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Automation in Construction 125 (2021) 103621 Contents lists available at ScienceDirect Automation in Construction journal homepage: www.elsevier.com/locate/autcon An ontology to represent synthetic building occupant characteristics and behavior Handi Chandra Putra a, Tianzhen Hong a, *, Clinton Andrews b a Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, United States of America b Rutgers Center for Green Building, Rutgers University, United States of America ARTICLE INFO ABSTRACT Keywords: Synthetic population Occupant model Occupant behavior Building simulation Occupant Agent-based modeling 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. 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 perfor- mance 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, pur- poses, and designs [9,10]. Models developed from such data have limited generalizability. There are emerging efforts to create larger, * Corresponding author. E-mail address: thong@lbl.gov (T. Hong). 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 ef- forts 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 con- siderations 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 pack- aged with standardized modeling systems. The recent development of https://doi.org/10.1016/j.autcon.2021.103621 Received 24 August 2020; Received in revised form 13 December 2020; Accepted 5 February 2021 Available online 13 February 2021 0926-5805/© 2021 Elsevier B.V. All rights reserved. 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 re- flections 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 pur- poses. 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 interna- tionally 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. 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 syn- thetic 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 appli- ances, elevators, lighting, and HVAC operations. The related building components are retrofitted, over the years, for fixes and upgrades to Table 1 Selected thermal comfort variables in ASHRAE Thermal Comfort Databases I & II. Demographic Thermal Thermal Thermal Thermal Sensation Comfort Preference Acceptability Sex Age Weight Height Met Last met. Activity Hot Warm Slightly Warm Neutral Slightly Cool Cool - Cold Very comfortable Comfortable Slightly comfortable Slightly uncomfortable Uncomfortable Very uncomfortable Warmer Acceptable No-change Cooler Unacceptable Source: [17,18]. Table 2 Use cases of occupant behavior data over the building lifecycle. Use Case Phase in Building Description Life Cycle Selection of facades Selection of lighting system Selection of HVAC system type and size equipment capacity Load calculation Occupant-centric sensing and controls Evaluate the energy savings of ECMs Building design - Envelope Building design - Lighting Building design - HVAC Building design - Load calculation Building operation Building retrofit Consideration of operable windows, moveable shades Controllability of lights: switch or dimming Selection of HVAC system type and sizing of equipment capacity considering zoning, access to thermostat, and occupant diversity. Calculation of space cooling, heating and ventilation loads Occupant sensing and occupancy-based control of HVAC, lighting, and MELs to save energy or provide energy flexibility Evaluate the impact of occupant behavior on energy savings of ECMs 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 signifi- cantly improve occupant comfort [27,28]. Naturally ventilated build- ings 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 win- dow 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 un- certainties [29]. Perceived sense of control affects thermostat adjust- ment. 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 calcula- tions 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 hierar- chies 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, ventila- tion 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 deter- mine targeting technologies (i.e., energy conservation measures, ECMs) to reduce energy use and improve occupant comfort and wellbeing. 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 occu- pant 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 be- tween ontological and epistemological concerns is clear on how occu- pant'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. 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 1290 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 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 Visual comfort IAQ Socio-economic characteristics Location Subjective values Activities at home Activities at work Occupant adaptive behaviors Group decision making Cooling temperature (a probability distribution, PDF) Heating temperature PDF Bright/dark (illuminance PDF) Sensitive to glare? Sensitive to IAQ (CO2) Gender, Age range, Marital status, Education, Employment, Income range, Country of origin Geographical location attributes, such as climate zones, country, and energy- related policy in place. Personal traits that drive either energy-saving or energy-consumption behaviors, i.e., cost-conscious, accommodating, and awareness of natural environment Indoor activities, such as sleeping, cooking, cleaning, working, and the use of appliances. Consume hot/cold drinks. Indoor activities are pertaining to presence, movement, and use of appliances. Consume hot/cold drinks. Open/close windows, Pull up/down blinds, Switch on/off or dim lights, Adjust the thermostat, Adjust clothing Majority, Authority, First-to-speak-out Sensation and perception of thermal comfort. Sensation and perception of lighting intensity that meets the illuminance level. Sensation and perception of the indoor air quality and smell, i.e., level of carbon dioxide (CO2) and other pollutants. Characteristics pertaining social, economic, and demographic. The building's location is viewed from climate zones and the governing administration. Individual occupant values and cultural perspectives in relation to energy consumption. Occupants' lifestyle and activities in residential buildings. Occupants' lifestyle and activities in commercial buildings. Individual choice of actions in adapting to or mitigating the changing indoor environmental conditions. Adaptive actions that pertain to shared controls with other occupants of the same zone. [17,35] [36,37] [38,39] [11]– 14,40 [17,18,41] [5,36,42] [16,40,43] [44,45] [26,46,47] [5,48] 1000 number of publications 900 800 700 600 500 400 300 200 100 0 946 8 10 344 131 142 5 28 thermal comfort 1970-1990 1991-2000 2001-2010 2011-2015 2016-5/2020 visual comfort year groups IAQ comfort Fig. 2. Literature reviews in building energy use and occupant behavior. (or IAQ). Fig. 2 (Right) shows that thermal comfort has the most dis- cussion with regards to occupant comfort and behavior, which also motivates this article to update the comfort component within the DNAS-framework. 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 tem- perature, air velocity, relative humidity, clothing insulation, and metabolic rate. The 2017 ASHRAE Standard 55 [50] specifies the pro- cedure 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 artifi- cial 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 con- trollers, 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, fra- grances, 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 collec- tively 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 toler- ance 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 con- ducted surveys, distributed questionnaires, and interviewed occupants to gather data on whether the building is behaving as intended, occu- pants 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 un- dertake to meet the desired level of comfort [21,54]. As a larger occu- pant 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 fac- tors 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 back- ground) 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 houlsehold 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 be- tween 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 attrib- uted 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 the- ories 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 delib- erate 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 occu- pant 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 dig- iboxes 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 tempo- rally. 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 behav- iors differently, and many of them speak exclusively to building mod- elers. 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, secu- rity, 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 ac- cess 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 house- hold. 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 ComfortTemper- atures, in which two sub-components are available, namely, Comfort- Cooling 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. A number of child elements are added under the Occupant element (Fig. 4) to detail the occupant characteristics. They are SocioEconomic, GeographicLocation, and SubjectiveValues. Per the discussion in the above section, each of these child elements has its own child elements. SocioEconomic element (Table 4) 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 (Table 5) has six child elements, with each has a categorical data type. They are Country, Cli- mateZone, CommuteMode, Policy, Infrastructure, and Cost structure. Sub- jectiveValues element (Table 6) has a selection of child elements of PastExperience, CostConscious, EnvironmentAwareness, TechnologyOr- iented, 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. 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 illustra- tion, 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 vari- ables 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 popu- lation 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. Fig. 5 shows the frequency distribution of air temperature (in oC) that is categorized based on other two variables, sex and thermal preference. The distribution suggests a successful synthesis of the dataset. Office buildings are often occupied by multiple tenants, within each Fig. 3. The tree diagram identifying comfort heating and cooling temperatures. Fig. 4. Occupant's attributes of social, economic, and demographic characteristics. Table 4 The child elements of the parent element Socio-economic and their data types. Variable Data Type Gender {male, female, other} Age Group levels: {15–25, 26–35, 36–50, 51–70, >70} Marital {single, married, partner} status Education {high school, bachelors, post- graduate} Income Group levels:{Low, Medium, High} Employment {unemployed, employed, self- employed} occupants have varied control privilege towards their built environ- ment. 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. Table 5 The child elements of the parent element GeographicLocation and their data types. Variable Country ASHRAE Climate Zone Commute Policy incentives Infrastructure Cost and fees Data Type unique {0, 1, 2, 3, 4, 5, 6, 7, 8} x {A, B, C} {walk, cycle, car, transit} {subsidies, tax-cuts, codes compliance, insurance mandate} {EV charging, microgrid, grid buyback} {cost of living, utility cost} 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. Fig. 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 be- tween 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 Table 6 The child elements of the parent element SubjectiveValues and their data types. Variable Past experience Cost-conscious Environment-awareness Technology-oriented lifestyle Accommodating Social influence Data Type {hi, md, lo} {hi, md , lo} {hi, md, lo} {hi, md, lo} {hi, md, lo} {hi, md, lo} assignments. Müller [78] developed an R package, MultilevelIPF, that assigns households to geographic areas. 5. Conclusion Since the introduction of DNAS framework and its obXML schema representation in 2013, it has become a standard to the building simu- lation 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 in- vestments of a municipality, are also behavioral determinants. More- over, energy-use behaviors are also different between commercial and residential buildings. It was found that energy-use behaviors in resi- dential 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 popu- lation generation effort. Researchers often collect their data that is Fig. 5. Comparison of the frequency distribution for key variables in observed and synthetic datasets. Fig. 6. Joint distribution of the air temperature and tenant group in a multi-tenant office building. 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. Declaration of Competing Interest None. Acknowledgments This work was supported by the Assistant Secretary for Energy Effi- ciency 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, V.I. Ugursal, Modeling of end-use energy consumption in the residential sector: A review of modeling techniques, Renew. Sust. Energ. Rev. 13 (8) (01-Oct- 2009) 1819–1835, https://doi.org/10.1016/j.rser.2008.09.033. Pergamon. [2] Energy Information Administration, Annual Energy Outlook 2020. https://www.ei a.gov/outlooks/aeo/, 2020. (Accessed 6 July 2020). [3]

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