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Publication Date

2021-05-01

DOI

10.1016/j.autcon.2021.103621

Peer reviewed

Building Technologies & Urban Systems Division
Energy Technologies Area
Lawrence Berkeley National Laboratory

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May 2021

DOI: 10.1016/j.autcon.2021.103621

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy,
Building Technologies Office, of the U.S. Department of Energy
under Contract No. DE-AC02-05CH11231.

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An ontology to represent synthetic building occupant characteristics and behavior

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Abstract

Since the introduction of the occupant behavior Drivers-Needs-Actions-Systems (DNAS) framework in 2013, researchers have used the framework or further developed it based on their case studies, which include efforts to collect new data on occupant behaviors. The effort is often costly for the relatively few new data points added. Problems emerge when the already collected data do not meet the modelers' interoperability requirements. Previous studies addressed this issue by developing more sophisticated ontologies that enable integration with other datasets and synthetic data methodologies that would meet unique research applications. This paper presents an extension of the DNAS framework for the representation of synthetic occupant data to support various applications and use cases across the building life cycle. An agent-based modeling application is one of our motivations that requires more elaborate characteristics of an occupant-agent or a group-of-agent. The extension, built upon a review of the literature, introduces new elements to the framework that fall into five categories, including socio-economic, geographical location, activities, subjective values, and individual and collective adaptive actions. On-going research includes identifying occupant datasets and developing data fusion methods to generate synthetic occupants, as well as to demonstrate its applications in agent-based modeling coupled with building performance simulation.

Keywords: synthetic population; occupant model; occupant behavior; building simulation; occupant; agent-based modeling

1. Introduction

Buildings are significant energy consumers worldwide and improving their performance is a global priority. Building performance simulation supports this endeavor in variety ways, by informing design, operational, investment, regulatory, and policy decisions at several levels of spatial and temporal detail [1]–[3]. It is now well understood that occupant behavior (OB) can play an important role in building performance and it should be considered when developing simulations [4]–[6]. Several approaches for incorporating OB into building performance modeling have

emerged that range from simple occupancy schedules to complex agent-based models [7]. Selecting the most appropriate model for the purpose of the specific modeling effort is an essential part of good modeling practice [8].

The weak link in many of these modeling efforts is OB data. There have been many case studies of OB of a specific type (e.g., window-opening behavior) in specific buildings with unique locations, purposes, and designs [9], [10]. Models developed from such data have limited generalizability. There are emerging efforts to create larger, multi-building databases that could provide a more robust basis for OB modeling. Higher-level OB data often includes demographic, economic, and social attributes of consumption [11]–[14]. Other disciplines, including environmental psychology [15], sociology [10], and urban planning [11], [16] have undertaken similar efforts. The most ambitious to date are the ASHRAE Thermal Comfort Database and ASHRAE Global Thermal Comfort Database [17], [18]. Even these ambitious, valuable efforts are extremely limited in scope, focusing only on a selection of thermal comfort aspects of OB. Needed are larger databases that include the rich dimensionality of OB by documenting the factors that lead to behaviors, the observed behaviors themselves, and the contextual considerations of location, timing, and design that situate the behavior. The OB research community could benefit from an ontology to guide the construction of such a database.

An ontology, or way of showing the properties of and relationships among objects, is useful when assembling a dataset, especially when aggregating many smaller contributions into a large dataset. It is also useful for guiding the construction of synthetic data that can be packaged with standardized modeling systems. The recent development of ontologies to represent occupant characteristics is for specific domain applications. Salimi et al. [19] reviewed and mapped existing ontologies to identify the integration gaps across multiple use cases. There is, however, less discussion on the use cases over the building lifecycle, starting from the design process, to operation, and retrofit. There is a clear tension between the sensible practice of fit-for-purpose modeling and the desired specification of a universal OB dataset [20], [21]. This paper proposes to resolve it by attaching the data specification to a useful—but not universal—modeling framework. It does so by linking its OB ontology development to the well-established DNAS framework as implemented in obXML [21], [22]. The remainder of this paper introduces the focal OB modeling use cases and associated OB characteristics that ought to be included in the ontology, the proposed schema, and reflections on feasibility and next steps.

1.1 Use cases of the synthetic population model

Data on occupant characteristics and behavior is useful for (1) building energy modeling, and (2) coupling with other large-data-driven models and datasets, such as demographic datasets, climate models, and terrain models [23]. This hints at the need for an integrated ontology to allow integration of disparate models and datasets. The provision of an ontology also enables data exchange between users for different purposes. One of the most extensive occupant data is the

ASHRAE Thermal Comfort Database I & II [17], [18]. Limited availability of data in even this well-resourced effort suggests that there is no complete and internationally accepted solution. The final standard used in the Comfort Database II (see Table 1) could not provide sufficiently for some aspects of thermal comfort descriptions (e.g., subjective values and habitual behaviors or activities). Within this context, this paper proposes a more comprehensive ontology of occupant behavior as a preparatory step in identifying the use cases of a synthetic occupant population model.

Table 1. Selected thermal comfort variables in ASHRAE Thermal Comfort Databases I & II.

Demographic	Thermal Sensation	Thermal Comfort	Thermal Preference	Thermal Acceptability
Sex	Hot	Very comfortable	Warmer	Acceptable
Age	Warm	Comfortable	No-change	Unacceptable
Weight	Slightly Warm	Slightly comfortable	Cooler	
Height	Neutral	Slightly uncomfortable		
Met	Slightly Cool	Uncomfortable		
Last met. activity	Cool - Cold	Very uncomfortable		

Source: [17], [18]

It is impossible to represent occupant behavior in its full dynamics and richness of detail. Therefore, it is necessary to select a particular subset of the domain concepts that are sufficient for developing synthetic population data [24]. Occupant behavior needs to maintain its relevance in research on the building life cycle as it is critical in achieving the goal of low or Zero-Net-Energy (ZNE) buildings (see Table 2). In order to support building design management practices during early stages of development projects, it is crucial to focus on considerations that strongly influence the building's life-cycle costs. Often, the amount of money invested in project development receives more attention than the costs likely to be paid for building operations and maintenance. Building occupancy and occupant behaviors strongly affect these life-cycle costs. During the operation phase, buildings' electricity usage is dependent on the number of occupants [25], [26]. Hence, occupancy is positively correlated to the utility costs for appliances, elevators, lighting, and HVAC operations. The related building components are retrofitted, over the years, for fixes and upgrades to ensure smooth operations, which also require fees.

User-friendly interfaces are a key factor linking OB and building energy consumption. Operable windows and moveable shades significantly improve occupant comfort [27], [28]. Naturally ventilated buildings and the experience of personal control contribute to comfort [16], [29]. Several simulation models have been developed to predict occupant-controlled ventilation, and these vary from simple ones that reflect either opened, closed, or adjustable window opening types; to the

overall facade design that also accounts for other parameters like window size, shape and location within the facade, and shading devices. Simulating the best and the worst scenario of occupant ventilation control on energy performance and/or comfort is more useful than having precise models that are embedded with the behavioral uncertainties [29]. Perceived sense of control affects thermostat adjustment. Thermostat technology has advanced to include features such as detection of occupancy, control of ventilation, interacting with the building internet network, and responding to electricity price signals [30]. Smarter household appliances (speakers and televisions) and lighting controls are also becoming ubiquitous.

Energy consumption during the full operation of a building can vary significantly from what was predicted during the design phase. Building energy researchers have advanced the state of the art in load calculations at both the building level and for end-uses. The 2009 and 2017 ASHRAE Fundamentals Handbook propose a general classification based on two models, namely a forward approach that uses equations and measured data as their input to predict the output, which is the load profiles. The data-driven approach considers measured data for both input and output to explain the relationship defining the overall systems. The top-down and bottom-up classification posits contrasting hierarchies of data inputs [1], [31]. Top-down models aggregate measured load profiles deterministically, usually, at the national level. Bottom-up models synthesize individual load curves by sampling the electricity consumption of a few representative households. These models regard input data that vary from household electricity bills to time of use survey data to represent human behavior. Another approach is to use statistical coefficients of multiple measured data, which falls under the category of hybrid models. The hybrid approach is added to classify models that combine elements of top-down models that consider the deterministic load profiles and those of bottom-up models that synthesize individual load profiles through representative samples [32]. Hybrid models often use a statistical coefficient of multiple measured data to describe the load profiles.

Another potential use case is energy management, whose task is to ensure the efficiency of electric power usage and optimization of energy usage. Energy management services rely greatly on the development of power meters and end-use device controls. Today's power meter is equipped with occupancy monitoring and prediction, and synthetic occupant data can potentially contribute to their processes. Applications for designing energy efficiency policies and energy pricing strategies may also be feasible.

Table 2 illustrates potential applications of occupant behavior data across the various phases of the building life cycle. During the building design phase, considerations of occupants and their behavior are critical to help determine whether operable windows, interior shades, what type of lighting systems and controls (on/off switching or dimming), what type of HVAC systems are appropriate. Occupant's release of sensible and latent heat, comfort temperatures for cooling and heating, ventilation needs, and visual comfort needs are determinant factors in the building HVAC

loads calculations and equipment sizing. During the building operation phase, occupant's presence and movement, as well as their interactions with building systems, change energy demand and drives the occupant-centric operation and controls. During the building retrofit, occupant's feedback on indoor environmental quality, as well as usability and interface of building systems, are crucial input to determine targeting technologies (i.e., energy conservation measures, ECMs) to reduce energy use and improve occupant comfort and wellbeing.

Table 2. Use cases of occupant behavior data over the building lifecycle.

Use Case	Phase in Building Life Cycle	Description
Selection of facades	Building design - Envelope	Consideration of operable windows, moveable shades
Selection of lighting system	Building design - Lighting	Controllability of lights: switch or dimming
Selection of HVAC system type and size equipment capacity	Building design - HVAC	Selection of HVAC system type and sizing of equipment capacity considering zoning, access to thermostat, and occupant diversity.
Load calculation	Building design - Load calculation	Calculation of space cooling, heating and ventilation loads
Occupant-centric sensing and controls	Building operation	Occupant sensing and occupancy-based control of HVAC, lighting, and MELs to save energy or provide energy flexibility
Evaluate the energy savings of ECMs	Building retrofit	Evaluate the impact of occupant behavior on energy savings of ECMs

2. Representation of the synthetic occupant population

Research in the occupant behavior domain employs multi-scale datasets. Previous works developed data ontologies that are specific to their domain of study [33], [34]. Occupant behavior research incorporates an interactive component between the occupants and building systems,

equipment, and mechanisms [22]. The epistemological model of occupant behavior uses the concept of comforts, which we divide into social-demography, location, subjective values, activities, and social influence. Comforts are specific combinations of the attributes of mechanisms and measures taken as consideration by an occupant. The distinction between ontological and epistemological concerns is clear on how occupant's perception of the environment depends on their characteristics, adopted values, experience, and particular activities [31]. Consider a case study of two tenants occupying an open office with partitions on one office floor; based on the activities, the attributes of office workers (e.g., 8-to-5 working hours), and their experience, the building manager set the thermostat and luminance level for the open office space, where the two tenants are occupying. Although the two tenants receive the same thermostat and luminance setpoints, one tenant perceives comfort differently from the other, because of the attributes (e.g., sitting by the window and under the ceiling diffuser) and the activity (e.g., to use a copier). This example shows how location, experience, or activities can highlight particular comforts rather than others.

The occupant is modeled as a rational agent trying to maximize its comfort measure, i.e., setting the temperature of the space (Fig. 1). We apply the extended ontology to the development of synthetic datasets that can be used in conjunction with agent-based modeling (ABM) tools. ABM has enabled researchers to explore the complexity and dynamics of occupant-occupant, as well as occupant-building interactions more closely [7]. With ABM application in mind, this article describes in detail the new components being added to the DNAS framework (Table 3), including:

1. Socio-economic characteristics,
2. Geographical location,
3. Subjective values,
4. Occupant activities,
5. Individual and collective adaptive action.

Fig. 1. Conceptual interaction of components of the building occupant.

Table 3. Proposed categories of the synthetic building occupant dataset.

Features	Attributes	Description	References
Thermal comfort	Cooling temperature (a probability distribution, PDF) Heating temperature PDF	Sensation and perception of thermal comfort.	[17], [35]
Visual comfort	Bright/dark (illuminance PDF) Sensitive to glare?	Sensation and perception of lighting intensity that meets the illuminance level.	[36], [37]
IAQ	Sensitive to IAQ (CO ₂)	Sensation and perception of the indoor air quality and smell, i.e., level of carbon dioxide (CO ₂) and other pollutants.	[38], [39]
Socio-economic characteristics	Gender, Age range, Marital status, Education, Employment, Income range, Country of origin	Characteristics pertaining social, economic, and demographic.	[11]–[14], [40]
Location	Geographical location attributes, such as climate zones, country, and energy-related policy in place.	The building’s location is viewed from climate zones and the governing administration.	[17], [18], [41]
Subjective values	Personal traits that drive either energy-saving or energy-consumption behaviors, i.e., cost-conscious, accommodating, and awareness of natural environment	Individual occupant values and cultural perspectives in relation to energy consumption.	[5], [36], [42]

Activities at home	Indoor activities, such as sleeping, cooking, cleaning, working, and the use of appliances. Consume hot/cold drinks.	Occupants' lifestyle and activities in residential buildings.	[16], [40], [43]
Activities at work	Indoor activities are pertaining to presence, movement, and use of appliances. Consume hot/cold drinks.	Occupants' lifestyle and activities in commercial buildings.	[44], [45]
Occupant adaptive behaviors	Open/close windows, Pull up/down blinds, Switch on/off or dim lights, Adjust the thermostat, Adjust clothing	Individual choice of actions in adapting to or mitigating the changing indoor environmental conditions.	[26], [46], [47]
Group decision making	Majority, Authority, First-to-speak-out	Adaptive actions that pertain to shared controls with other occupants of the same zone.	[5], [48]

2.1 Comfort features

Literature in building energy use and occupant behavior has grown much in the last decade. Between 2011 and May-2020 of the writing of this paper, there were 1,290 articles published in the field (Fig. 2 Left). The literature review was performed in the Web of Science search engine using TS= (comfort AND behavior) AND (building AND energy). Among those, we identified articles with a title that has keywords of “thermal comfort,” “visual comfort” (or lighting comfort), and Indoor Air Quality (or IAQ). Fig. 2 (Right) shows that thermal comfort has the most discussion with regards to occupant comfort and behavior, which also motivates this article to update the comfort component within the DNAS-framework.

Fig. 2. Literature reviews in building energy use and occupant behavior.

2.1.1 Thermal comfort feature

The widely-used approach to capture occupant thermal comfort is the Predicted Mean Vote (PMV) – Predicted Percentage Dissatisfied (PPD) model. The model is developed based on the physics heat-balance model [35], [49]. The model has components that include indoor temperature, air velocity, relative humidity, clothing insulation, and metabolic rate. The 2017 ASHRAE Standard 55 [50] specifies the procedure for calculating operative temperature to include occupant adaptation for the adaptive thermal comfort model. A more-recent comfort model incorporates the standard effective temperature (SET) to improve accuracy and application [51]. While much of the thermal comfort discussion is around a commercial building environment, i.e., office buildings, assessing thermal comfort in residential buildings goes well beyond regulating the heat balance parameters. Rather, perceptions and responses to the thermal comfort of the environments may be driven by an interaction between people and their environment, psychological traits, and cultural practices, which will be discussed in the following sections.

2.1.2 Visual comfort feature

Researchers have conducted surveys to collect data to assess visual comfort, which is around the lighting condition and control. Data on the lighting condition usually varies from the amount of natural and artificial lights to the amount of glare, also, from the two identifiable sources. Controls over lighting fixtures often include the adjustment of window blinds, illuminance intensity on task light, and overhead light [36]. The rise of machine learning and its application also contributes to the development of better lighting controls. Advancement in lighting controllers, LightLearn, has been proposed to consider occupant behavior and preferences on the illuminance level [37], [52]

2.1.3 Indoor Air Quality (IAQ) feature

Indoor air quality is another topic of increasing interest in occupant comfort and behaviors. Researchers ask questions on IAQ around the following categories, such as building characteristics and occupants' satisfaction (perception of odor and air quality) and self-report health conditions (dry eyes, dry throat, stuffy nose, and headache). Common IAQ measurements in buildings are the amount of CO₂, radon, TVOC, formaldehyde, and fungal ecology forming units [38]. IAQ is also often related to occupant's lifestyles and activities in the indoor environment. These include pet ownership, smoking, the presence of plants, fragrances, and insecticides [36]. CO₂ is usually used as a proxy of IAQ in the built environment to determine ventilation needs.

2.2 Occupant characteristics, traits, and activities

Occupants perform adaptive actions either individually or collectively via group decision-making schemes based on comfort perceptions, as suggested in the above section. Occupants, however, perceive their environment and act upon as their adaptive mechanisms based on inherent characteristics and personality traits. Occupants in a building that is geographically-located in the equator tend to have a high tolerance of warmer ambient temperature compared to those who reside in the North or South of the equator—the types of activities that they do also inform their perception of and adaptation to the environment. A receptionist staff in a hotel may find himself feeling slightly cooler than his friend, who works as a luggage porter in the same hotel. The type of job he performs does not require more metabolic activity compared to his counterparts.

This section covers the frequently-appearing characteristics, traits, and activities in comfort and behavior research. Researchers have conducted surveys, distributed questionnaires, and interviewed occupants to gather data on whether the building is behaving as intended, occupants are happy with the results, and their way to cope with the built environment. Post-occupancy evaluation (POE) is one known method that was introduced by Sim Van der Ryn and Murray Silverstein in 1967 [53]. Since it was first used in a case study of student dormitories at Berkeley, building researchers and architects have developed better questionnaires to capture the occupant experience with regards to thermal comfort, visual comfort, and the overall indoor environmental quality.

2.2.1 Socio-economic characteristics

Studies on occupant behavior in building energy simulation have emphasized comfort perception and control actions that occupants undertake to meet the desired level of comfort [21], [54]. As a larger occupant population becomes the interest, it is known that thermal comfort influencing real energy use in buildings is not independent of socio-economic characteristics [73]. The literature on socio-economic factors has covered both residential and office buildings. These factors vary from physiological factors such as age and gender to economic factors like income and employment status, as well as tenure type of space or dwelling unit.

Residential building tends to be occupied by occupants with more diverse and unique characteristics than those in office buildings. Several characteristics (e.g., education, employment, belief, and cultural background) of the households that influence electricity consumption have been summarized in [55]. Previous research has indicated that gender and age have some effects on the overall building comfort and electricity consumption [56], [57]. The age composition of occupants also matters in that the number of children in residential buildings have shown positive effects on the amount of electricity consumed by the household. O'Doherty et al. [58] found that household members under the age of 40 has the most appliances yet the most energy saving appliances. Bedir and Kara [59] stated that income level does not necessarily correlate with electricity consumption. According to Genjo et al.'s [60], economic affluence influenced the grouping of the households based on electricity consumption. Jafary and Shephard [61] indicated a significant increase in the appliance electricity consumption for every \$24,000 increase in household income. However, there was an exception for households with income in the range of \$100,000-\$149,000, in which the electricity consumption is lower and close to households with income range of \$50,000-\$74,999. They also analyzed the electricity consumption in apartments, which income was negatively correlated to the average electricity consumption.

2.2.2 Location characteristics

Occupant comfort and energy use in buildings are highly correlated with the location of the buildings where the occupant resides. Building occupants and behavior are usually studied using methods that are specific to climate zones, countries, cities, and a block in a city [17], [18]. A study differentiates occupant behavior in downtown high-rises from that in suburban low-rise residential buildings [41]. The behaviors are also different between conventional and green buildings [62] and between hot and cold climates [63]. Location characteristics are also strongly related to infrastructural investments and policies of the authorizing administration on energy use in buildings [13].

2.2.3 Subjective values

Occupant personal characteristics and adaptive actions are attributed to subjective values. The field of environmental psychology offers frameworks on human subjective values and character traits

that have helped to explain energy use in buildings. One of the best known theories in the field that explains naturalistic decision making with regards to control is the Theory of Planned Behavior (TPB) [64]. A framework suggests a spectrum of energy use behavior from reasoned and deliberate to unplanned and habitual [16]. The findings from the study show that the values-based framework did not predict habitual behaviors very well. Several occupant archetypes were developed to understand behavior to reduce electricity consumption and maintain comfort [42], [65]. Personality traits and subjective values also determine occupant capacity to share controls [5], [36].

2.2.4 Occupant activities

Activities among occupants in residential buildings are different from those in the commercial buildings. Research on occupant activities draws more to the residential sectors as more diversity can be observed. These activities are related to appliances that are available for use, such as the following common activities: using a microwave, stove, oven, and a clothes washer and dryer. Entertainment appliances on electricity consumption. TV, portable TV, video player, video console, and digiboxes are also included in this category [66]–[69].

The frequency of using appliances is particularly related to occupant presence and activity patterns that are diverse depending upon the type of households. Households with children have a greater occupancy rate than those without. On the other hand, the pattern of occupancy for office buildings has a relatively fixed schedule [26], [70], [71]. Occupant activities in office buildings are also constrained spatially and temporally. Occupants in an open-office building layout tend to have a higher mobility rate compared to those in enclosed offices. Their activities also peak at certain time periods throughout the day, e.g., the beginning and end of office hours and at lunch hour. Hence, the use of activity-related appliances is affected. Other than IT appliances such as a desktop computer and a laptop computer, office occupants use minor cooking appliances, like a microwave and an electric kettle during lunch-breaks.

Occupant activities that do not use appliances are mostly related to the comfort level of the occupant. Studies have indicated that smoking in the interior space, which is commonly found in residential buildings, contributes the most to the indoor air quality and temperature. Other activities like indoor exercise and cleaning with chemical substances also contribute to the occupant level of comfort [38], [72].

2.3 Individual adaptive actions

Previous studies have framed individual occupant adaptive behaviors differently, and many of them speak exclusively to building modelers. Building modelers need quantifiable data. However, information on behaviors and the behind-motivations are collected qualitatively. POE has been useful in addressing problems in building performance from the perspective of building occupants

[73]. Other methodologies include case study, survey, field study, and empirical study, as suggested in [74]. These methodologies use questionnaires to collect data, and they pertain to the following issues, including health and safety, security, leakage, poor signage and way-finding, indoor air quality, and thermal comfort. Respondents self-report their behaviors in adapting to the situation that they feel at that time. When the collected data is transferred to the modelers, there is a challenge in translating such rich information into a machine-readable format [75].

2.4 Collective adaptive actions

Building controllability influences adaptive occupant behaviors, and these controls are often shared with other occupants. The success of communication among occupants, therefore, becomes an important factor that strongly relates to the organizational characteristics of the building control management. In office buildings, for example, building occupants often have limited access to specific control and adjustments, such as overhead lighting, operable windows, movable shades, and thermostat. A tenant representative plays a mediator role to transmit the occupants' requests to the building manager, who possesses direct access to the controls [48], [76]. Similarly, in residential building units with rather decentralized control, the head of a household often gains more access to this control than the rest of the members in the same household. Therefore, both a tenant representative of an office building and the head of a household need to adopt a decision process that works for the group. This paper considers three types of decision processes. The first is a majority decision process, in which a majority of members in a group favor to a certain decision. The second is a hierarchical decision process, in which priorities drive the decisions and implemented them through authority. The final one is a decision that favors the first in a request-queue.

3. Schema

This paper provides an extension to the existing occupant behavior ontology, namely Drivers-Needs-Actions-Systems (DNAS) framework [20], [21]. DNAS framework standardizes the energy-related occupant behavior modeling and has been widely used and become part of other developed ontologies, such as in [19]. The extension of the DNAS framework also utilizes the same schema format, which is known as obXML (occupant behavior XML) [22].

The additional elements that are added to the framework include some that are internal, and others that are external to the framework. An additional child element to the Needs component is *ComfortTemperatures*, in which two sub-components are available, namely, *ComfortCooling* and *ComfortHeating* (Fig. 3). This additional element is based on analysis of the comfort temperatures [35] using the ASHRAE Global Thermal Comfort Database [18]. The resulting distribution of both cooling and heating temperature follow the Gaussian distribution.

Fig. 3. The tree diagram identifying comfort heating and cooling temperatures

A number of child elements are added under the Occupant element to detail the occupant characteristics. They are *SocioEconomic*, *GeographicLocation*, and *SubjectiveValues*.

Fig. 4. Occupant's attributes of social, economic, and demographic characteristics.

Per the discussion in the above section, each of these child elements has its own child elements. *SocioEconomic* has *Age*, *Gender*, *LifeStyle*, *JobType*, *MaritalStatus*, *Education*, *IncomeGroup*, and *Employment*. Each of these components has a unique data type that is categorical. Similarly, *GeographicLocation* element has six child elements, with each has a categorical data type. They are *Country*, *ClimateZone*, *CommuteMode*, *Policy*, *Infrastructure*, and *Cost* structure. *SubjectiveValues* element has a selection of child elements of *PastExperience*, *CostConscious*, *EnvironmentAwareness*, *TechnologyOriented*, *Accommodating*, and *SocialInfluence*. Each of the child elements has the same level of categories, which are high, medium, and low, to describe the weights to the overall determining traits.

Table 4. The child elements of the parent element *Socio-economic* and their data types.

Variable	Data Type
Age	Gender	{male, female, other}
Gender	Age	Group levels: {15-25, 26-35, 36-50, 51-70, >70}
LifeStyle	Marital status	{single, married, partner}
JobType	Education	{high school, bachelors, post-graduate}
MaritalStatus	Income	Group levels:{Low, Medium, High}
Education	Employment	{unemployed, employed, self-employed}
IncomeGroup		
Employment		

Table 5. The child elements of the parent element *GeographicLocation* and their data types.

Variable	Data Type
Country	Country	unique
ClimateZone	ASHRAE Climate Zone	{0, 1, 2, 3, 4, 5, 6, 7, 8} x {A, B, C}
CommuteMode	Commute	{walk, cycle, car, transit}
Policy	Policy incentives	{subsidies, tax-cuts, codes compliance, insurance mandate}
Infrastructure	Infrastructure	{EV charging, microgrid, grid buyback}
Cost	Cost and fees	{cost of living, utility cost}

Table 6. The child elements of the parent element *SubjectiveValues* and their data types.

	Variable	Data Type
	Past experience	{hi, md, lo}
	Cost-conscious	{hi, md, lo}
	Environment-awareness	{hi, md, lo}

Technology-oriented lifestyle Accommodating Social influence	{hi, md, lo} {hi, md, lo} {hi, md, lo}
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4. A case of population synthesis

To illustrate the use of ontology in guiding population synthesis, we used a subset of occupant behavior data from ASHRAE Thermal Comfort database II. A total of 34,095 data subset is selected to represent office occupants and their behaviors. There are 65 columns, within which 49 are thermal comfort related variables for each record. For this illustration, we selected the occupant variables that follow the proposed extended DNAS framework, which fall under the socio-demographic and thermal comfort categories. We selected three socio-demographic variables *Age*, *Height*, and *Weight*. The thermal comfort variables are *Thermal Preference*, *PMV* and *Air Temperature*. Other useful variables in the dataset are relevant to the location attributes (*Season*, *Climate*, *City*, and *Country*). These attributes are great to illustrate a more complex population synthesis process that considers fusion of the behavior dataset with detailed location-specific census datasets, such as American Time Use Survey (ATUS) and Public Use Microdata Area (PUMA). A more elaborate population synthesis methodology and datasets fusion is part of an ongoing work and a bigger research agenda.

The resulting synthetic datasets show comparable distributions with the observed data has. Figure 5 shows the frequency distribution of air temperature (in °C) that is categorized based on other two variables, sex and thermal preference. The distribution suggests a successful synthesis of the dataset.

Fig 5. Comparison of the frequency distribution for key variables in observed and synthetic datasets.

Office buildings are often occupied by multiple tenants, within each occupants have varied control privilege towards their built environment. In buildings with centralized controls, building operators have the greatest privilege to adjust the thermostat or overhead lighting of the common areas, such as those in the lobby, atrium, corridors, and stairs. Each tenant group occupying a section of the building may also have a true privilege to adjust to the built environment within the area. A tenant representative is usually appointed to do the tasks.

To represent a multi-tenanted office building, we created a 5-level categorical variable, *GroupID* in the observed dataset, with each level corresponds to a tenant group. The variable is applied at random and equally distributed across the dataset. Figure 6 shows the joint distribution of air temperature and the tenant groups and synthetic data. It illustrates that the population synthesis using Iterative Proportional Fitting (IPF) satisfies the joint distribution of variables. One can observe that the pairs of variables are not independent, and the dependency structures between the two are preserved.

Assigning individual occupants to occupants-groups, like tenant-groups of the above example and households in residential buildings, is another challenge in generating synthetic population for building occupants. Individual-to-group assignment within population synthesis has gained a lot of attention in the transportation field. Fournier, et al [77] proposed an integrated approach for household and workplace assignments. Müller [78] developed an R package, MultilevelIPF, that assigns households to geographic areas.

Fig 6. Joint distribution of the air temperature and tenant group in a multi-tenant office building

5. Conclusion

Since the introduction of DNAS framework and its obXML schema representation in 2013, it has become a standard to the building simulation community on modeling energy-related occupant behavior in buildings. Currently, the ontology is missing two important parts. The current interoperability of the framework is still limited to a general model but not to known use cases in the building phase lifecycle. The framework is not updated to the recent development of theories of building and occupant interactions. To this extent, this paper fills in the lack of updates with the extended version of the DNAS framework. The main motivation behind the extension was the growing of datasets on occupant behavior that serve particular research purposes. The multiple ontologies that define these data, an effort for ontology integration has also been made. This paper intends to develop an ontology that serves specific use cases and for the use of the development of the synthetic occupant population.

The core components of the ontology that draws upon adaptive behavioral constructs, namely Drivers, Needs, Actions, and Systems, remain unchanged. Nevertheless, the extension attempts to include more-detailed characteristics of an occupant, such as the level of income and employment status. Many case studies from around the world also indicate that occupant behaviors are determined by some geographical location attributes, such as climate zone, urban, and rural regions. Relevant energy-related policies in-place, as well as infrastructural investments of a municipality, are also behavioral determinants. Moreover, energy-use behaviors are also different between commercial and residential buildings. It was found that energy-use behaviors in residential buildings are more dynamic than those in commercial buildings.

From the use-case viewpoint of how the DNAS ontology is extended, the proposed version of the framework also serves the synthetic population generation effort. Researchers often collect their data that is recent, small, follow a specific ontology and mix-types between cross-sectional and longitudinal data depending on the purpose of the study. An on-going work is to identify existing

occupant datasets and models, and develop a method to fuse different datasets to generate the synthetic occupants represented in the aforementioned extended DNAS ontology and the obXML schema.

Acknowledgments

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technologies of the United States Department of Energy, under Contract No. DE-AC02-05CH11231. Authors benefited from participation and discussion in the project (2018-2023) Annex 79, Occupant-centric building design and operation, under the International Energy Agency's Energy in Buildings and Communities Program.

References

- [1] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8. Pergamon, pp. 1819–1835, 01-Oct-2009, doi: 10.1016/j.rser.2008.09.033.
- [2] Energy Information Administration, "Annual Energy Outlook 2020," 2020. Accessed July 6, 2020. <https://www.eia.gov/outlooks/aeo/>
- [3] International Energy Agency, "Key World Energy Statistics," 2020. Accessed November 17, 2020. <https://www.iea.org/reports/key-world-energy-statistics-2020>
- [4] A. Mahdavi and M. Taheri, "An ontology for building monitoring," *Journal of Building Performance Simulation*, vol. 10, no. 5–6, pp. 499–508, Nov. 2017, doi: 10.1080/19401493.2016.1243730.
- [5] T. Hong, C. fei Chen, Z. Wang, and X. Xu, "Linking human-building interactions in shared offices with personality traits," *Building and Environment*, vol. 170, no. 106602, Mar. 2020, doi: 10.1016/j.buildenv.2019.106602.
- [6] S. D'Oca, T. Hong, and J. Langevin, "The human dimensions of energy use in buildings: A review," *Renewable and Sustainable Energy Reviews*, vol. 81, no. 1, pp. 731–742, Jan. 2018, doi: 10.1016/j.rser.2017.08.019.
- [7] C. Berger and A. Mahdavi, "Review of current trends in agent-based modeling of building occupants for energy and indoor-environmental performance analysis," *Building and Environment*, vol. 173, no. 106726, Apr. 2020, doi: 10.1016/j.buildenv.2020.106726.
- [8] W. O'Brien, A. Wagner, and J. K. Day, "Introduction to occupant research approaches," in *Exploring Occupant Behavior in Buildings: Methods and Challenges*, A. Wagner, W. O'Brien, and B. Dong, Eds. Springer International Publishing, 2017, pp. 107–127. ISBN 9783319614649

- [9] J. Widén and E. Wäckelgård, "A high-resolution stochastic model of domestic activity patterns and electricity demand," *Applied Energy*, vol. 87, no. 6, pp. 1880–1892, 2010, doi: 10.1016/j.apenergy.2009.11.006.
- [10] S. Barr, G. Shaw, and T. Coles, "Sustainable lifestyles: Sites, practices, and policy," *Environment and Planning A*, vol. 43, no. 12, pp. 3011–3029, 2011, doi: 10.1068/a43529.
- [11] C. J. Andrews, "The Changing Socioeconomic Context of Buildings," *Journal of Solar Energy Engineering, Transactions of the ASME*, vol. 139, no. 1, SI, Feb. 2017, doi: 10.1115/1.4034911.
- [12] R. McKenna, L. Hofmann, E. Merkel, W. Fichtner, and N. Strachan, "Analysing socioeconomic diversity and scaling effects on residential electricity load profiles in the context of low carbon technology uptake," *Energy Policy*, vol. 97, pp. 13–26, Oct. 2016, doi: 10.1016/j.enpol.2016.06.042.
- [13] M. Mrówczyńska, M. Skiba, A. Bazan-Krzywoszańska, and M. Sztubecka, "Household standards and socio-economic aspects as a factor determining energy consumption in the city," *Applied Energy*, vol. 264, Apr. 2020, doi: 10.1016/j.apenergy.2020.114680.
- [14] C. E. Kontokosta and R. K. Jain, "Modeling the determinants of large-scale building water use: Implications for data-driven urban sustainability policy," *Sustainable Cities and Society*, vol. 18, pp. 44–55, Nov. 2015, doi: 10.1016/j.scs.2015.05.007.
- [15] N. Hanus, G. Wong-Parodi, M. J. Small, and I. Grossmann, "The role of psychology and social influences in energy efficiency adoption," *Energy Efficiency*, vol. 11, no. 2, pp. 371–391, Feb. 2018, doi: 10.1007/s12053-017-9568-6.
- [16] E. L. Hewitt, C. J. Andrews, J. A. Senick, R. E. Wener, U. Krogmann, and M. Sorensen Allacci, "Distinguishing between green building occupants' reasoned and unplanned behaviours," *Building Research & Information*, vol. 44, no. 2, pp. 119–134, Feb. 2016, doi: 10.1080/09613218.2015.1015854.
- [17] R. de Dear and G. S. Brager, "Developing an adaptive model of thermal comfort and preference," *ASHRAE Transactions*, vol. 104 Part 1, 1998. Accessed July 6, 2020. https://www.sydney.edu.au/architecture/documents/staff/richard_de_dear/RP884_Final_Report.pdf
- [18] V. F. Licina *et al.*, "Development of the ASHRAE Global Thermal Comfort Database II," *Building and Environment*, vol. 142, pp. 502–512, Sep. 2018, doi: 10.1016/j.buildenv.2018.06.022.
- [19] S. Salimi, M. Nik-Bakht, and A. Hammad, "Towards an ontology for holistic building occupant information modelling," *IOP Conference Series: Materials Science and Engineering*, vol. 609, no. 62025, Oct. 2019, doi: 10.1088/1757-899x/609/6/062025.
- [20] W. J. N. Turner and T. Hong, "A technical framework to describe energy-related occupant behavior in buildings," in *Behavior, Energy & Climate Change conference*, 2013. Accessed July 6, 2020. <https://escholarship.org/uc/item/0jv0j8kx>

- [21] T. Hong, S. D'Oca, W. J. N. Turner, and S. C. Taylor-Lange, "An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework," *Building and Environment*, vol. 92, pp. 764–777, Oct. 2015, doi: 10.1016/j.buildenv.2015.02.019.
- [22] T. Hong, S. D'Oca, S. C. Taylor-Lange, W. J. N. Turner, Y. Chen, and S. P. Corgnati, "An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAs framework using an XML schema," *Building and Environment*, vol. 94, pp. 196–205, Dec. 2015, doi: 10.1016/j.buildenv.2015.08.006.
- [23] R. Buffat, A. Froemelt, N. Heeren, M. Raubal, and S. Hellweg, "Big data GIS analysis for novel approaches in building stock modelling," *Applied Energy*, vol. 208, pp. 277–290, Dec. 2017, doi: 10.1016/j.apenergy.2017.10.041.
- [24] M. Genesereth and N. Nilsson, *Logical Foundations of Artificial Intelligence*. Morgan Kaufmann, 1987. ISBN 978-0-934613-31-6
- [25] T. Hong, D. Yan, S. D'Oca, and C. fei Chen, "Ten questions concerning occupant behavior in buildings: The big picture," *Building and Environment*, vol. 114, pp. 518–530, Mar. 2017, doi: 10.1016/j.buildenv.2016.12.006.
- [26] Y. Chen, T. Hong, and X. Luo, "An agent-based stochastic Occupancy Simulator," *Building Simulation*, vol. 11, no. 1, pp. 37–49, Feb. 2018, doi: 10.1007/s12273-017-0379-7.
- [27] G. Brager, G. Paliaga, and R. de Dear, "Operable windows, personal control and occupant comfort," *ASHRAE Transactions*, vol. 110 Part 2, pp. 17–35, 2004. Accessed July 6, 2020. <https://escholarship.org/uc/item/4x57v1pf>
- [28] W. O'Brien, K. Kapsis, and A. K. Athienitis, "Manually-operated window shade patterns in office buildings: A critical review," *Building and Environment*, vol. 60, pp. 319–338, Feb-2013, doi: 10.1016/j.buildenv.2012.10.003.
- [29] A. Roetzel, A. Tsangrassoulis, U. Dietrich, and S. Busching, "A review of occupant control on natural ventilation," *Renewable and Sustainable Energy Reviews*, vol. 14, no. 3, pp. 1001–1013, Apr. 2010, doi: 10.1016/j.rser.2009.11.005.
- [30] T. Pepper, M. Pritoni, A. Meier, C. Aragon, and D. Perry, "How people use thermostats in homes: A review," *Building and Environment*, vol. 46, no. 12, pp. 2529–2541, Dec. 2011, doi: 10.1016/j.buildenv.2011.06.002.
- [31] A. Grandjean, J. Adnot, and G. Binet, "A review and an analysis of the residential electric load curve models," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 9, pp. 6539–6565, 2012, doi: 10.1016/j.rser.2012.08.013.
- [32] H. X. Zhao and F. Magoulès, "Parallel Support Vector Machines Applied to the Prediction of Multiple Buildings Energy Consumption," *Journal of Algorithms & Computational Technology*, vol. 4, no. 2, pp. 231–249, Jun. 2010, doi: 10.1260/1748-3018.4.2.231.
- [33] T. R. Gruber, "A translation approach to portable ontology specifications," *Knowledge Acquisition*, vol. 5, no. 2, pp. 199–220, Jun. 1993, doi: 10.1006/knac.1993.1008.

- [34] B. Chandrasekaran, J. R. Josephson, and V. R. Benjamins, "What are ontologies, and why do we need them?," *IEEE Intelligent Systems and Their Applications*, vol. 14, no. 1, pp. 20–26, 1999, doi: 10.1109/5254.747902.
- [35] Z. Wang and T. Hong, "Learning occupants' indoor comfort temperature through a Bayesian inference approach for office buildings in United States," *Renewable and Sustainable Energy Reviews*, vol. 119, no. 109593, Mar. 2020, doi: 10.1016/j.rser.2019.109593.
- [36] C. J. Andrews, M. S. Allacci, J. Senick, H. Chandra-Putra, and I. Tsoulou, "Using synthetic population data for prospective modeling of occupant behavior during design," *Energy and Buildings*, vol. 126, pp. 415–423, Aug. 2016, doi: 10.1016/j.enbuild.2016.05.049.
- [37] Z. Nagy, F. Y. Yong, and A. Schlueter, "Occupant centered lighting control: A user study on balancing comfort, acceptance, and energy consumption," *Energy and Buildings*, vol. 126, pp. 310–322, Aug. 2016, doi: 10.1016/j.enbuild.2016.05.075.
- [38] S. Yang, J. G. Pernot, C. H. Jörin, H. Niculita-Hirzel, V. Perret, and D. Licina, "Energy, indoor air quality, occupant behavior, self-reported symptoms and satisfaction in energy-efficient dwellings in Switzerland," *Building and Environment*, vol. 171, Mar. 2020, doi: 10.1016/j.buildenv.2019.106618.
- [39] A. Steinemann, P. Wargocki, and B. Rismanchi, "Ten questions concerning green buildings and indoor air quality," *Building and Environment*, vol. 112, pp. 351–358, Feb. 2017, doi: 10.1016/j.buildenv.2016.11.010.
- [40] I. Tsoulou, C. J. Andrews, R. He, G. Mainelis, and J. Senick, "Summertime thermal conditions and senior resident behaviors in public housing: A case study in Elizabeth, NJ, USA," *Building and Environment*, vol. 168, no. 106411, Jan. 2020, doi: 10.1016/j.buildenv.2019.106411.
- [41] P. Du, A. Wood, and B. Stephens, "Empirical Operational Energy Analysis of Downtown High-Rise vs. Suburban Low-Rise Lifestyles: A Chicago Case Study," *Energies*, vol. 9, no. 6, Jun. 2016, doi: 10.3390/en9060445.
- [42] M. A. Ortiz and P. M. Bluysen, "Developing home occupant archetypes: First results of mixed-methods study to understand occupant comfort behaviours and energy use in homes," *Building and Environment*, vol. 163, no. 106331, Oct. 2019, doi: 10.1016/j.buildenv.2019.106331.
- [43] J. Malik and R. Bardhan, "Energy target pinch analysis for optimising thermal comfort in low-income dwellings," *Journal of Building Engineering*, vol. 28, Mar. 2020, doi: 10.1016/j.job.2019.101045.
- [44] P. Gandhi and G. S. Brager, "Commercial office plug load energy consumption trends and the role of occupant behavior," *Energy and Buildings*, vol. 125, pp. 1–8, Aug. 2016, doi: 10.1016/j.enbuild.2016.04.057.
- [45] M. Indraganti, R. Ooka, and H. B. Rijal, "Thermal comfort in offices in India: Behavioral adaptation and the effect of age and gender," *Energy and Buildings*, vol. 103, pp. 284–295, Jul. 2015, doi: 10.1016/j.enbuild.2015.05.042.

- [46] S. Zhang and Z. Lin, "Extending Predicted Mean Vote using adaptive approach," *Building and Environment*, vol. 171, Mar. 2020, doi: 10.1016/j.buildenv.2020.106665.
- [47] R. T. Hellwig *et al.*, "A framework for adopting adaptive thermal comfort principles in design and operation of buildings," *Energy and Buildings*, vol. 205, Dec. 2019, doi: 10.1016/j.enbuild.2019.109476.
- [48] H. Chandra-Putra, C. J. Andrews, and J. A. Senick, "An agent-based model of building occupant behavior during load shedding," *Building Simulation*, vol. 10, no. 6, pp. 845–859, Dec. 2017, doi: 10.1007/s12273-017-0384-x.
- [49] P. O. Fanger, *Thermal Comfort. Analysis and Applications in Environmental Engineering*. Copenhagen: Danish Technical Press., 1970. ISBN 9788757103410
- [50] ASHRAE, *Standard 55: Thermal Environmental Conditions for Human Occupancy*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 2017. Accessed July 6, 2020. <https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy>
- [51] S. Zhang and Z. Lin, "Standard effective temperature based adaptive-rational thermal comfort model," *Applied Energy*, vol. 264, no. 114723, Apr. 2020, doi: 10.1016/j.apenergy.2020.114723.
- [52] J. Y. Park, T. Dougherty, H. Fritz, and Z. Nagy, "LightLearn: An adaptive and occupant centered controller for lighting based on reinforcement learning," *Building and Environment*, vol. 147, pp. 397–414, Jan. 2019, doi: 10.1016/j.buildenv.2018.10.028.
- [53] M. Sillverstein and S. van der Ryn, *Dorms at Berkeley, An Environmental Analysis*. Center for Planning and Development Research, University of California, 1967. <https://eric.ed.gov/?id=ED018073>
- [54] V. Fabi, R. Vinther Andersen, S. P. Corgnati, B. W. Olesen, and M. Filippi, "Description of occupant behaviour in building energy simulation: State-of-art and concepts for improvements," in *Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association*, 2011.
- [55] Z. Guo, K. Zhou, C. Zhang, X. Lu, W. Chen, and S. Yang, "Residential electricity consumption behavior: Influencing factors, related theories and intervention strategies," *Renewable and Sustainable Energy Reviews*, vol. 81. Elsevier Ltd, pp. 399–412, 01-Jan-2018, doi: 10.1016/j.rser.2017.07.046.
- [56] M. Indraganti and K. D. Rao, "Effect of age, gender, economic group and tenure on thermal comfort: A field study in residential buildings in hot and dry climate with seasonal variations," *Energy and Buildings*, vol. 42, no. 3, pp. 273–281, Mar. 2010, doi: 10.1016/j.enbuild.2009.09.003.
- [57] K. C. Parsons, "The effects of gender, acclimation state, the opportunity to adjust clothing and physical disability on requirements for thermal comfort," in *Energy and Buildings*, 2002, vol. 34, no. 6, pp. 593–599, doi: 10.1016/S0378-7788(02)00009-9.

- [58] J. O'Doherty, S. Lyons, and R. S. J. Tol, "Energy-using appliances and energy-saving features: Determinants of ownership in Ireland," *Applied Energy*, vol. 85, no. 7, pp. 650–662, Jul. 2008, doi: 10.1016/j.apenergy.2008.01.001.
- [59] M. Bedir and E. C. Kara, "Behavioral patterns and profiles of electricity consumption in dutch dwellings," *Energy and Buildings*, vol. 150, pp. 339–352, Sep. 2017, doi: 10.1016/j.enbuild.2017.06.015.
- [60] K. Genjo, S. I. Tanabe, S. I. Matsumoto, K. I. Hasegawa, and H. Yoshino, "Relationship between possession of electric appliances and electricity for lighting and others in Japanese households," *Energy and Buildings*, vol. 37, no. 3, pp. 259–272, Mar. 2005, doi: 10.1016/j.enbuild.2004.06.025.
- [61] M. Jafary and L. Shephard, "Modeling the determinants of residential appliance electricity use single-family homes, homes with electric vehicles and apartments," in *IEEE Green Technologies Conference*, 2018, vol. 2018-April, pp. 119–126, doi: 10.1109/GreenTech.2018.00030.
- [62] E. Hewitt, A. Oberg, C. Coronado, and C. Andrews, "Assessing 'green' and 'resilient' building features using a purposeful systems approach," *Sustainable Cities and Society*, vol. 48, p. 101546, Jul. 2019, doi: 10.1016/j.scs.2019.101546.
- [63] L. Fei and H. Pingfang, "A baseline model for office building energy consumption in hot summer and cold winter region," in *Proceedings - International Conference on Management and Service Science, MASS 2009*, 2009, doi: 10.1109/ICMSS.2009.5301031.
- [64] I. Ajzen, "The theory of planned behavior," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179–211, 1991, doi: 10.1016/0749-5978(91)90020-T.
- [65] H. Ben and K. Steemers, "Household archetypes and behavioural patterns in UK domestic energy use," *Energy Efficiency*, vol. 11, no. 3, pp. 761–771, Mar. 2018, doi: 10.1007/s12053-017-9609-1.
- [66] J. L. Ramírez-Mendiola, P. Grünewald, and N. Eyre, "The diversity of residential electricity demand – A comparative analysis of metered and simulated data," *Energy and Buildings*, vol. 151, pp. 121–131, 2017, doi: 10.1016/j.enbuild.2017.06.006.
- [67] X. Xu and C. fei Chen, "Energy efficiency and energy justice for U.S. low-income households: An analysis of multifaceted challenges and potential," *Energy Policy*, vol. 128, pp. 763–774, May 2019, doi: 10.1016/j.enpol.2019.01.020.
- [68] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study," *Energy and Buildings*, vol. 48, pp. 240–248, May 2012, doi: 10.1016/j.enbuild.2012.01.037.
- [69] J. H. Broehl, "An end-use approach to demand forecastinacg," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-100, no. 6, pp. 2714–2718, 1981, doi: 10.1109/TPAS.1981.316363.
- [70] X. Feng, D. Yan, and T. Hong, "Simulation of occupancy in buildings," *Energy and Buildings*, vol. 87, pp. 348–359, Jan. 2015, doi: 10.1016/j.enbuild.2014.11.067.

- [71] X. Luo, K. P. Lam, Y. Chen, and T. Hong, "Performance evaluation of an agent-based occupancy simulation model," *Building and Environment*, vol. 115, pp. 42–53, Apr. 2017, doi: 10.1016/j.buildenv.2017.01.015.
- [72] M. D. Colton *et al.*, "Indoor air quality in green vs conventional multifamily low-income housing," *Environmental Science and Technology*, vol. 48, no. 14, pp. 7833–7841, Jul. 2014, doi: 10.1021/es501489u.
- [73] W. F. E. Preiser, "Post-occupancy evaluation: How to make buildings work better," *Facilities*, vol. 13, no. 11, pp. 19–28, 1995, doi: 10.1108/02632779510097787.
- [74] A. Paone and J.-P. Bacher, "The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art," *Energies*, vol. 11, no. 4, p. 953, Apr. 2018, doi: 10.3390/en11040953.
- [75] P. de Wilde, "The gap between predicted and measured energy performance of buildings: A framework for investigation," *Automation in Construction*, vol. 41, pp. 40–49, May 2014, doi: 10.1016/j.autcon.2014.02.009.
- [76] International Energy Agency, "Energy in buildings and communities program. Annex 66: definition and simulation of occupant behavior in buildings," 2017. [Online]. Accessed July 6, 2020. <http://www.annex66.org/>.
- [77] N. Fournier, E. Christofa, A. P. Akkinapally, and C. L. Azevedo, "Integrated population synthesis and workplace assignment using an efficient optimization-based person-household matching method," *Transportation*, 2020, doi: 10.1007/s11116-020-10090-3.
- [78] K. Müller, "A generalized approach to population synthesis," 2017. PhD Dissertation. ETH Zurich. doi: 10.3929/ethz-b-000171586