability of DRM services in the long run.

3.5.2 Limitation and Future Research Direction

I conclude this chapter by discussing the limitations that the proposed methodology should address toward real-world application. First, the slow computation in large instances indicates that improving the efficiency of the proposed algorithm is critical for its large-scale applications. Since the algorithm is based on a LS algorithm for GT, it should be effective to focus on accelerating the LS algorithm. In particular, techniques to alleviate the evaluation of neighborhoods are helpful. According to Irnich (2008), it is straightforward to augment GT-based LS algorithms with some metaheuristics, such as tabu search (TS), a greedy randomized adaptive search procedure (GRASP), and variable neighborhood search (VNS). He also indicates that some hybrid solution algorithms, such as genetic algorithms, are applicable.

Second, incorporating various operational strategies into the ABPDP framework will help planners devise better operational schemes. ABPDP only considers point-to-point services, whereas some researchers suggest that other operational strategies, such as route-/point-deviation services, improve the operational efficiency of DRM services (Currie and Fournier, 2020; Pan and Shaheen, 2025). In addition, utilizing DRM within multimodal transportation systems can alleviate the inefficiency of DRM. While the smaller vehicles of DRM provide wider spatial coverage but have limited seating capacity, conventional fixed-route transit systems can be more efficient when demand density is high.

Third, travel demand modeling based on real-world data is necessary. Planners must synthesize the population in the study area and model TAP formulation process as well as mode choice behavior. It is also important to explore DRM adoption among the population. If DRM has not yet been introduced in the study area, an additional survey will be required.

Finally, realistic DRM evaluation should capture the supply-demand interaction between vehicle operation and TAP formulation process. Passengers may change their travel behavior according to the LOS that they experience. This will lead to the changes in the demand for and accordingly the operation of the DRM. Modeling this supply-demand equilibration is important in DRM planning.

CHAPTER IV: Chance-Constrained Time Windows

4.1 Introduction

It is crucial for efficient DRM to design vehicle routes and schedules that match travel demand in the service area. VRP is a useful framework to plan optimal vehicle routes and schedules, given a priori spatial and temporal information on trips: passengers' origin and destination locations as well as desired departure and arrival times.

Moreover, the possible ranges, so called time windows, of trip departure and arrival times are essential for the efficiency of vehicle operation. Early papers on VRPs, such as Jaw et al. (1986) and Dumas et al. (1991), report the evident effect of time windows on the objective function of their VRPs. Both conclude that wider time windows lead to better solutions. Quadrifoglio et al. (2008) draw the same conclusion through agent-based simulation. To take advantage of the temporal flexibility of trips, DRM planners have to infer such time windows from the travel behavior in the service area.

Although it is not difficult to collect trip departure/arrival times from historical data, such as travel diary surveys, their possible ranges are often unobservable. Trip departure time (or activity start time) choice modeling is a traditional topic of travel behavior research. However, most of the time choice models are not designed to estimate time windows that VRPs need. In addition, while time windows estimated for each destination are desirable for DRM operation, behavioral information at a specific place is often limited and insufficient for effective estimation.

The goal of this chapter is to answer the following questions: how do we infer reasonable time windows for daily trips from observed travel behavior? What is the appropriate method for this inference even with limited observations? How do time windows differ from one place to another? The approach to answering these questions utilizes the concept of CCP (Charnes and Cooper, 1959) as well as the extreme value theory in statistics. Based on these theories, this chapter estimates time windows from real-world travel behavior observed in the 2022 national household travel survey (NHTS) (Federal Highway Administration, 2022). It moreover compares three methods for population density estimation and investigates their applicability for our time window estimation.

The chapter is organized as follows. The next section reviews existing time-of-day choice models and some relevant methodologies. Section 3 introduces the proposed methodology, and Section 4 describes its application to the NHTS dataset and compares different approaches to population density distribution estimation on a small sample. Section 5 concludes the chapter with future research directions.

4.2 Literature Review

4.2.1 Chance-constrained VRP

I first review the applications of CCP in the context of VRP. Table 4.1 summarizes research works that apply CCP to VRP. Most of them use CCP to deal with stochasticity in demand, travel time, and service time. Recent works by Men et al. (2019) and Zhao and Cao (2020) use CCP to restrict accidental risks of hazardous materials during transportation. Dong et al. (2022) formulate a chance-constrained dial-a-ride problem that considers user preference for demand-responsive transit versus private modes. Li et al. (2024) apply CCP to uncertainty in network capacity and vehicle emission factors. Despite these various applications of CCP to VRP, stochasticity in time window is rarely considered in literature.

Table 4.1 Research on Chance-constrained VRP

Reference	Demand	Travel time	Service time	Accident	Other stochasticity
Stewart & Golden (1983)	x				
Dror et al. (1993)	x				
Miranda and Garrido (2004)	x				
Li et al. (2010)		x	x		
Zhang et al. (2012)		x			
Gounaris et al. (2013)	x				
Zhang et al. (2013)		x	x		
Chen et al. (2014)		x	x		
Beraldi et al. (2015)	x				
Ehmke et al. (2015)		x			
Errico et al. (2016)		x	x		
Gómez et al. (2016)		x	x		
Mendoza et al. (2016)	x				
Miranda and Conceição (2016)		x	x		
Zhang et al. (2016)	x				
Chen et al. (2018)	x				
Dinh et al. (2018)	x				
Errico et al. (2018)			x		
Noorizadegan and Chen (2018)	x				
Men et al. (2019)				x	
Sihombing et al. (2019)	x				
Ghosal and Wiesemann (2020)	x				
Zhao & Cao (2020)				x	
Dong et al. (2022)					Customer preference
Messaoud (2023)		x			
Sluijk et al. (2023)	x				
Li et al. (2024)					Network capacity, carbon emission factors
Su et al. (2024)		x			

4.2.2 Time Choice Model

Estimating travelers' time-of-day choice (e.g. trip departure, trip arrival, and activity start times) provides information on time windows for their trips. We may forecast ride request timings based on the estimation of time-of-day choices. Departure time choice has been well discussed since Vickrey's morning commute problem (Vickrey, 1969), but this subsection focuses on the literature of arrival time, or activity start time choice from the view of the activity-based approach. The main tenet of this approach is that "travel is a demand derived from the demand for activity participation" (McNally & Rindt, 2007). In this regard, travelers choose departure time so that they can arrive at their destination. The information on DRM customers' desired arrival time is thus more meaningful for DRM operators in supporting the customers' successful activity participation.

Econometric discrete choice modeling based on the utility maximization principle is a mainstream approach to replicating rational activity timing choice behavior. Those models assume that travelers decide on trip and activity timings to maximize the utility they perceive from resulting TAPs. As one of the earliest examples, Small (1982) estimates multinomial logit models for work start time choice. He focuses on the choice of the deviation from the official work start time rather than on arbitrary timing. Time-of-day choice is often jointly modeled with other facets of activities, such as duration, location, and transportation mode. Pendyala and Bhat (2004), for example, investigate the relationship between activity duration and timing by examining two differently structured discrete choice models. Moreover, some operational ABTDMs, such as ADAPTS (Auld and Mohammadian, 2009), incorporate activity timing choice. However, regardless of the sophistication in modeling, discrete choice modeling necessarily discretizes the time horizon into a priori intervals. The bounds of activity timing accordingly depend on this assumption of discretization.

Some choice models maintain the continuity of activity timing. Ettema et al. (2007) estimate an activity pattern choice model with a marginal utility function of activity participation.

Integrating the function over a certain time interval gives the utility of the activity participation within the interval. This function helps the choice model capture the continuity of activity timing. Habib et al. (2008) and Habib (2012) apply econometric hazards model to activity start time choice in conjunction with the choices of activity participant, activity duration, and transportation mode.

The utility maximization principle behind activity scheduling leads to a mathematical programming approach to modeling the complex scheduling process. The advantage of this approach is the capability of handling constraints on TAP formulation. Wang (1996) estimates a Weibull distribution function as the time-dependent utility of activity timing and applies integer programming that incorporates the estimated utility function into modeling activity scheduling behavior. The household activity pattern problem (HAPP) models the activity scheduling process through a mixed-integer linear programming, namely the pick-up and delivery problem with time window constraints (Recker, 1995). In this framework, while integer decision variables are concerned with spatial scheduling, continuous decision variables correspond to temporal decisions.

4.2.3 Time window estimation

Although the above models can represent continuous time, they only provide point estimates of choices that do not directly represent time windows. We still need a technique that translates such point estimates to time windows. Research related to HAPP that investigates time windows for travel behavior has been scarce. To apply HAPP to measure the impacts of behavioral changes on vehicle emissions, Recker and Parimi (1999) constructed time window constraints from household travel survey data. To set one's time windows, they use either his/her observed activity start/end times or the sample means. Nevertheless, sample means do not mean the possible latest times. Chow and Recker (2012) estimated goal arrival times at activities as well as relative weights of objective function terms, by using the inverse optimization technique. They assume soft time windows that solutions may violate. Since such violation is penalized based on the deviation from the goal arrival time estimates, their estimates should be regarded as desired arrival time rather than possible time range.

Overall, suitable methodologies for time window estimation are scarce in the literature. The next section proposes a methodology to estimate realistic time windows from observed activity times, rather than a point estimate. In addition, to consider more specific conditions for meaningful estimation, the methodology is designed to be applicable on small samples.

4.3 Methodology

4.3.1 Problem Statement

This chapter is concerned with time windows for activities. I define an activity time window as the earliest and latest times of a period during which an activity is participable. It represents the temporal availability of an activity and relates to the arrival and departure times of trips to and from the activity. The business hours of a facility may determine the time windows for activities performed there. However, time windows even at the same place may differ from person to person. For example, a store owner comes to work earlier than the opening of his/her store and leaves after the store closes, while customers visit during business hours. To infer the activity time window for the former case, it is necessary to use the store owner's behavioral data.

It is noted that, while this chapter estimates activity time windows, time window constraints in VRPs are associated with departure and arrival times. To estimate time windows for departure and arrival times, we must consider activity duration in addition to activity time window. For example, one's latest arrival time at a certain place is equal to the latest activity end time window minus his or her activity duration.

An issue to address is that we must infer latent time windows based on the revealed timings of activities. Moreover, this latency of time windows means their stochasticity. To address the difficulties in handling stochastic time windows, this research employs the concepts of CPP and the extreme value theory in statistics. CPP deals with stochastic constraints by keeping the risk of violating such constraints below a certain level. In other words, CPP enables the solution to satisfy constraints for a certain (usually high) rate of any realization of constraint parameters. In addition, the extreme value theory helps us estimate the unobserved bounds for samples.

In summary, the problem for this research to solve is as follows: given observations of the start and end times of activities with the same purpose, find a time window within which all people can participate in those activities with probability greater than p. The rest of this section describes the problem solution approach to this problem.

4.3.2 Chance-constrained Programming

This subsection introduces the concept of CPP particularly for stochastic constraints. Consider stochastic constraint $g(x) \leq b$, where $g(x)$ is a linear function of decision variable vector x, and b is a random variable. Let Pr $(\cdot)$ denote the probability that the condition in the parentheses is satisfied. CPP imposes chance constraint $\Pr(g(x) \leq b) \geq p$ so that solution x^* to satisfy $g(x^*) \leq b$ at probability p. In other words, x^* satisfies the condition for $100p$% of the realization of b.

The chance constraint is nonlinear, but we can linearize it by considering the cumulative distribution function for b, $F_b(z) = \Pr(b \leq z)$. Hence, we can transform $\Pr(g(x) \leq b) \geq p$;

$$\Pr(g(x) \le b) = 1 - F_b\big(g(x)\big) \ge p$$

$$\Rightarrow F_b\big(g(x)\big) \le 1 - p$$

$$\Rightarrow g(x) \le F_b^{-1}(1 - p), \tag{4.1}$$

where $F_b^{-1}(1-p)$ corresponds to the $100(1-p)$th percentile of b. This corollary means that, if we know the mathematical form of F_b, we can analytically transform the chance constraint into a linear constraint as long as $g(x)$ is linear. For example, if b_j follows a uniform distribution over interval $[0,1]$, constraint $g(x) \le 1 - p$ will guarantee $\Pr(g(x) \le b) \ge p$.

4.3.3 Extreme Value Theory

4.3.3.1 Generalized Extreme Value Distribution

I next examine the distribution of constraint parameters. Let us consider time window constraint $A_u \le T_u \le B_u$, where T_u is a decision variable associated with node u and may indicate either its start or end time. When A_u and B_u are both unobservable random variables, we interpret this time window constraint as chance constraints $\Pr(A_u \le T_u) \ge \alpha$ and $\Pr(T_u \le B_u) \ge \beta$, where α and β are the probabilities that conditions $A_u \le T_u$ and $T_u \le B_u$ are satisfied, respectively. According to the result of the previous subsection, we must estimate the distributions of A_u and B_u to linearize those chance constraints.

For an activity time window, we should consider two nodes representing the start and end of the activity. Let T and $\tilde{T}$ denote decision variables representing the arrival and departure times of a certain activity, respectively. Considering their time windows, $A \le T \le B$ and $\tilde{A} \le \tilde{T} \le \tilde{B}$, estimating the activity time window is equivalent to estimating A and $\widetilde{B}$. Furthermore, let T denote a random variable associated with T and $\boldsymbol{\tau} = \{\tau_1, \dots, \tau_i, \dots, \tau_m\}$ be m observations of T. Similarly, let $\widetilde{\mathrm{T}}$ denote a random variable associated with $\tilde{T}$ and $\tilde{\boldsymbol{\tau}} = \{\tilde{\tau}_1, \dots, \tilde{\tau}_i, \dots, \tilde{\tau}_m\}$ be m observations of $\widetilde{\mathrm{T}}$. The activity time window accordingly corresponds to the lower bound of

T and the upper bound of $\widetilde{\mathrm{T}}$. As we discussed, we can observe $\boldsymbol{\tau}$ and $\tilde{\boldsymbol{\tau}}$ but do not directly observe A and $\widetilde{B}$. Thus, by supposing that $A = \min\{\tau_1, \dots, \tau_i, \dots\}$ and $\tilde{B} = \max\{\tilde{\tau}_1, \dots, \tilde{\tau}_i, \dots\}$, we thus rely on the extreme value theory to estimate the distributions of A and $\tilde{B}$ on $\boldsymbol{\tau}$ and $\tilde{\boldsymbol{\tau}}$.

First, we discuss the distribution of upper bound $\tilde{B}$. Let $\tilde{B}_{(l)} = \max\{\tilde{\tau}_1, \dots, \tilde{\tau}_i, \dots, \tilde{\tau}_l\}$. According to the Fisher–Tippett–Gnedenko theorem (Fisher & Tippett, 1928; Gnedenko, 1943), if $\tilde{\tau}_1, \dots, \tilde{\tau}_i, \dots, \tilde{\tau}_l$ are IID and follow the same probability distribution with a finite variance, the probability distribution function of $\tilde{B}_{(l)}$ for large l converges to a non-degenerate generalized extreme value (GEV) distribution function:

$$F_{\tilde{B}_{(l)}}(t) = \Pr\left(\tilde{B}_{(l)} \le t\right) = \begin{cases} \exp\left\{-\left[1 + \xi_{\tilde{B}_{(l)}}\left(\dfrac{t - \mu_{\tilde{B}_{(l)}}}{\sigma_{\tilde{B}_{(l)}}}\right)\right]^{-\frac{1}{\xi_{\tilde{B}_{(l)}}}}\right\} & \xi_{\tilde{B}_{(l)}} \neq 0 \\ \exp\left\{-\exp\left[-\left(\dfrac{t - \mu_{\tilde{B}_{(l)}}}{\sigma_{\tilde{B}_{(l)}}}\right)\right]\right\} & \xi_{\tilde{B}_{(l)}} = 0 \end{cases}, \qquad (4.2)$$

where $\mu_{\tilde{B}_{(l)}}$ is a location parameter; $\sigma_{\tilde{B}_{(l)}}$ is a scale parameter; and $\xi_{\tilde{B}_{(l)}}$ is a shape parameter. Note that these parameters may depend on block size l, but, for simplicity, we drop subscript l for the rest of the paper. Having $F_{\tilde{B}}(t)$ in a closed form enables us to transform chance constraint $\Pr\left(\tilde{T} \le \tilde{B}\right) \ge \beta$ into a linear constraint:

$$\Pr\left(\tilde{T} \le \tilde{B}\right) \ge \beta \Rightarrow T \le q_{1-\beta}\left(\tilde{B}\right) = \begin{cases} \mu_{\tilde{B}} - \dfrac{\sigma_{\tilde{B}}}{\xi_{\tilde{B}}}\left\{1 - [-\log(1-\beta)]^{-\xi_{\tilde{B}}}\right\} & \xi_{\tilde{B}} \neq 0 \\ \mu_{\tilde{B}} - \sigma_{\tilde{B}} \log(-\log(1-\beta)), & \xi_{\tilde{B}} = 0 \end{cases}, \qquad (4.3)$$

where $q_p(X)$ denotes the p-quantile of random variable X because

$$\Pr\left(T \le \tilde{B}\right) = 1 - \Pr\left(\tilde{B} \le T\right) = 1 - F_{\tilde{B}}(T) = \begin{cases} 1 - \exp\left\{-\left[1 + \xi_{\tilde{B}}\left(\dfrac{T - \mu_{\tilde{B}}}{\sigma_{\tilde{B}}}\right)\right]^{-\frac{1}{\xi_{\tilde{B}}}}\right\}, & \xi_{\tilde{B}} \neq 0 \\ 1 - \exp\left\{-\exp\left[-\left(\dfrac{T - \mu_{\tilde{B}}}{\sigma_{\tilde{B}}}\right)\right]\right\}, & \xi_{\tilde{B}} = 0 \end{cases}. \qquad (4.4)$$

Next, we derive the distribution of lower bound A by utilizing the fact $A = \min\{\tau_1, \dots, \tau_i, \dots\} = -\max\{-\tau_1, \dots, -\tau_i, \dots\}$. Let $\breve{A} = \max\{-\tau_1, \dots, -\tau_i, \dots\}$. Following the same manner as B, we can estimate the GEV distribution function form for $\tilde{a}$:

$$F_{\breve{A}}(t) = \begin{cases} \exp\left\{-\left[1 + \xi_{\breve{A}}\left(\frac{t - \mu_{\breve{A}}}{\sigma_{\breve{A}}}\right)\right]^{-\frac{1}{\xi_{\breve{A}}}}\right\}, & \xi_{\breve{A}} \neq 0 \\ \exp\left\{-\exp\left[-\left(\frac{t - \mu_{\breve{A}}}{\sigma_{\breve{A}}}\right)\right]\right\}, & \xi_{\breve{A}} = 0 \end{cases}. \tag{4.5}$$

Since $\Pr(A \le t) = \Pr(-\breve{A} \le t) = \Pr(\breve{A} \ge -t) = 1 - \Pr(\breve{A} \le -t)$), reversing $F_{\breve{A}}(t)$ around $t = 0$ yields the GEV distribution function for A:

$$F_A(t) = \Pr(A \le t) = \begin{cases} 1 - \exp\left\{-\left[1 - \xi_A\left(\frac{t - \mu_A}{\sigma_A}\right)\right]^{-\frac{1}{\xi_A}}\right\}, & \xi_A \neq 0 \\ 1 - \exp\left[-\exp\left(\frac{t - \mu_A}{\sigma_A}\right)\right], & \xi_A = 0 \end{cases}, \tag{4.6}$$

where $\mu_A = -\mu_{\breve{A}}$, $\sigma_A = \sigma_{\breve{A}}$, $\xi_A = \xi_{\breve{A}}$. This consequently gives us chance constraint

$$\Pr(A \le T) \ge \alpha \Rightarrow T \ge q_\alpha(a) = \begin{cases} \mu_A + \frac{\sigma_A}{\xi_A}\{1 - [-\log(1-\alpha)]^{-\xi_A}\}, & \xi_A \neq 0 \\ \mu_A + \sigma_A \log(-\log(1-\alpha)), & \xi_A = 0 \end{cases}. \tag{4.7}$$

4.3.3.2 GEV Distribution Parameter Estimation

A conventional method to estimate distribution parameters for A and $\tilde{B}$ on observations $\boldsymbol{\tau}$ and $\tilde{\boldsymbol{\tau}}$ involves two tasks: sampling block-extrema (i.e., maxima and minima) and estimating the parameters based on the sampled block-extrema (Coles, 2001). Once we obtain a set of block-extrema, the latter is straightforward by using the maximum likelihood estimation method. This method identifies model parameters that maximize likelihood function given data. Let a_j and $\tilde{b}_j$ denote the minimum and maximum of jth block of $\boldsymbol{\tau}$ and $\tilde{\boldsymbol{\tau}}$, respectively. Also, suppose $\boldsymbol{\tau}$ and $\tilde{\boldsymbol{\tau}}$ are split into n blocks of the same length. Given sample block-minima $a = \{a_1, a_2, \dots, a_n\}$ and sample block-maxima $\tilde{\boldsymbol{b}} = \{\tilde{b}_1, \tilde{b}_2, \dots, \tilde{b}_n\}$, the likelihood functions to be maximized are $\mathcal{L}(\mu_A, \sigma_A, \xi_A) = \prod_{i=1}^{n} f_A(a_i | \mu_A, \sigma_A, \xi_A)$ and $\mathcal{L}(\mu_{\tilde{B}}, \sigma_{\tilde{B}}, \xi_{\tilde{B}}) = \prod_{i=1}^{n} f_{\tilde{B}}(\tilde{b}_i | \mu_{\tilde{B}}, \sigma_{\tilde{B}}, \xi_{\tilde{B}})$, where f_A and $f_{\tilde{B}}$ are the probability density functions for A and $\tilde{B}$, respectively. However, those likelihood functions are hard to maximize. We instead use log-likelihood functions: $\mathcal{LL}(\mu_A, \sigma_A, \xi_A) = \sum_{i=1}^{n} \log f_A(a_i | \mu_A, \sigma_A, \xi_A)$ and $\mathcal{LL}(\mu_{\tilde{B}}, \sigma_{\tilde{B}}, \xi_{\tilde{B}}) = \sum_{i=1}^{n} \log f_{\tilde{B}}(\tilde{b}_i | \mu_{\tilde{B}}, \sigma_{\tilde{B}}, \xi_{\tilde{B}})$. Although there is no analytical solution to the maximization problem of these log-likelihood functions, we can use an existing optimization algorithm to maximize them.

4.3.4 Sampling Block-Extrema

4.3.4.1 Bootstrap sampling

If a given dataset is associated with attributes suitable for blocking, it is easy to find block extrema from the dataset (Coles, 2001). Ideal blocking makes the statistics of the blocks follow the same distributions. Coles (2001) uses as an example yearly blocking for sea level data to cancel its seasonal fluctuation. Nevertheless, the NHTS dataset is not associated with attributes that can group the dataset into appropriate blocks. I then describe how to sample block-extrema from ungrouped observations.

I first consider a case where sample size is sufficiently large. In my case without suitable attributes for blocking, random blocking is one possible way. Random blocking nonetheless creates almost infinite grouping patterns and leads to different parameter estimates, depending on the grouping patterns. I therefore devise a bootstrap method that repeats resampling block-extrema. Specifically, I iterate the random splitting of an observation into, say, n blocks of the same length as well as estimating GEV distribution parameters on the extrema of the blocks, yielding sets of bootstrap parameter estimates. We can then estimate the population parameters of the GEV distribution by averaging those bootstrap parameter estimates. Note that this bootstrap method allows for resampling, meaning that the same datum may be included in multiple bootstrapping samples as a block extreme.

4.3.4.2 Monte Carlo Sampling from Estimated Population Density

Next, I introduce the second approach to sampling block maxima. The bootstrap sampling is only applicable when sample size is large enough to make sufficiently many sizable blocks. An alternative approach for limited sample size is to synthesize sample blocks by using Monte Carlo sampling from an approximate population density estimated on the original dataset. This approach enables us to draw an arbitrary number of samples from the estimated density distribution and to estimate GEV parameters on the extrema of arbitrarily long blocks.

The crucial part of this approach is the estimation of population density distribution. One common way of density estimation is parametric estimation that fits a mathematically well-defined probability distribution function to observations. This estimation requires choosing the mathematical form of distribution that best fits the observation.

Another method is non-parametric estimation that does not require specifying a priori parametric density function. It rather constructs a probability density function directly from the given data. Among several non-parametric methods, this study applies kernel density estimation (KDE) and empirical cumulative density function (ECFD). KDE flexibly estimates the shape of density function for a sample by assigning a kernel density function to each data point. To evaluate the density at a new point, we sum up the values of each kernel function at the new point. The kernel density estimator on n IID observations $\{x_1, \dots, x_n\}$ that are drawn from some univariate distribution is

$$\widehat{f_h}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right), \tag{4.8}$$

where $K(\cdot)$ is the kernel function, and h is the bandwidth. I use the Gaussian kernel $K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}}$ and select bandwidth h by Silverman's rule (Silverman, 1998).

ECDF evaluates the value of cumulative distribution function by computing the fraction of observations that are less than or equal to a given number. The ECDF for the same IID sample $\{x_1, \dots, x_n\}$ is

$$\hat{F}(x) = \frac{1}{n} |\{i | x_i \leq x\}|, \tag{4.9}$$

where $|\{i | x_i \leq x\}|$ represents the number of samples smaller than or equal to x. Since this is a stepwise function, its inverse function only takes a finite number of values. To implement Monte Carlo simulation, I use the interpolated version of ECDF. Let $\{y_1, \dots, y_n\}$, where $y_1 \leq y_2 \leq \cdots \leq y_n$, be an ordered set of $\{x_1, \dots, x_n\}$. The interpolated ECDF is then

$$\hat{F}(x) = \begin{cases} 0 & x < y_i \\ \frac{1}{n-1}\left[i - 1 + \frac{(x - y_i)}{(y_{i+1} - y_i)}\right] & y_i \leq x \leq y_{i+1}. \\ 1 & y_n \leq x \end{cases} \tag{4.10}$$

In addition, to sample $\tilde{x}$ from the interpolated ECDF, we can use the inverse CDF method:

1. Draw $r \sim U(0,1)$;
2. Set $i = \lceil (n-1)r \rceil$;
3. Return $\tilde{x} = y + (n-1)(y_{i+1} - y_i)\left(r - \frac{i-1}{n-1}\right)$.

Synthesized samples from the three estimation methods show different properties and will lead to different estimates of GEV distribution parameters even on the same dataset. The next section conducts numerical experiments to compare the GEV distribution parameter estimates obtained via the three estimation methods to those from the bootstrap sampling method.

4.4 Experiment

4.4.1 NHTS data

4.4.1.1 Data Description

This section experiments with the proposed methodology on the 2022 NHTS dataset. The dataset contains 31,074 trips of 16,997 individuals in 7,893 households. Its data collection period spans from January 2022 to January 2023. The NHTS dataset provides information on people's daily TAPs as each household reports its members' daily sequence of trips, so called trip chain, on a certain survey day during the data collection period.

To demonstrate the methodology presented above, I analyze time windows for work activities at workplace. Since work is the most frequent activity purpose in the dataset, I can use enough samples to use the conventional GEV distribution estimation method.

4.4.1.2 Data Preprocessing

I preprocess the dataset to select data appropriate for the analysis. The rest of this subsection describes the data preprocessing procedure. I first filter out inappropriate records on the basis of the daily trip chain for each individual. This filtering excludes spatially disconnected trip chains that contain two successive trips that are not connected at the same place. Since the NHTS dataset does not reveal the exact locations of trip origin and destination, I determine the connectivity of trips based on the attributes of trip origin and destination. Specifically, I refer to the activity purposes at the destination and origin as well as the socio-demographic attributes, such as population density category, of the destination and origin. Second, since my analysis is only concerned with TAPs that do not involve an out-of-home overnight stay, I drop trip chains that either begin or end away from home. I assume that such individuals stay away from home before or after the survey day or fail to report departure or arrival home. I thirdly exclude trip chains that have any trip with multiple participants from the same household. This exclusion intends to avoid doubly counting the joint trips in the same household. Fourth, I only use trip chains that belong to individuals with employment status to focus on the start and end times of work at workplace. I require those trip chains to have one or more non-zero duration activities of "work at a non-home location" purpose. Lastly, to focus on work activities at regular workplace, I only use trip chains that either start or end their work activity of the day at workplace. For this filtering, I require that such work activities be performed at a place with the same attributes of individuals' regular workplace reported in the NHTS dataset.

Through the filtering above, I finally identify 1,875 valid trip chains that begin working at workplace and 1,854 trip chains that end working at workplace. Note that their numbers are different because some trip chains do not start or end working at workplace. **Error! Reference source not found.**Table 4.1 and

summarize the start and end times of the work activities at workplace. The start time distribution skews to right, while the distribution of the end times is almost symmetric but with slightly more samples in the right tail. In addition, I observe that the NHTS dataset seems to be truncated at 4 am because all the trips in the original NHTS dataset depart no earlier than 4 am.

4.4.2 Bootstrap Sampling of Block-maxima via Random Blocking

We are interested in the earliest work start time and the latest work end time and thus estimate GEV distributions for the block minimum of work start time and the block maximum of the work end time. This subsection uses the conventional method described in 4.3.4.1. I split the trip chains into random blocks of the same lengths: $l = 25$, 50, 100, and 200. For each block length, I obtain 1,000 bootstrap samples by randomly partitioning the datasets and accordingly estimate 1,000 different parameter sets. Note that I only use the block-extrema of l-long blocks

Table 4.2 Summary Statistics of Work Activity Start and End Times

	n	Mean	Std.	Min	Q1	Median	Q3	Max
Start time	1875	8.51	2.45	4.20	7.08	8.00	9.00	22.00
End time	1854	16.92	2.39	5.25	15.67	17.00	18.00	27.25

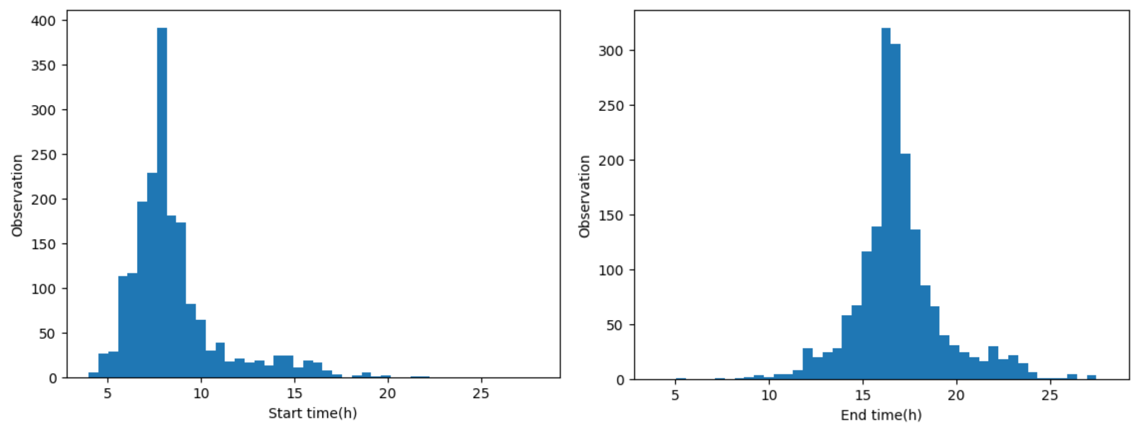

Figure 4.1 Histograms of Work Activity Start and End Times

for estimation and discard one surplus block. For example, a bootstrap sample that corresponds to 100-long block contains 18 block-extrema.

I first estimate the GEV distribution, assuming shape parameter $\xi \neq 0$. I code the estimation procedure in Python and use statistical functions (i.e., scipy.stats) in the Scipy package (Virtanen et al., 2020) for the maximum likelihood estimation. **Error! Reference source not found.**Table 4.3 summarizes the means and the standard deviations of estimates for each l. The distribution shifts earlier with large worker group size. This result is intuitive because larger groups contain more diverse start times than small groups. $\hat{\xi}_A$ is negative for all l, implying that the block-minimum of the work start time follows the reversed Weibull distribution.

On the other hand, as in Table 4.4, the bootstrap variance of $\hat{\xi}_{\tilde{B}}$ is too large to conclude that $\xi_{\tilde{B}}$ is statistically significantly different from zero. Moreover, the estimation for end time sometimes fails when l =200 due to the insufficient sample size. I thus assume $\xi_{\tilde{B}} = 0$ and,

Table 4.3 GEV Distribution Parameters for Earliest Work Start Time by Conventional Method ($\xi \neq 0$)

		$\hat{\mu}_A$		$\hat{\sigma}_A$		$\hat{\xi}_A$	
l	n	Mean	Std.	Mean	Std.	Mean	Std.
25	72	5.60	0.04	0.58	0.05	-0.30	0.07
50	36	5.19	0.05	0.51	0.04	-0.45	0.07
100	18	4.86	0.06	0.40	0.07	-0.54	0.14
200	9	4.60	0.07	0.29	0.09	-0.57	0.87

Table 4.4 GEV Distribution Parameters for Latest Work End Time by Conventional Method ($\xi \neq 0$)

		$\hat{\mu}_{\tilde{B}}$		$\hat{\sigma}_{\tilde{B}}$		$\hat{\xi}_{\tilde{B}}$	
l	n	Mean	Std.	Mean	Std.	Mean	Std.
25	70	22.01	0.13	1.82	0.12	-0.23	0.03
50	35	23.09	0.12	1.39	0.22	-0.11	0.12
100	17	23.91	0.26	1.16	0.29	0.09	0.47
200	8	-	-	-	-	-	-

furthermore, that the block maximum of work end time follows the Gumbel distribution.

According to the results above, I next estimate parameters for the Gumbel distribution on the same bootstrap samples of the work activity end time. Table 4.5 summarizes the means and standard deviations of $\hat{\mu}_{\tilde{B}}$ and $\hat{\sigma}_{\tilde{B}}$ for each l. This result implies that the maximum of longer blocks will likely be larger than those of short blocks. The standard deviations of $\hat{\mu}_{\tilde{B}}$ and $\hat{\sigma}_{\tilde{B}}$ become greater as l increases because we have fewer blocks for large block sizes.

I presume that those estimates of GEV distribution parameter via the conventional method best represent the population parameter. The next subsection uses them as a benchmark to select a population density estimation method.

Those bootstrap means of parameters enable us to estimate the chance-constrained time window on work activity at workplace:

$$\hat{a}_\alpha = \hat{\mu}_A + \frac{\hat{\sigma}_A}{\hat{\xi}_A}\left\{1 - [-\log(1-\alpha)]^{-\hat{\xi}_A}\right\}, \tag{4.11}$$

I suppose $\alpha = \beta = 0.95$, meaning that randomly selected l workers start and end working within

Table 4.5 Gumbel Distribution Parameters for Latest Work End Time by Conventional Method

		$\hat{\mu}_{\tilde{B}}$		$\hat{\sigma}_{\tilde{B}}$	
l	n	Mean	Std.	Mean	Std.
25	70	21.78	0.15	1.80	0.12
50	35	22.99	0.16	1.39	0.21
100	17	23.92	0.17	1.20	0.15
200	8	24.82	0.29	1.25	0.13

$$\hat{b}_\beta = \hat{\mu}_{\tilde{B}} - \hat{\sigma}_{\tilde{B}} \log(-\log(1-\beta)). \tag{4.12}$$

the estimated time window at 95% of probability. Table 4.6 reports the chance-constrained time windows $[\hat{a}_{0.95}, \hat{b}_{0.95}]$ for each l. These chance-constrained time windows on work activity may inform the operational hours of a transportation service for a certain worker group. For example, operating transportation service from 5:27 am to 10:37 pm will be early and late enough for 100 workers to commute to workplace with 95% probability. Expectedly, the longer l is, the wider the time window should be.

4.4.3 Monte Carlo Sampling of Block-maxima from Estimated Distribution

For more meaningful time window estimation in a situation with more specific but limited information, our second approach aims to estimate extreme value distribution even when sample size is small. This approach is based on a Monte Carlo simulation that samples block-maxima from a population density distribution estimated on the sample. Critical for this approach is the estimation of the population distribution. This subsection examines different estimation methods including both parametric and nonparametric techniques.

We compare a parametric estimation method to two nonparametric estimation methods: KDE with Gaussian kernel and interpolated ECDF. For candidate parametric distributions to fit, we consider positive-valued distributions, namely, log-normal, gamma, and Weibull, as well as the normal distribution. For both datasets, we select a log-normal distribution

Table 4.6 Chance-constrained Time Window Estimates for Work Activity by Conventional Method

	$\hat{a}_{0.95}$		$\hat{b}_{0.95}$	
l	Mean	Std.	Mean	Std.
25	6.74	0.08	19.81	0.26
50	6.04	0.11	21.47	0.37
100	5.44	0.11	22.61	0.26
200	-	-	23.45	0.35

$$\hat{f}(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{log\, x - \mu}{\sigma}\right), \tag{4.12}$$

where μ and σ are location and scale parameters. respectively.

To choose the estimation method that best helps GEV distribution estimation on a small sample, I conduct another bootstrap experiment. This experiment takes 1,000 subsamples with replacement from the original dataset. Moreover, I experiment with different resampling rates among 0.05, 0.10, 0.25, and 0.50 and fix block size $l = 100$. For each subsample, the experiment repeats following steps: estimating three distributions on the subsample, generating three sets of block-maxima from them, and finally estimate GEV distribution parameters on the three block-maxima sets. For each density estimation method and each resampling rate, I obtain 1,000 bootstrap estimates of GEV distribution parameters.

Table 4.7 summarizes the parameter estimates. The estimates through the parametric estimation are biased even for a large sample size probably because the parametric method fails to capture the tail shape of the population distribution. Both nonparametric methods have their estimates approach the benchmark parameters obtained by the conventional method, as the resampling rate increases. The KDE-based method tends to overestimate shape parameter ξ_s, while the ECDF-based method underestimates it. Regarding other parameters, the bootstrap means found via the KDE method are closer than those from the ECDF method when the subsample size is small,

Table 4.7 GEV Distribution Parameter Estimates for Work Activity Start and End Times by Proposed Method ($l = 100$)

Method	Resampling Rate	$\hat{\mu}_A$		$\hat{\sigma}_A$		$\hat{\xi}_A$		$\hat{\mu}_{\tilde{B}}$		$\hat{\sigma}_{\tilde{B}}$	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Parametric (log-normal)	.05	2.87	0.53	0.88	0.11	-0.08	0.00	22.89	0.87	1.07	0.22
	.10	2.85	0.37	0.89	0.07	-0.08	0.00	22.83	0.60	1.04	0.15
	.25	2.82	0.22	0.89	0.04	-0.08	0.00	22.80	0.34	1.02	0.09
	.50	2.82	0.12	0.89	0.02	-0.08	0.00	22.78	0.20	1.00	0.05
KDE (Gaussian)	.05	4.84	0.30	0.40	0.09	-0.25	0.05	23.72	0.97	1.05	0.48
	.10	4.83	0.21	0.41	0.07	-0.26	0.05	23.82	0.70	1.16	0.41
	.25	4.86	0.13	0.42	0.05	-0.29	0.05	23.89	0.43	1.22	0.26
	.50	4.86	0.08	0.42	0.03	-0.31	0.04	23.90	0.25	1.24	0.17
Interpolated ECDF	.05	5.12	0.35	0.26	0.13	-0.92	0.34	23.21	0.87	0.87	0.36
	.10	4.98	0.26	0.31	0.11	-0.86	0.37	23.45	0.62	0.96	0.32
	.25	4.91	0.15	0.38	0.09	-0.77	0.26	23.69	0.40	1.07	0.25
	.50	4.89	0.09	0.39	0.05	-0.63	0.15	23.78	0.24	1.14	0.16
Conventional		4.87	0.06	0.42	0.07	-0.57	0.14	23.92	0.17	1.20	0.15

implying that the KDE method is less biased than the ECDF method. I suspect that this is because the maximum of the draw from the ECDF method is bound up to the subsample maximum, while that from the KDE method is unbounded with the Gaussian kernel. KDE with Gaussian kernel extrapolates subsamples, while the original dataset is truncated at 4am. Considering the bootstrap standard deviations of $\hat{\mu}_{\tilde{B}}$ and $\hat{\sigma}_{\tilde{B}}$, estimates via the KDE method are less efficient with a small sample than ECDF, but their efficiency improves with large samples. I conclude that, on the same sample, the KDE method can approximate population block-maxima the best among the three density estimation methods.

We can estimate chance-constrained time windows on a small (unbiased) sample. Here, I demonstrate the KDE-based estimation of chance-constrained time windows. I also use probabilities $\alpha = \beta = 0.95$. Table 4.8 shows the bootstrap means and standard deviation of the chance-constrained time windows. Regardless of the subsample rate, the means of $\hat{A}_{0.95}$ and $\hat{\tilde{B}}_{0.95}$ are fairly close to those by the conventional method. The standard deviations

Table 4.8 Chance-constrained Time Window Estimates for Work Activity by the Proposed Method with Gaussian Kernel KDE

Sampling	$\hat{A}_{0.95}$		$\hat{\tilde{B}}_{0.95}$	
rate	Mean	Std.	Mean	Std.
0.05	5.35	0.27	22.57	0.81
0.10	5.36	0.20	22.54	0.53
0.25	5.40	0.13	22.56	0.30
0.50	5.41	0.08	22.55	0.17

imply that using more than 25% of the dataset can have estimates comparably efficient to the conventional method.

4.4.4 Experiment on Conditioned Dataset

For more meaningful estimation, we should analyze a more specifically conditioned dataset. Although conditioning may only avail us of a small dataset, we can apply the proposed methodology to estimate GEV distributions for the data. I demonstrate this application by analyzing how workplace locations affect chance-constrained time windows for work activities. I split the two datasets into five groups, based on the NHTS's urban/rural indicator for the census blocks. The five categories include rural, small town, second city, suburban, and urban areas. Table 4.9 summarizes the minimum/maximum and some of the quantiles for each category.

For the estimation on those conditioned datasets, I again use $l = 100$ for block size and probabilities $\alpha = \beta = 0.95$. Table 4.10 summarizes the estimates for each census category. The result implies that urban areas, except for suburban areas, tend to have chance-constrained time windows later than rural areas. This difference perhaps reflects different types of jobs available in the census block categories. We can see that, while $\hat{A}_{0.95}$ seems to relate to its quantiles, we do not observe that $\hat{\tilde{B}}_{0.95}$ systematically relates to those common statistics. This prevents us from inferring chance constraints from simple statistics.

Table 4.9 Extrema and Quantiles of Conditioned Work Start and End Times at Workplace

Census block	Start time					End time				
category	n	Min.	$q_{0.01}$	$q_{0.05}$	Med.	n	Med.	$q_{0.95}$	$q_{0.99}$	Max.
Rural	235	4.30	4.78	5.50	7.75	234	16.67	21.12	22.83	25.42
Small Town	426	4.33	4.57	5.75	7.75	416	16.75	22.00	23.69	27.00
Second City	371	4.58	5.31	6.00	8.08	367	17.00	22.60	23.50	25.17
Suburban	578	4.50	4.93	5.67	7.98	577	17.00	21.37	23.44	27.25
Urban	265	4.20	5.89	6.29	8.37	260	17.00	21.52	25.12	26.25

Table 4.10 GEV Distribution Parameter and Chance-constrained Time Window Estimates for the Conditioned Data

Census block	Start time				End time		
category	$\hat{\mu}_A$	$\hat{\sigma}_A$	$\hat{\xi}_A$	$\hat{A}_{0.95}$	$\hat{\mu}_{\tilde{B}}$	$\hat{\sigma}_{\tilde{B}}$	$\hat{\tilde{B}}_{0.95}$
Rural	4.61	0.36	0.36	4.94	23.26	1.01	22.16
Small Town	4.62	0.41	0.41	4.98	23.79	0.99	22.71
Second City	5.19	0.45	0.45	5.58	23.80	0.69	23.05
Suburban	4.89	0.34	0.34	5.21	23.67	1.58	21.94
Urban	5.50	0.52	0.52	5.94	24.83	1.48	23.20

4.5 Conclusion

This chapter develops a methodology to infer time windows for activities, based on the concept of chance-constrained programming (CCP) as well as the extreme value theory. This methodology uses a bootstrap sampling of block extrema to estimate the generalized extreme value distribution on an ungrouped dataset. Since this methodology requires large sample size, this chapter moreover proposes and evaluates an alternative estimation methodology that is applicable to small datasets. The alternative estimation methodology is three-fold: it first estimates population distribution, estimates extreme value distribution on block-extrema generated by Monte Carlo simulation, and computes the quantiles of the estimated extreme value distribution for the chance-constrained time window.

The chapter demonstrates the methodologies on the national household travel survey (NHTS) dataset and finds that using the kernel density estimation in the first step of the alternative methodology leads to better estimates than using parametric estimation and empirical cumulative density function (ECDF). Lastly, the chapter applies the alternative estimation method to small datasets conditioned by census block category and shows the differences of possible work start and end times among the categories.

One limitation of this chapter is concerned with the dataset. This chapter uses the NHTS data for the purpose of demonstration. However, the NHTS dataset merely provides general information on the travel behavior of the US residents, whereas a real-world DRM operation requires more specific time windows for each passenger and/or origin/destination. Therefore, for more practically meaningful time windows, we should consider more conditioned samples, for example, of the same purpose and at a particular place. In addition, the NHTS dataset is truncated at 4 am, which might bias the result particularly for activity start times. Extrapolation outside the truncation may be necessary for more accurate estimation.

Finally, the proposed methodology requires specifying several hyperparameters, such as block size, population density estimation method, and the choice of kernel for KDE. In our case study, KDE with Gaussian kernel works the best due to the extrapolating effect of the Gaussian KDE. However, if the data has a bounded support, it may be more reasonable to use KDE with another kernel or ECDF for population density estimation. It is necessary to investigate the generalizability of the proposed methodology on different datasets.

CHAPTER V: Evaluation of Proactive Activity Management Strategies with GPS Trajectories

5.1 Introduction

The goal of this chapter is to demonstrate the feasibility of the evaluation framework proposed in the previous two chapters and to explore proactive activity management strategies that improve the viability of DRM services. The chapter conducts a case study with real-world travel-activity data in the context of a feeder service for long-distance travelers in Japan, expecting that such a feeder service will help long-distance travelers shift from air/car to rail and furthermore reduce the environmental impacts from the transportation sector.

Long-distance travel is supposed to be more impactful on the environment than daily travel (Wadud et al., 2024), while many decarbonization measures in the transportation sector focus on daily short-distance travel in urban transportation systems. In addition, railways have the lowest GHG emission per passenger mile among several transportation modes (Congressional Budget Office, 2022).

However, rail systems have limited reach to travelers' ultimate origin and destination. Since trains can only stop at stations, passengers must walk or take other modes to fill the gaps between their trip endpoints and stations. This so-called last-mile problem requires that rail transportation be supplemented by feeder transportation systems to enable its passengers to complete their trips. As Yao and Morikawa (2005) show, access and egress times are an important factor for mode choice in linehaul trips. Reliable feeder services are necessary in supporting long-distance rail systems.

Moreover, feeder transportation for long-distance travel relies on local transportation systems around stations. However, the labor shortages in Japan, due to the rapidly aging and declining population, force many public transit operators, even taxi companies, to cut down on their services and raise the concern about the sustainability of those local transportation systems. The declines in local transportation systems negatively affect linehaul rail ridership in long-distance travel and may have nationwide effects on the environmental impacts.

This chapter needs to address an additional methodological challenge regarding data collection in rural areas. The application of methodologies proposed in the previous chapters to a real-world transportation system requires detailed information on TAPs. Travel diary surveys are a common way to obtain such information but are seldom conducted in rural areas due to their high cost. In addition, regional travel diary surveys often exclude visitors to their survey areas.

To overcome the limitation of behavioral data, this research uses GPS trajectory data from smartphone apps. GPS trajectory datasets provide a large amount of high-resolution behavioral information without relying on people's memory. Moreover, samples from these datasets are not restricted to a particular area and cover diverse market segments. The research also presents a procedure to analyze raw GPS trajectories with many tracking errors and insufficient attributes.

The chapter first introduces the long-distance transportation systems in Japan and the study area. It then describes the trajectory dataset as well as a data preprocessing procedure to obtain TAP data from the trajectory data. It finally conducts a case study on the TAP data and evaluates activity management strategies.

5.2 Background Information

5.2.1 Long-distance Transportation Systems in Japan

Japan has well-established transportation systems for long-distance travel. Besides air transportation, car expressways and high-speed rail (Shinkansen) networks are the primary long-distance surface transportation systems. Those transportation systems have helped Japan's economic development by connecting not only metropolitan cities but also small towns. The Shinkansen network is unifocal on the Tokyo metropolitan area, since the majority of long-distance travel is from or to the most populated Tokyo area. While the Tokyo area has highly developed public transit systems, rural Shinkansen stations often lack sufficient feeder services. Since both access and egress of trips are equally important in linehaul mode choice, more efforts to maintain rural feeder transportation systems are needed to maintain the Shinkansen ridership between Tokyo and the rural areas. It is thus important to sustain the local transportation systems for long-distance rail services.

5.2.2 Study Area

The study area for this research is Karuizawa town in Nagano Prefecture, Japan. The town is located about 130km (≅ 80 miles) away from the Tokyo center and has a station on the Hokuriku Shinkansen line. Shinkansen is therefore one of the major transportation modes to visit the town from Tokyo in addition to private vehicles and buses. It takes less than one and half hours from Tokyo to Karuizawa on most Shinkansen trains; this accessibility, in conjunction with other tourism attractions, makes the town a popular tourist destination.

The population of Karuizawa town is approximately 19,000, according to the 2020 Population Census of Japan (Ministry of Internal Affairs and Communications Statistics Bureau, 2020). The daily average number of Shinkansen passengers who boarded at Karuizawa station is about 3,500, with about 600 commuter pass holders, in 2019. (East Japan Railway Company, n.d.) Moreover, the town has about 16,000 private vacation villas for temporary stays (Town of Karuizawa, n.d.). These figures are comparable with the resident population and highlight the

Figure 5.1 Location of Karuizawa Town (JR East, n.d.)

fact that a large portion of the travelers in the area are visitors. The DRM planning must take into account this unignorable number of visitors.

5.3 Data and Preprocessing

5.3.1 Agoop Data

This research utilizes a GPS trajectory dataset collected through smartphone apps by AGOOP Corp. (n.d.). The trajectories of the dataset consist of timestamped and geo-coordinated points and represent app users' travel behavior. Figure 5.2 displays an example plot of a trajectory. The apps automatically track the users who permit tracking. However, it is noted that, for the purpose of privacy protection, this dataset disjoints the multi-day trajectory of the same user into daily trajectories. In other words, several daily trajectories in the dataset may belong to the same users.

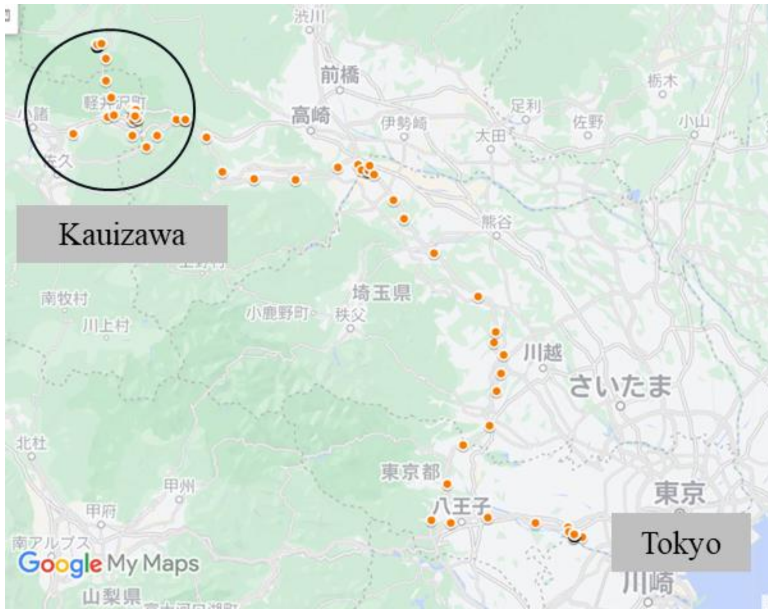

Figure 5.2 Example Plot of a Trajectory

The case study of this chapter evaluates a DRM service for Shinkansen passengers who use Karuizawa station. Since most Shinkansen passengers are long-distance visitors to the study area, the case study only uses the trajectories of visitors. Moreover, it focuses on one-day round trip travelers because their home locations are easier to infer. The following data preprocessing procedure considers this market segmentation.

The dataset for the case study contains 355,281 daily trajectories that have at least one point located in Karuizawa town from April 1st, 2019, to March 31, 2020. Each trajectory therefore represents an app user's trajectory on the day when he/she visits or just passes through the town and may contain points outside the town. The total number of trajectory points is 60,504,702, which means that each trajectory has 170.3 points and is tracked every 8.5 minutes on average.

The dataset nonetheless requires extra data preprocessing steps because GPS trajectories are not readily analyzable due to positioning errors as well as lack of personal information. The data preprocessing is designed to derive TAPs from the trajectories as well as to remove anomalous points. The rest of this section describes the five steps of the data preprocessing procedure.

5.3.2 Step 1: Preliminary Trajectory Filtering

This research analyzes long-distance visitors to the study area. Since Agoop trajectories are not associated with personal information, it is not straightforward to distinguish the trajectories of occasional visitors from those of residents and commuters in the area. For this reason, the filtering focuses on one-day round visitors who depart from and return to the same place because we can infer their home location by examining the shape of trajectories. Note that it is not necessary to identify exact home locations due to the next filtering criterion. City- or prefecture-level inference for home locations suffices for this filtering.

The second filtering criterion finds the trajectories of one-day visitors who come from and return outside the study area. However, workers who live outside and commute to the area also form the same pattern of trajectory. It is additionally necessary to differentiate those trajectories from those of long-distance visitors. According to the Japanese census data, most of Karuizawa workers live either in Nagano prefecture (94.4 %) or Gumma prefecture (3.4%) (Ministry of Internal Affairs and Communications Statistics Bureau, 2020). For this reason, the second filtering only leaves trajectories coming from the prefectures other than these two prefectures.

The third filtering criterion is intended to select trajectories with activities in Karuizawa town. The trajectories in the dataset have at least one point in the area. This does not necessarily mean that the users of the trajectories have activities within the area. It is necessary to remove trajectories that only pass through the area. To identify clusters, this criterion applies the density-

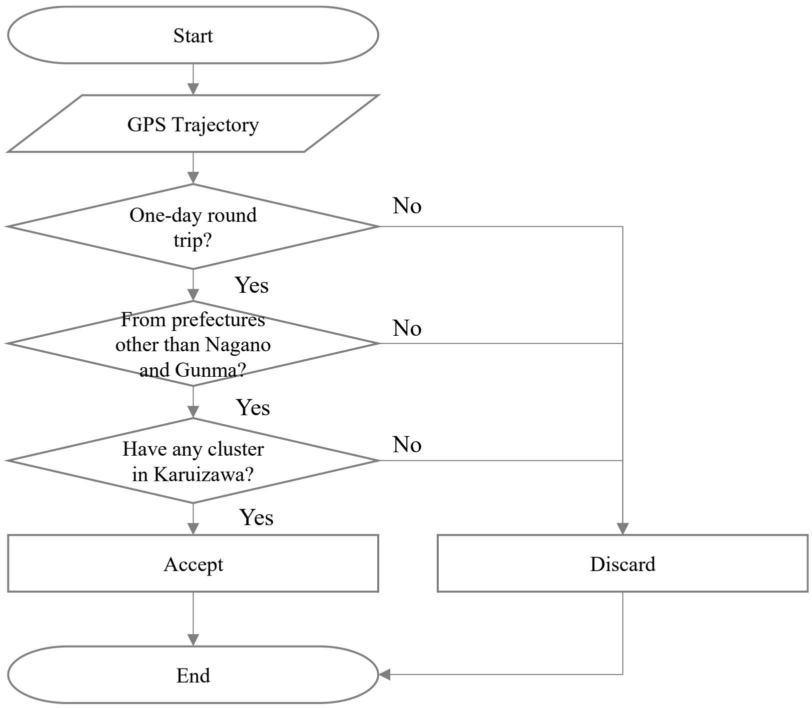

Figure 5.3 Flowchart of Preliminary Trajectory Filtering

based spatial clustering of applications with noise (DBSCAN) algorithm (Ester et al., 1996) with the radius of a neighborhood ϵ = 100m and the minimum cluster size of two. It finally filters trajectories that have any in-Karuizawa clusters of differently timestamped points.

Based on the three criteria above, this preliminary filtering chooses 12,925 candidate trajectories for the following cleaning step, out of the 355,281 trajectories.

5.3.3 Step 2: Activity-trip Classification and Cleaning

The goal of the second preprocessing step is to classify trajectory points into those of activity and those of trip. When plotted, the trajectory points of an activity make a cluster (i.e., gather close to each other) around the place of the activity, while those of a trip disperse along the path. To identify clusters of activity points, this step again employs the DBSCAN algorithm with ϵ = 30m and the minimum cluster size of two.

It is important to note that, at this point, some of the clusters may not belong to activity. One type of non-activity cluster pertains to points tracked during the stops of trips, for example, waiting at a signal. Another type of non-activity cluster is due to tracking failures. The tracking system of the dataset sometimes assigns 'proxy' coordinates to a point when it fails to position it. By observation, those proxy coordinates are based on the grid system and often locate several failed points exactly at the same location. Those points with proxy coordinates make a cluster but may not be necessarily near their correct locations and, furthermore, create 'fake' activities and trips that distort the following analysis.

It is necessary to detect those two types of non-activity clusters. For this detection, this step uses a machine-learning-based classification algorithm plus manual examination. This algorithm is based on support vector machine and considers the accuracy of trajectory points and the variety of coordinates. A cluster of variously coordinated points with high accuracy is likely to represent an activity, whereas that of single pair of coordinates with low accuracy is less likely an activity.

This step finally removes those anomalous points based on the speed of between the points. This is because GPS trajectories often contain many anomalous points that are positioned far from the correct positions.

5.3.4 Step 3: Labeling Clusters

This step associates activities at the same place with common location labels for the following aggregation of the activities. This labeling scheme uses parcel data that represent common activity locations in the study area. Figure 5.4 maps the parcels. If one or more of the points in a cluster overlap with a parcel, the cluster is associated with the parcel so that we can readily collect activities labeled with the same parcel. Based on the plot of clustered trajectory points, this step uses 259 parcels that represent publicly available activity places for visitors in Karuizawa town. Note that these parcels are categorized into either major or minor activities. The next step considers these categories.

One advantage of this parcel-based labeling is that we can relate different clusters of the same activity performed at one large place. DBSCAN only considers distances between points and may make multiple clusters for an identical activity that involves short moves. For example, trajectory points recorded during outdoor activities in a large yard may be classified as multiple activities and trips. With this labeling, I regard the consecutive points within the same parcel as the same activity in the place despite the distances between them.

This labeling scheme is also advantageous to some existing research that applies two-step clustering methodologies for the same purpose. These methods first cluster points of trajectories and again cluster those clusters. However, those methods are not directly applicable in areas where activities are dense because they may combine irrelevant but spatially close clusters into the same activity due to the inherent GPS tracking errors. The labeling method avoids this confusion by explicitly considering boundaries between clusters.

Since most of the clusters in the study area are labeled with parcels, unlabeled clusters are distant enough from each other. This labeling step can finally group these unlabeled clusters by the DBSCAN algorithm based on the centroids of each cluster.

5.3.5 Step 4: TAP Filtering

The fourth step of preprocessing selects analyzable TAPs from the cleaned and labeled TAPs. Some of the TAPs still lack necessary information or do not represent DRM users' possible behavior. This step considers three filtering criteria. The first filtering removes TAPs that have no activity in the study area. The second filtering criterion is about tracking

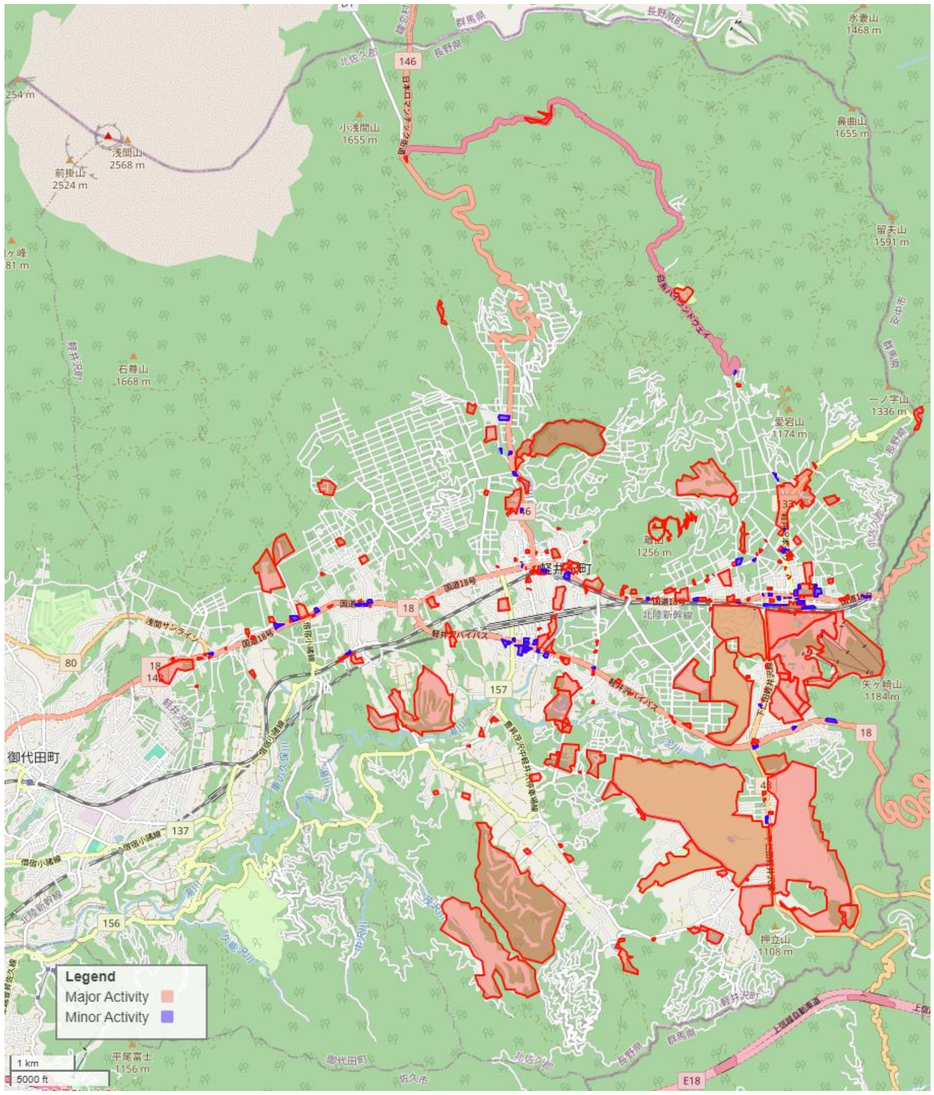

Figure 5.4 Activity Parcel Map

rates. Since this research analyzes the temporal aspects of TAPs, it should avoid trajectories with long tracking blanks. Specifically, this criterion eliminates TAPs with trips missing points for more than ten minutes within the study area. The third filtering removes the TAPs of users who only participate in 'minor' activities for travelers. I define minor activities as activities that could not be the major reason for the visit to the study area. The minor activities in this research include those at nationwide chain stores/restaurants (e.g. convenience stores and fast food restaurants), gas stations, car rentals, public (i.e., not on-site) parking lots, and train stations. In addition, activities lasting shorter than 5 minutes are additionally considered minor regardless of their location. The assumption behind the third filtering is that a DRM service is only useful for visitors who stay in the service area for a certain period. In other words, visitors who just stop by and do minor activities at the study area do not represent the potential TAPs of DRM users.

After the TAP filtering, I finally identify 2,121 analyzable TAPs out of the 12,925 one-day round trajectories.

5.3.6 Step 5: Activity Aggregation

The preprocessed TAPs have commonly labeled activities. Each activity label can be associated with the statistics of temporal activity attributes, start time, end time, and duration, by aggregating activities with the same label. Note that if a TAP has multiple activities of the same label, this aggregation only considers the start time and the end time of the first and the last ones of those activities, respectively, as well as the sum of activity duration.

In addition, we can use the start and end times of each activity to estimate the chance-constrained time window for the activity. This estimation relies on the methodology developed in Chapter 4. The method first estimates the population density distributions by the kernel density estimation technique, uses the Monte-Carlo sampling from the estimated population density to obtain block extrema, and fits the generalized extreme value distributions to the block extrema. This chapter specifically uses the Gaussian kernel as well as the Silverman's rule of thumb for the population density estimation and assumed the Gumbel distribution for the GEV distributions. 95% satisfaction for block-length of 100.

5.4 Case Study Setting

5.4.1 Service Setting

The case study evaluates a DRM system within Karuizawa town, using the TAP data obtained in the previous section. This section first introduces the settings of the DRM system. There are two types of entity in the system: DRM passenger groups and a DRM operator. A single person may form a passenger group. The passengers want to complete their planned activities within the study area and use DRM to travel between activities if necessary. The DRM operator operates their vehicles to satisfy the passengers' travel demand as well as activity participation. So, to use the DRM service, passengers must provide the DRM operator with information on their activity schedule or TAP. Specifically, they must list a sequence of activity locations in conjunction with stay duration at each location. In addition to these activity locations, passengers need to specify the origin of the first trip and the destination of the last trip. Those two points are not associated with activity duration. Passengers can also optionally request desired arrival times at destination. Figure 5.5 illustrates the image of the request form. One form corresponds to the activity schedule of a passenger group and may consist of multiple ride requests. Note that those ride requests are not necessarily spatially connected (i.e., consecutive trips may not end and start at the same place, respectively) if passengers use different modes between two activities.

The DRM operator then decides on vehicle routes based on requests from passenger groups. Before routing, the operator selects which trips to serve by examining the walkability of trips. This decision is deterministic; specifically, if the trip distance along the shortest path on the road network is shorter than a walkable distance, say 800m, passengers are supposed to walk for the trip. In other words, passengers can only use DRM for unwalkable trips.

The operator allows passengers to get on and off DRM vehicles only at designated meeting points and requires them to walk from/to their activity locations to/from those meeting points. Passengers do not have to specify meeting points they use. The operator assigns walkable meeting points to each ride, if available, based on the activity locations provided. If an activity location is walkable from different meeting points, the operator assigns the best point that minimizes the total travel time, considering the other end of the trip. If the operator cannot assign any walkable meeting points to one or more activities in the requested TAP, it rejects the entire TAP including other trips.

Additionally, the operator checks if each TAP is temporally completable with the DRM service. The operator calculates minimum travel times including access and egress times to/from meeting points for the trips of the TAP. Each activity is associated with a time window either specified by its user or estimated by the operator. The operator accepts the TAP if it is feasible with all the time windows on its activities with those minimum travel times; otherwise, the operator additionally rejects the entire TAP. Figure 5.6 summarizes the flow of the DRM service.

The DRM operator finally assigns vehicles for the filtered trips so that the passengers can participate in all the activities in their schedule. In this assignment, the operator also wants to minimize the total operational cost.

5.4.2 Case Study Procedure

The case study simulates and evaluates the operation of the DRM service. Since DRM systems operate upon request, the simulation first generates demand and then assign vehicles to it. This demand generation process is based on the TAP data in the previous section. The generation process examines and modifies the TAPs into a set of possible requests for the DRM service. The simulation randomly draws a subsample from the set of modified TAPs and inputs

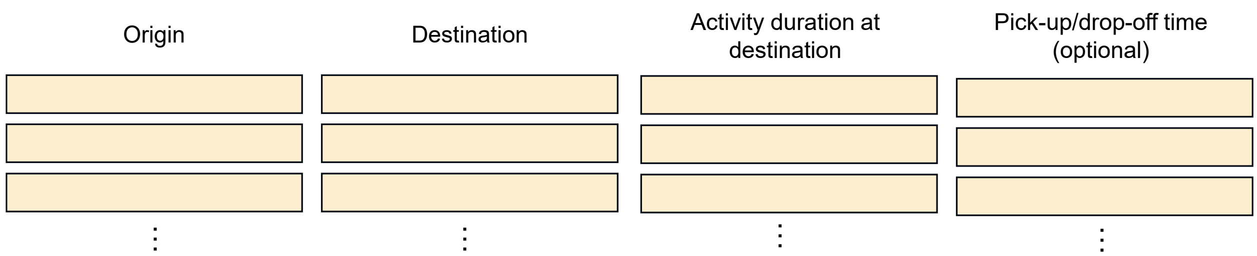

Figure 5.5 Activity-based DRM Service Request Form

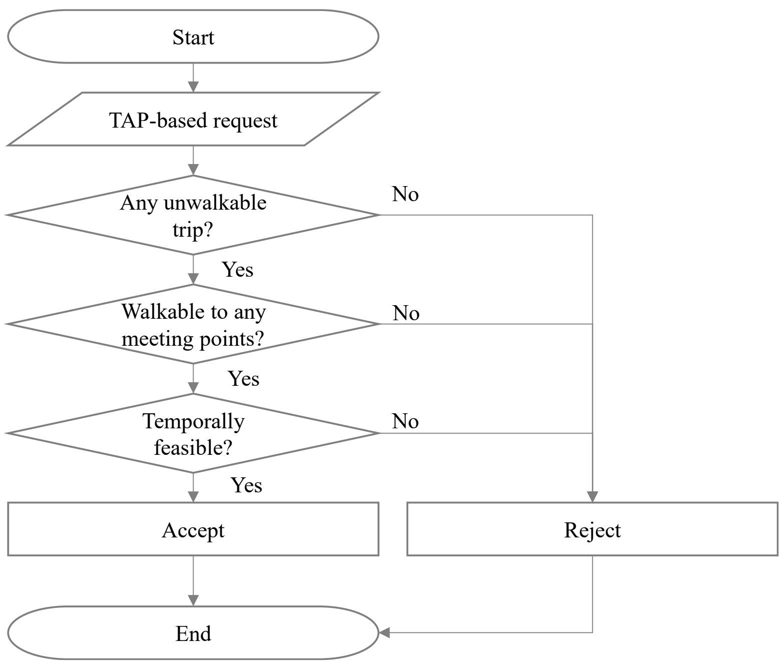

Figure 5.6 Flowchart of Request Acceptance

into the following vehicle routing process.

The vehicle routing process is based on solving an ABPDP instance on a demand subsample. The vehicles only serve unwalkable trips, but the vehicle scheduling considers travel time for walking so that passengers can complete their activities in TAPs. By examining the solution routes, we can compute the performance metrics of DRM operation, such as operational costs and VMT.

The rest of this section describes the details of modeling demand and supply sides in this case study.

5.4.3 Demand-side Modeling

5.4.3.1 Assumption

The case study focuses on DRM passengers who come from outside of Karuizawa by Shinkansen and do not bring any private travel mode. However, many of the preprocessed TAPs belong to car visitors who behave differently from rail visitors. They do not directly represent potential DRM passengers. Moreover, the observed TAPs of Shinkansen visitors also rely on existing transportation services (e.g., rental car, taxi, bus, bicycle, and walk). The demand generation process thus requires several assumptions to transform the preprocessed TAPs into possible DRM requests.

First, I assume that the observed combinations of in-Karuizawa activities represent the activity combinations that DRM passengers would perform in Karuizawa. Second, they participate in the activities for the same duration as observed. In other words, a combination of activities is only associated with observed patterns of activity durations. Third, DRM passengers start and end their daily TAP at the Karuizawa station because the dataset only contains one-day round TAPs. Fourth, DRM passengers either use DRM or walk for trips within the study area. This assumption is based on another assumption that the DRM operator has an unlimited number of vehicles and drivers to serve them. Although it is possible for them to combine different modes, the operator can always serve requested unwalkable trips. Fifth, it is assumed that DRM passengers only participate in activities within Karuizawa between their arrival at and departure from the area. Since the DRM service is only available within Karuizawa, they are not supposed to go outside the area on other modes according to the third assumption. Sixth, I assume that DRM passengers do not bother to be engaged in minor activities.

It is noted that, for this case study, I refrain from modeling a TAP generation process that is sensitive to the quality of DRM service. The dataset is only concerned with travel behavior without DRM services. It is therefore hard to estimate behavioral responses to such a non-existent transportation service. In addition, due to the lack of personal information, I refrain from synthesizing population TAPs.

5.4.3.2 TAP Transformation and Feasibility Check

Based on the assumptions introduced above, I further transform the preprocessed TAPs into candidate requests. First, I truncate the first and last parts that involve out-of-Karuizawa activities. Next, I replace the truncated parts with two trips that connect the Karuizawa station to the first and last in-Karuizawa activities. Third, I drop minor activities from the TAPs and connect major activities before and after the minor activities. Fourth, I identify walkable trips whose shortest path along the pedestrian network is shorter than the maximum walkable distance. The walkability of a trip is determined based on the shortest path length on the pedestrian network of OpenStreetMap (n.d.). A trip is considered walkable if its path length is shorter than 800m.

I then check the feasibility of the transformed TAPs for candidate request based on the four conditions: 1) out-of-Karuizawa activity; 2) trip walkability; 3) walkability to meeting points; 4) temporal feasibility with Shinkansen schedule. The first three conditions are easy to check. I just drop TAPs either with any out-of-Karuizawa activity between first and last in-Karuizawa activities, all trips walkable, or any activity far from any meeting point.

To determine the fourth feasibility, I first compute the shortest DRM travel times for unwalkable trips (the sum of in-vehicle time and walking times to and from meeting points) and walking times for walkable trips, respectively. These travel times assume constant speeds of 25 km/h and 4 km/h for vehicle and walking, respectively. Both trips and activities are associated with minimum duration, and TAPs have accordingly necessary duration to complete. I next compute time windows for activities, considering the estimated chance-constrained time windows for activities in addition to the actual activity start and end times of TAPs. The earliest arrival at an activity is either the lower bound of the chance-constrained time window or the actual start time, whichever comes first. Likewise, the latest departure form an activity is either the upper bound of the chance-constrained time window or the actual end time, whichever comes last. Third, I consider the schedule of Shinkansen trains at the Karuizawa station. A TAP is determined to be temporally feasible if there is any pair of arriving and departing trains that allow for performing the TAP. Time difference between the rains must be larger than the necessary time for the TAP. The arriving and departing trains must be early and late enough, respectively, for the activities of the TAP to be performed within the estimated time windows, given the shortest travel times. If there is no pair of trains that enable a TAP, the TAP is dropped.

Note that the feasibility of TAPs depends on the allocation of meeting points. Sparse allocation will likely make more TAPs infeasible with the DRM service because access and egress distances are longer.

5.4.3.3 Trip Time Window Setting

During the feasibility check for each TAP, I compute shortest travel times as well as time windows for activities. Using this information, we compute time windows for trip departures and arrivals. For this computation, we additionally need the possible earliest start time and the possible latest end time of each TAP. Since the TAPs are supposed to be of one-day Shinkansen travelers, a pair of Shinkansen trains used determines these times. However, there might be multiple train pairs that are feasible with a TAP. I therefore choose a shinkansen schedule pair that minimizes the sum of the (absolute) difference between train arrival time and the actual TAP start time and that between the actual TAP end time and train departure time. Given the earliest start time and the latest arrival time, we can associate trip departures and arrivals with time windows by using the method introduced in Chapter 3. The vehicle routing for DRM introduced in the next subsection considers these time windows.

5.4.3.4 Sample from Pooled Candidates

The transformed and feasible TAPs represent possible DRM passengers' TAPs all of which depart from and return to Karuizawa within a day. Those TAPs are pooled for the following vehicle routing process. I assume that a random sample from the pooled TAPs is a possible set of requests for a day. This sampling at TAP level, rather than sampling at individual trip level, maintains the interrelationships, namely, inter-route duration constraints, between the trips of the same traveler.

5.4.4 Supply-side Modeling

5.4.4.1 Assumption

Next, I describe the assumptions about the DRM operator. First, I assume that an unlimited number of vehicles are available. This is because this research is interested in determining the scale of operation given a demand level, rather than estimating accommodable demand given a fixed fleet size. In addition to planning vehicle routes, the operator determines the number of vehicles to dispatch so that they minimize total operational costs. The second assumption is that the DRM service is a prebooking system. That is, the operator knows all the

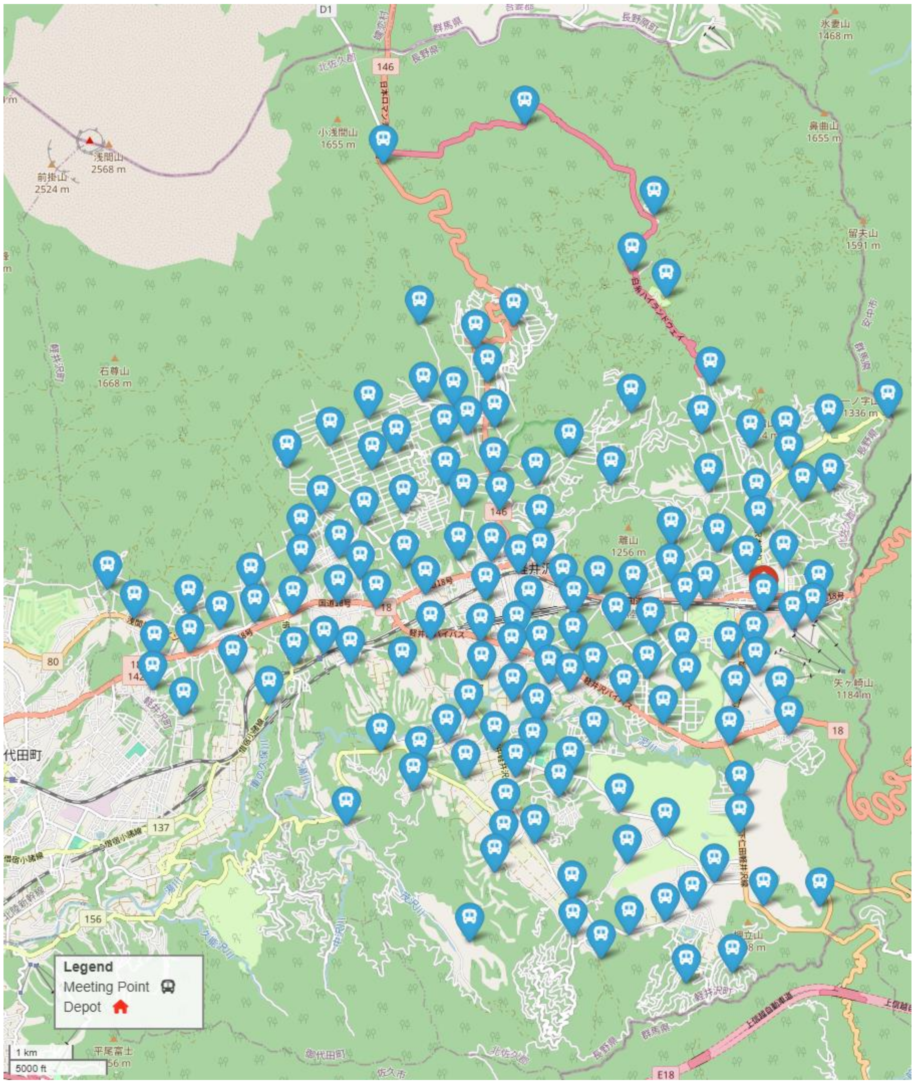

Figure 5.7 Meeting Point Allocation

requests to serve before the beginning of daily operation and will neither accept additional requests nor reschedule the existing requests after it determines the optimal routes. Third, travel times and service times are assumed to be static. I use an average speed of 25km/h to compute travel time and 30 seconds for the service times of both pick-ups and drop-offs. Fourth, there are 150 meeting points over the study area. Most of them are located at common activity places, and some are at the intersections of the road network. Fifth, the system has only one vehicle depot located at Karuizawa station. Figure 5.7 displays the allocation of the meeting points and the vehicle depot. Lastly, the vehicle capacity is ten passengers.

5.4.4.2 Vehicle routing

Given TAPs, the DRM operator plans vehicle routes before beginning operation. Since the service is a prebooking system, the operator can determine the vehicle routes by solving static VRP, specifically ABPDP introduced in Chapter 3.

The objective of this vehicle routing is to minimize the sum of operational costs, such as per-vehicle fixed cost and running cost, and driver salaries. The per-vehicle fixed cost for this problem includes those of vehicle price, insurance, maintenance, tax, backend computer system, and legal registration. I translate those costs on a per-day basis. The running cost corresponds to per-kilometer fuel cost. Driver salaries are based on the operational hours of each vehicle. Table 5.1 summarizes the parameters of operational costs.

5.5 Case Study

The objective of this case study is to verify the effectiveness of proactive activity management strategies. These strategies exploit knowledge about activities performed in the study area. In particular, the strategies proposed are based on the statistics of temporal attributes. The evaluation is the performance metrics for ten 30-group instances. The passenger group size is assumed to be all one.

5.5.1 Case 1: Base case

The first case is a base case without any management strategy and assumes that passengers want to complete their activity schedule as quickly as possible. Each TAP is

Table 5.1 Operational Costs for Case Study

Unit cost	Cost (1JPY ≅0.625¢)		Note
Per-vehicle	6,000	JPY/day/veh.	Including vehicle price (Toyota Hiace,5-year depreciation), insurance, maintenance, tax, backend computer system, and legal registration.
Fuel	30	JPY/km	160 JPY/l (Fuel price)÷6.1 km/l (Toyota Hiace fuel economy)
Driver wage	2,000	JPY/hr.	Including management fees.

associated with time windows for trips. Those time windows include earliest possible arrival times at activities, assuming no detours on trips and minimum activity duration. This case assumes the passengers only allow for at most 5-minute delays from those earliest arrivals, except for the last trip to the station.

Table 5.2 summarizes the result of this case. Per-group and per-ride costs are on average approximately 4,084 JPY and 1,569 JPY, respectively (1JPY ≅0.625¢). These are in fact less expensive than taxi fares. If passengers in the problem instances use taxis for unwalkable trips instead of the DRM service, they will need to pay approximately 2,100 JPY per ride on average. This result implies that, if passengers are willing to share each of their taxi rides for this cost difference (≅ 530 JPY), this DRM service can be as financially viable as taxis. In all instances, the total vehicle kilometers traveled (VKT) increases compared to the VKT of a hypothetical case in which all passengers use private vehicles for unwalkable trips (VKT-PV). More demand density is necessary for this DRM service to materialize environmental benefits.

5.5.2 Case 2: Chance-constrained Activity Time Window

The next case assumes that the DRM operator utilizes temporal information on activities in the service area and guarantees passengers' in-time arrivals that enable them to perform activities for the minimum duration. Specifically, the operator knows the latest departure times necessary activity duration, these latest departure times enables the operator to derive the latest

Table 5.2 Case 1 Result

Instance	# requests	VKT-PV	Fleet size	Total cost (1,000 JPY)	VKT-DRM	Empty VKT-DRM
A	78	289.20	6	115.67	417.77	148.87
B	75	275.09	4	112.55	397.39	126.51
C	83	285.44	6	124.83	457.01	180.02
D	78	296.49	7	118.17	429.44	148.44
E	77	293.96	6	119.98	430.31	153.83
F	85	302.26	7	137.07	416.51	127.38
G	79	346.26	5	115.83	458.92	141.49
H	77	326.03	7	130.64	486.34	178.39
I	70	320.16	6	111.97	450.93	150.70
J	79	352.39	8	138.52	446.11	127.36
Mean	78.1	308.73	6.2	122.52	439.07	148.30

from activities by using the chance-constrained activity time window estimation. Given arrival times that guarantee the activity duration. This case also assumes that passengers will accept such in-time arrivals as long as they can participate in their activities for necessary duration.

Figure 5.8 compares the performance metrics of each instance. In Case 2, the total operational cost decreases in every instance, whereas the necessary fleet size and VKT increase in some instances. This implies that the overall cost reduction is mainly because of the decrease in drivers' working hours. The result verifies the importance of flexibility in activity start and end times in reducing vehicle operational hours. Operators' knowledge about such flexibility can safely lead passengers to shift activity timings while guaranteeing their sufficient activity participation.

5.5.3 Case 3: Nudging on Activity Duration

The last case study is based on the insight from Chapter 3. The insight implies that the shorter passengers' activities are, the more efficient DRM operation can be. In other words, if the operator can prevent passengers from participating in unnecessarily long activities, it may be able to introduce more temporal flexibility to DRM operation. The activity management

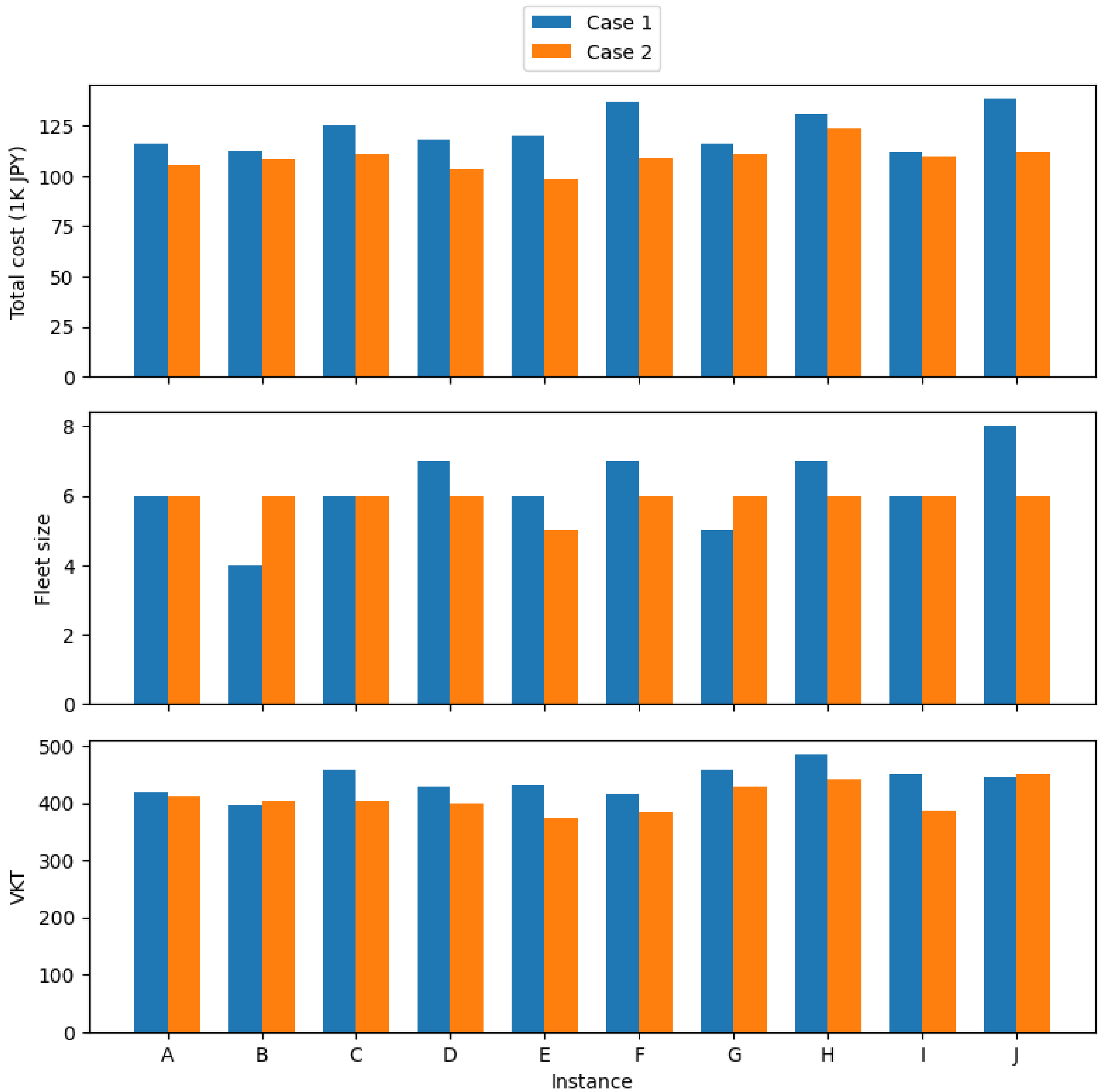

Figure 5.8 Performance Metrics Comparison of Cases 1 and 2

strategy in Case 3 is concerned with information provision to nudge passengers to perform activities for 'standard' duration.

To reserve the DRM service, passengers are supposed to provide their activity schedule including activity durations. I assume that, if the activity duration provided by a passenger is longer than a standard duration based on past observations, the reservation system will display the standard duration to the passenger. I additionally assume that some of the passengers will accept this suggestion by adjusting their request duration to the standard duration.

This case conducts an experiment to simulate and evaluate DRM operations with the nudging strategy on the same 30 instances of 30 passenger groups. The experiment compares the performance metrics with the nudging strategy to those obtained in the same way as Case 2. It is assumed that, with the nudging strategy, users may reduce their activity duration that is longer than the median of observation, according to a certain probability, which is fixed to 0.5 in this case.

Figure 5.9 displays the box plots of total operational cost, necessary fleet size, and VKT. According to this result, the nudging system seems to decrease the operational costs, whereas its effects on the other metrics are invisible. To confirm those influences, I conduct the Wilcoxon-signed rank test that considers the correspondence between two samples, since Cases 2 and 3 use the same TAP instances, except for possible reductions in activity durations. Table 5.3 summarizes the statistics of the three performance metrics for the two cases as well as the test statistics. The p-value for operational cost indicates that the cost reduction is statistically significant at the significance level of 5%. The differences in vehicle size and VKT are statistically insignificant. Overall, the result of this case shows that nudging on activity duration can enhance the effects of temporal flexibility of activities; it can help vehicle operational hours decrease but does not clearly affect fleet size and VKT.

5.5.4 Discussion

The case studies in this section verify the effectiveness of the two proposed activity management strategies regarding temporal aspects. Both strategies aim to increase flexibility in activity timings and can enhance the efficiency of DRM operation mainly by reducing overall

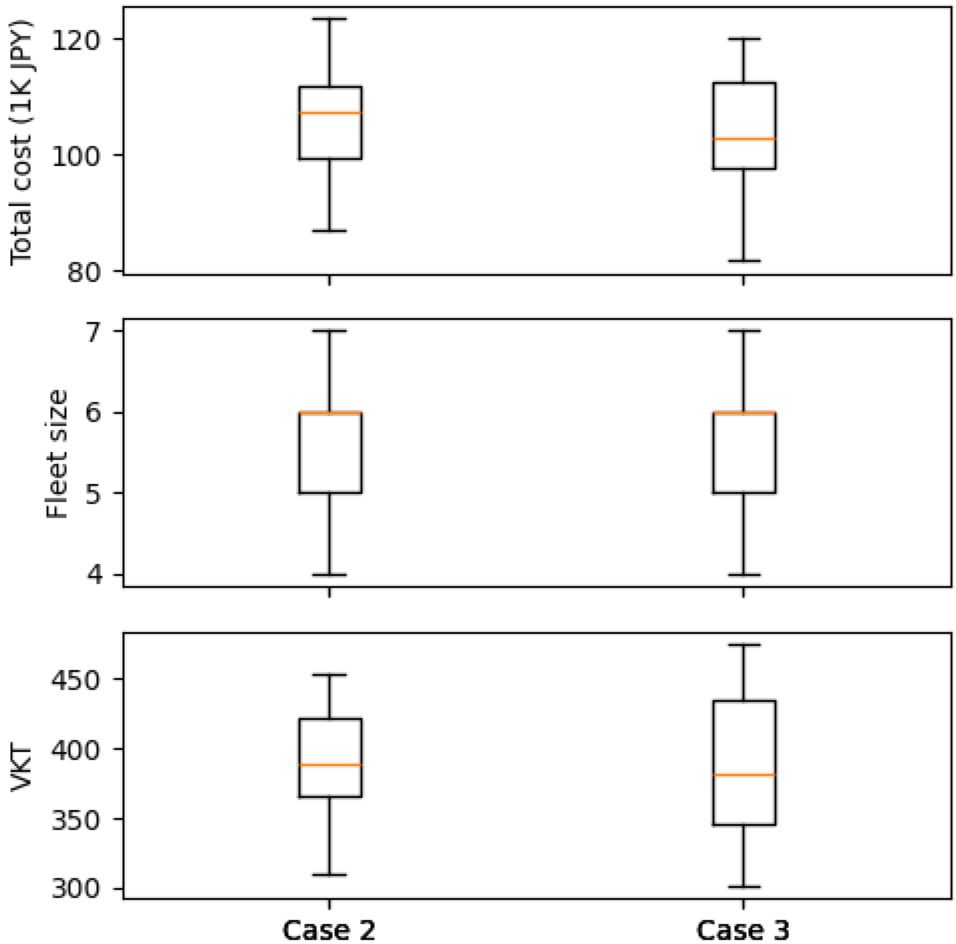

Figure 5.9 Performance Metrics Comparison of Cases 2 and 3

Table 5.3 Wilcoxon-signed Rank Test on Cases 2 and 3

Metric	Case 2			Case 3			Stat.	p-value
	Mean	Med.	Std.	Mean	Med.	Std.		
Cost (1K JPY)	105.82	107.14	9.75	103.46	102.77	10.31	112	0.012
Fleet size	5.73	6.00	0.83	5.57	6.00	0.90	26	0.284
VKT	389.48	388.21	40.06	386.47	382.00	52.96	197	0.477

vehicle operational hours rather than improving vehicle routing. The estimated per-ride cost is less than the average taxi fare even in Case 1, implying the possible viability of the DRM service in comparison to taxis. The activity management strategies will improve viability by reducing operational costs, while guaranteeing successful activity participation. Since these strategies rely on prior knowledge about passengers' activities, this result indicates the importance of activity information for DRM operation.

5.6 Conclusion

5.6.1 Summary

This chapter evaluates proactive activity management strategies for prebooking DRM systems. These management strategies take advantage of temporal flexibility of activities. The evaluation uses smartphone-based GPS trajectory data to estimate activity flexibility as well as potential demand for the DRM system. The research also presents a preprocessing method to construct TAPs from the error-prone GPS trajectories. To my knowledge, this research is the first study that uses GPS trajectory for DRM evaluation.

This chapter employs the proposed proactive activity management strategies in conjunction with the meeting point and prebooking strategies and conducts case studies that apply ABPDP to simulated TAP-based requests. The case studies show the effectiveness of the proposed strategies, highlighting the usefulness of knowledge about the temporal attributes of activities.

5.6.2 Future Research Direction

The case studies are based on several assumptions. Relaxing those assumptions is necessary for more realistic evaluation. In the proposed DRM service, passenger groups request rides in the form of TAP, and the operator then offers rides or notifies them of the infeasibility of the request. Considering this procedure, this subsection discusses research directions regarding 1) feasibility check, 2) offering design, and 3) passengers' acceptance of offers.

The case studies consider the temporal flexibility of activities and the walkability of trips in the feasibility checks of requests. Those checks should be more specific to each passenger. This study estimates temporal flexibility at market segment level, focusing on one-day round trip travelers to the study area. To find more acceptable options, it is more effective to estimate flexibility that better meets individual's needs. In addition, in the proposed system, the operator deterministically decides on the walkability of trips in requested TAPs to select which trips to serve. However, the walkable distance depends on passengers' characteristics. More behavioral information helps realistic feasibility.

Offering design is concerned with the assumptions of the supply side. The case study assumes an unlimited fleet size. Although this assumption is useful in estimating the necessary fleet size in a certain circumstance, fleet size is limited in realistic DRM systems. It is important for those systems to prioritize requests to take most advantage of the limited operational resources. This prioritization requires solving an optimization problem to select the best set of requests to serve. This prioritization problem must also be activity-based in that its solution guarantees activity participation. As existing research on prioritization strategies is trip-based, it is meaningful to investigate activity-based prioritization strategies. It is necessary but more difficult for activity-based DRM services with limited fleet to accept multiple ride requests at a time. One alternative strategy is to offer a combination of various transportation modes that can support the requested TAP. This strategy will mitigate dissatisfaction with the service by avoiding completely rejecting infeasible requests.

This research assumes that passengers always accept the ride offers. This acceptance is nevertheless stochastic, depending on their preferences. The activity management strategies should consider passengers' choice behavior to design more acceptable offers. Estimating preferences for arrival time and duration and incorporating them into ABPDP will enable the DRM service to provide better service quality.

CHAPTER VI: Summary and Conclusion

6.1 Summary

Demand Responsive Mobility (DRM) systems are expected to bridge gaps among existing transportation modes. However, the implementations of DRM are not always successful and thus require deliberate planning and operational schemes. To expand operational strategies with DRM systems, this dissertation aims to address the methodological challenges in considering activities in DRM systems planning and operation.

Chapter 2 reviews literature on operational strategies, service quality, and evaluation methodologies for DRM systems. Reviews on operational strategies indicate that information about travel behavior can enhance the operational efficiency and the service quality of DRM systems. However, while it is critical for behavioral analysis to consider activities, activity consideration is limited in those strategies. Few DRM supply models can explicitly capture the effects of activities on DRM performance. Moreover, it is hard to access data on detailed travel-activity patterns (TAPs). High-resolution taxi or TNC datasets only provide information on vehicle trips, and activity-based travel demand forecast models are spatially and temporally discretized. Based on the literature review, this chapter identifies three research questions to answer to establish proactive activity management strategies for DRM systems.

Chapter 3 develops the activity-based pick-up and drop-off problem (ABPDP) by adding inter-route activity duration constraints to the well-known pick-up and delivery problem with time window constraints (PDPTW). To handle the inter-route constraints, this chapter also develops a heuristic solution algorithm based on a Local Search (LS) algorithm with the Giant Tour (GT) representation. Computational experiments with simulated TAPs verify the effects of passengers' activity duration on the performance of DRM systems, suggesting an activity management strategy.

Chapter 4 explores a methodology to infer the temporal flexibility of activities. This method is based on chance-constrained programming (CCP) as well as the statistical extreme value theory and can estimate the generalized extreme value (GEV) distributions of activity start and end times. Since the conventional estimation method for GEV distributions requires a large sample, this chapter investigates an alternative estimation method that can be used with small a sample size. The alternative method synthesizes sample blocks from the population density distribution estimated on a given sample. An experiment with the national household travel survey (NHTS) dataset reveals that using kernel density estimation (KDE) for the population density distribution yields more comparable results to the conventional method than parametric estimation and empirical cumulative density function (ECDF).

Chapter 5 uses the methodologies developed in the previous two chapters to evaluate proactive activity management strategies that exploit empirical information regarding the temporal flexibility of activities. This evaluation uses smartphone-based GPS trajectory data to estimate potential demand for a DRM system for train passengers in Japan as well as activity flexibility. This chapter also presents a procedure to transform the GPS trajectories into TAPs. Case studies confirm the effectiveness of the proposed activity management strategy in improving the operational performance of DRM systems.

6.2 Further Developments

This dissertation concludes by discussing modeling issues and potential model extensions with respect to the supply and demand sides of DRM systems.

6.2.1 Supply Modeling

6.2.1.1 Modeling dynamic operation and stochasticity

The proposed ABPDP assumes a static situation, where all the requests are known before the beginning of the operation. In a realistic operation, however, some passengers may want a dynamic DRM operation that offers more flexibility for immediate requests and rescheduling existing bookings. While the prebooking system leads to better operational efficiency, it is worth incorporating a dynamic service that takes requests during an operation in order to satisfy a wider range of customer needs.

Dynamic DRM operation repeatedly accepts new ride requests and reoptimizes vehicle routes with existing bookings. ABPDP only takes deterministic information and assumes that the DRM operator knows all the necessary information to plan the best vehicle routes. ABPDP can plan initial routes, which, however, may not lead to the best routes if ride requests are added. In the real-world dynamic DRM operation, additional requests are stochastic and unknown before their realization. Incorporating recourse into ABPDP is a possible enhancement to provide a quality initial solution that considers the stochasticity of additional requests. In addition to stochasticity in demand, delays in travel and service times are also stochastic and an important factor for real-world DRM operation. Planning reliable vehicle routes that are robust to such delays also relies on the techniques of stochastic programming, such as chance-constrained programming.

For dynamic operation, it is also important to devise information provision strategies to control both service quality and operational efficiency because information on ride offers may restrict reoptimizing vehicle routes with new requests. The route reoptimization must consider the schedules of rides already offered if accepted passengers are informed of those schedules.

While passengers need to know their ride schedules in advance, the DRM operator may want to maintain operational flexibility to shift some of the requests for better vehicle routes as late as possible. In addition to estimating passengers' acceptable ranges of schedule changes, strategies that ask passengers to wait for information on ride offers will help flexible DRM operation.

6.2.1.2 Congestion effect

The case study in this research assumes static travel time. Although this assumption is plausible in sparse rural areas, it limits the applications of ABPDP in urban settings where travel times depend on traffic on the road network. Since most DRM services use a relatively small fleet size, it is reasonable to assume that they do not solely contribute to traffic congestion. Simulating such a case can use time-dependent travel time based on historical traffic data, rather than dynamic traffic assignment. ABPDP may adopt methodologies for time-dependent VRPs. Gendreau et al. (2015) and Adamo et al. (2024) provide extensive reviews on such methodologies.

On the other hand, the evaluation of city-wide DRM systems with huge fleet size should assume that the DRM operation affects the transportation network performance and, furthermore, the service level of other modes. It is necessary for large-scale DRM evaluations to model the equilibration of entire transportation systems in the study area by using dynamic traffic assignment as well as travel demand models.

6.2.2 Extensions to the activity management strategy

The proactive activity management strategies presented in this research are only concerned with the temporal attributes of activities and do not change activity order. More advanced activity management strategies that suggest alternative TAPs to a given TAP may furthermore improve operational efficiency. Such strategies may suggest, for example, different orders of the same activities or feasible TAPs including other activities. To identify such alternative TAPs, it is necessary to reformulate the ABPDP to incorporate the optimization of activity orders; otherwise, we need to repeat checking the feasibility of those alternatives and solving ABPDP instances for each alternative. This reformulation of ABPDP will increase the complexity of the problem and require another solution algorithm.

6.2.3 Demand Modeling

6.2.3.1 Population synthesis

Chapter 5 uses GPS trajectories from smartphone apps as possible demand data for a DRM service to demonstrate the feasibility of the proposed methodology. A limitation is that the case study focuses on one-day visitors' travel behavior due to the single-day nature of the type of travel and the insufficiency of socio-demographic information in the dataset. More diverse market segments of users, such as residents, commuters, and visitors with overnight stays, must be included for realistic assessments. The methodologies that this research proposes are extensible to multi-day tours and other market segments, such as residents and non-resident commuters, though additional data and analysis are mandatory. For example, behavioral information of residents and non-resident commuters is necessary for more accountable evaluation, as the Agoop dataset only samples small parts of them.

This research moreover refrains from synthesizing the population demand and estimating the actual scale of operation because it is difficult to estimate the number of external visitors, who comprise most of Shinkansen passengers. The population census in Japan only provides the demographic information on the residents and the non-resident commuters of each area. It is possible that detailed analysis of Shinkansen ticketing data will show the arrival and departure patterns of Shinkansen visitors and can help with more realistic population synthesis.

6.2.3.2 Behavioral modeling

This research lacks developing activity-based travel demand models (ABTDMs), although modeling travel behavior sensitive to the service level of transportation systems is necessary to model the equilibration of transportation systems. Despite the detailed behavioral information of GPS trajectories, it is still hard to develop an ABTDM in the study area because developing ABTDMs requires more data on behavioral aspects, such as mode choice, activity purposes, and the number of participants. The development of ABTDM requires more data sources as well as advanced methodologies to infer further behavioral information from GPS trajectories.

Data collection for demand modeling is also limited. Since the DRM service was not introduced in the study area, the trajectory dataset used in this research does not include DRM users. The dataset is only associated with travelers using other existing modes and may not represent the behavior of DRM passengers. The calibration of the activity management system furthermore necessitates the behavioral data of DRM users. A traditional travel survey on DRM users is possible but may be too expensive for frequent model updates. Instead, the activity-based DRM service request system proposed in Chapter 5 can work as a data collection system. The integration of vehicle routing system with this request system leads to a self-contained DRM operation system that collects the TAP data of DRM users through daily operation.

Additionally, this research assumes that DRM passengers have no preference for their activity start times as long as they can complete activities within estimated activity time windows. In reality, people prefer to participate in some activities at specific times for certain durations; that is, utility perceived from activity participation should depend on start time and duration. In this research, the objective function of ABPDP does not include terms associated with passengers' preferences for the temporal attributes of activities. Considering preferences in vehicle scheduling will improve service quality but requires estimating customer preferences for those temporal attributes. This estimation may rely on existing methodologies, such as Chow and Recker (2012) and Allahviranloo and Axhausen (2018).

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APPENDIX A: Abbreviation

ABA	Activity-based Approach
ABPDP	Activity-based Pick-up and Drop-off Problem
ABTDM	Activity-based Travel Demand Model
CCP	Chance-constrained Programing
DARP	Dial-a-ride Problem
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DRM	Demand-responsive Mobility
FTA	Federal Transit Administration
GPS	Global Positioning System
GT	Giant Tour
KDE	Kernel Density Estimation
LS	Local Search
MND	Mobile phone Network Data
MOD	Mobility on Demand
MPC	Model Predictive Control
NHTS	National Household Travel Survey
NYC	New York City
PDPTW	Pick-up and Delivery Problem with Time Window Constraints
PT	Public Transit
TAP	Travel-Activity Pattern
TDM	Travel Demand Management
TNC	Transportation Network Company
VMT	Vehicle Miles Traveled
VKT	Vehicle Kilometers Traveled
VRP	Vehicle Routing Problem

APPENDIX B: Arc Elimination Criteria by Dumas et al. (1991)

(a) priority: arcs $(\varphi_v^+, n+u), (n+u, u), (\varphi_v^-, \varphi_v^+), (\varphi_v^-, u), (\varphi_v^-, n+u)$ $\forall u \in P^+$.

(b) pairing: arcs (u, φ_v^-) $\forall u \in P^+$.

(c) vehicle capacity: arcs $(u,w), (w,u), (u, w+n), (w, u+n), (u+n, w+n)$ $(w+n, u+n)$ $\forall (u,w) \in \{(i,j) \in P^+ \times P^+ | d_i + d_j > k_v,\ u \neq w\}$.

(d) time windows: $(u,w) \in \{(i,j) \in P \times P | a_i + t_{ij}^v > b_j\}$.

(e) time windows and pairing of requests: if the travel times satisfy the triangle inequality, and $u \neq w$,

- arc $(u, w+n)$ if path $w \to u \to u+n \to w+n$ is infeasible with $T_w = a_w$.
- arc $(u+n, w)$ if path $u \to u+n \to w \to w+n$ is infeasible with $T_u = a_u$. (a special case of (d)).
- arc (u,w) if paths $u \to w \to u+n \to w+n$ and $u \to w \to w+n \to u+n$ are infeasible with $T_u = a_u$.
- arc $(u+n, w+n)$ if paths $u \to w \to u+n \to w+n$ and $w \to u \to u+n \to w+n$ are infeasible with $T_u = a_u$ and with $T_w = a_w$.

(f) same location: arc $(u,w) \in \{(i,j), (i+n, j+n), (i, j+n) | \forall i,j \in P^+, i \neq j\}$ if $t_{uw}^v = 0$, $b_u \geq b_w$, and $a_u \geq a_w$with at least one strict inequality, or if $t_{uw}^v = 0$ and $b_u = b_w$, $a_u = a_w$, and $i < j$.

Note that it is after setting the time windows as described in the following section that we apply rules (d) and (e).

APPENDIX C: Proof for (3.28')

We have $\sum_{u \in N} \alpha_{ru} \lambda_u = \sum_{u \in P^+} \alpha_{ru} \lambda_u$ and $\sum_{u \in N} \beta_{ruw} \lambda_u = \sum_{u \in P^+} \beta_{ruw} \lambda_u$ because $\lambda_u = 0 \ \forall u \in N \backslash P^+$. Since admissible routes have no loop,

$$\alpha_{ru} = \begin{cases} \sum_{w \in N} \beta_{ruw} & \forall u \in N \backslash \bigcup_v \varphi_v^- \\ \sum_{w \in N} \beta_{rwu} & \forall u \in \bigcup_v \varphi_v^- \end{cases}.$$

Hence,

$$\sum_{u \in P^+} \alpha_{ru} \lambda_u = \sum_{u \in N} \alpha_{ru} \lambda_u = \sum_{u \in N \backslash \bigcup_v \varphi_v^-} \left(\sum_{w \in N} \beta_{ruw} \right) \lambda_u + \sum_{u \in \bigcup_v \varphi_v^-} \left(\sum_{w \in N} \beta_{rwu} \right) \lambda_u$$

$$= \sum_{w \in N} \sum_{u \in N \backslash \bigcup_v \varphi_v^-} \beta_{ruw} \lambda_u + \sum_{w \in N} \sum_{u \in \bigcup_v \varphi_v^-} \beta_{rwu} \lambda_u$$

$$= \sum_{w \in N} \left(\sum_{u \in N \backslash \bigcup_v \varphi_v^-} \beta_{ruw} \lambda_u + \sum_{u \in \bigcup_v \varphi_v^-} \beta_{rwu} \lambda_u \right)$$

$$= \sum_{w \in N} \left(\sum_{u \in P^+} \beta_{ruw} \lambda_u \right) = \sum_{w \in N} \sum_{u \in N} \beta_{ruw} \lambda_u \ \blacksquare.$$

APPENDIX D: MERGE Heuristic

MERGE Heuristic

Let Ω be the basis of the current solution. Let Γ be the set of new routes already generated. Let $\sigma(r)$ be the set of requests covered by route r. Let $\upsilon(r)$ be the vehicle type corresponding to route r.

Step 0. Initialize $\Gamma = \emptyset$.

Step 1. From Ω, pick two routes r_1 and r_2 such that that have not been merged so far and $r_1 \neq r_2$ and $\sigma(r_1) \neq \sigma(r_2)$. Let $\Psi = \sigma(r_1) \cup \sigma(r_2)$.

Step 2. Suppose the vehicle type for the new route by the following rules:

i) If $\upsilon(r_1) = \upsilon(r_2)$, suppose $\upsilon(r_1)$ and go to Step 3.

ii) If $\upsilon(r_1) \neq \upsilon(r_2)$ and the vehicle type $\upsilon(r_1)$ is compatible with every order in $\sigma(r_2)$, suppose $\upsilon(r_1)$ and go to Step 3.

iii) If $\upsilon(r_1) \neq \upsilon(r_2)$ and the vehicle type $\upsilon(r_2)$ is compatible with every request in $\sigma(r_1)$, suppose $\upsilon(r_2)$ and go to Step 3. Otherwise, return to Step 1.

Step 3. Call the subroutine GENERATE to form a new route ρ covering all the orders in Ψ by the vehicle type supposed in Step 2. If the new trip is found has a negative reduced cost, then let $\Gamma = \Gamma \cup \{\rho\}$.

Step 4. If the number of trips in Γ has already reached a prespecified number M_M or all the pairs of the routes in Ω have been checked so far, stop. Otherwise, go to Step 1.

GENERATE Subroutine

Step 0. Set up an initial node sequence σ that covers the requests in Ψ and satisfy the vehicle capacity constraint. Let the best sequence generated so far be $\eta = \sigma$, and the best feasible route generated so far be $\rho = \emptyset$.

Step 1. For each request j in Ψ, do the following:

i) Remove request j (both j and $j+n$) from η.

ii) Let θ be the best feasible route generated in (iii) and $\theta = \emptyset$.

iii) Insert request j (both j and $j+n$) back in η. For every possible insertion such that the resulting sequence ξ satisfies the vehicle capacity constraint and the time-window constraints on the nodes in η, if $\theta = \emptyset$ or ξ is better than θ, let $\theta = \xi$.

iv) If $\theta \neq \emptyset$ and θ is better than ρ, let $\rho = \theta$ and η be the node sequence of θ.

Step 2. Repeat Step 1 for a prespecified number I_G of times. Return the best feasible route generated so far ρ.

APPENDIX E: TAP Simulation Procedure

This simulation synthesizes traveler groups and TAPs. The following procedure systematically simulates the attributes of the traveler groups and out-of-home activities. After initialization with given information, this procedure first generates an out-of-home activity set that is available in the given transportation network. Then, the procedure simulates traveler groups and selects out of the activity set activities for them to participate in.

0. Initialize the simulation with a transportation network, the number of traveler groups, and the number of out-of-home activities in the network.
1. Initialize activity set ACT by randomly assigning the following attributes:
    a. Location (i.e., a node of the transportation network): uniformly sampled from the network nodes.
    b. Duration range.
        i. Longest duration (upper bound): $LD_i \sim U(0.5, 12)$
        ii. Shortest duration (lower bound): $SD_i = r \times LD_i | r \sim U(0.25, 0.75)$
    c. Temporal availability (i.e., opening hours).
        i. Open: $OP_i \sim U(6, 23 - LD_i)$
        ii. Close: $CL_i \sim U(OP_i + LD_i, 23)$
2. Initialize traveler groups by randomly assigning the following attributes:
    a. Group size (fixed to one)
    b. Origin and destination locations: OR_g, DS_g ~uniformly from the network nodes.
    c. Earliest arrival and latest departure times
        i. Latest departure time from origin: $LO_g = \max_{i \in ACT} \{CL_i - SD_i - t_{h_g,i}\}$
        ii. Earliest arrival at destination: $ED_g = \min_{i \in ACT} \{OP_i + SD_i + t_{i,h_g}\}$

d. Out-of-home time window

i. Earliest departure time from origin:

$$EO_g = \begin{cases} r \mid r \sim U\left(6, \min\{11, LO_g\}\right) & 6 < LO_g \\ LO_g & \text{otherwise} \end{cases}.$$

ii. Latest arrival time at destination

$$LD_g = \begin{cases} r \mid r \sim U\left(\max\{16, ED_g\}, 23\right) & ED_g < 23 \\ ED_g & \text{otherwise} \end{cases}.$$

e. Set of activities available for particiaption $PA_g = ACT$ except:

i. Activities that group g cannot participate in for the activities' shortest duration.

ii. Activities at g's origin and destination.

f. Number of activities to participate in $n_g = \min\{r, |PA_g|\} | r \sim G(0.5)$

g. Activities to participate in: $A_g \sim$ uniformly sample n_g activities from PA_g.

h. The order of activities:

i. Generate a set of activity sequences by enumerating all the possible orders of activities in A_g.

ii. Sample an activity sequence from the activity sequence set and check its temporal feasibility. If any activity sequence is feasible, go to the next step.; otherwise set $n_g := n_g - 1$ and return to 2-g.

iii. Order the activities to minimize the total travel distance between them.

- $U(a, b)$: uniform distribution with upper bound a and lower bound b.
- $G(p)$: geometric distribution with success probability p.
- t_{ij}: travel time between nodes i and j.