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Publication Date
2022-07-01

DOI
10.1016/j.autcon.2022.104290

Peer reviewed

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

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Energy Technologies Area
July 2022

https://doi.org/10.1016/j.autcon.2022.104290

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.

A level-of-details framework for representing occupant behavior in agent-based models

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Abstract

Agent-based modeling is an advanced computational technique capable of representing complex and dynamic processes of human behavior in building performance simulation. Though the agent-based approach supports diverse applications concerning human behavior modeling within the built environment, there is no consensus on the optimal amount of information or level of granularity needed for occupant information representation. This paper attempts to formalize the level of details (LoD) needed for occupant behavior representation in agent-based environments. A novel framework, grounded on the concept of LoD, is proposed to select the required details in representing occupants in agent-based models. Ten attributes related to occupants' presence, movement, behavioral processes, and repertoire are considered to define the LoD. The framework identifies use case parameters as the guiding principle and allows a hybrid approach for selecting varying degrees of occupant attributes to serve the purpose of simulation. A discussion on the pertinence of different occupant behavior LoDs in relation to the desired objective and simulation context is also presented. The study intends to support the occupant behavior research by advancing agent-based occupant modeling in building performance simulation.

Keywords: level of detail, occupant behavior, agent-based model, building simulation, behavioral theory

1. Introduction

Human behavior is a complex subject influenced by multidisciplinary factors. Occupant behavior (OB) modeling is a growing field of interest in simulation research, especially since 2008 when the International Energy Agency's Energy in Buildings and Communities (IEA EBC) Annex 53 [1], on "Total Energy Use in Buildings: Analysis and Evaluation Methods" started. The annex aimed to understand the driving factors influencing building energy use. Advanced occupant modeling techniques that capture human behavior properties such as stochasticity, diversity, and complexity can contribute to improving the reliability of building performance simulation (BPS) programs. Agent-based modeling (ABM) is one such method that has received significant attention in OB modeling, as it is capable of simulating complex human behavior as a time-dependent dynamic model. The fundamental feature of ABM is that it captures human behavior and behavior feedback, thereby representing the reasoning and decision making of the human–building interactions in building performance [2]. Moreover, it applies stochasticity to reflect dynamic and variable behavior and is flexible enough to incorporate new behavioral models. In certain use cases, ABM may be advantageous over other modeling techniques because it has the potential to capture emergent phenomena at the macro level arising out of the micro-level interactions among independent agents or occupants. Studies in the ABM context have covered implementation approaches (e.g., [3]), occupant-centric ontologies to represent OB (e.g., [4]), and simulation and co-simulation approaches for BPS (e.g., [5]). However, there is a paucity of research on the degree of detail or the level of abstraction needed for modeling OB and interactions in ABM.

With the growing availability of big data and high-performance computing resources, there is a tendency among researchers to develop detailed ABM in pursuit of higher accuracy and usefulness [6]. However, Abdou et al. [7] state that *"At the extreme, if a model becomes as complicated as the real world, it will be just as difficult to interpret and offer no explanatory power"*. In fact, the model has to be built at the right level of representation, using the right amount of details to serve its purpose while saving time and resources for the ABM users [8]. Stazi et al. [9] highlight that one of the biggest challenges in ABM for OB modeling is choosing an adequate level of spatial and temporal resolution, representation of processes, and interactions in relation to research aims. Similarly, in their 2020 review of ABM for building occupants, Berger and Mahdavi [5] highlighted the need to explore the influence of the resolution in agents' behavioral repertoires, in addition to the spatial and temporal resolution on the outcomes of simulation. In practice, the level of details (LoD) choice for representing OB in ABM is often arbitrary and subject to the modeler's judgment in the absence of practical guidelines for agent-based occupant modeling. For instance, modelers may develop detailed occupant models overloaded by information with little relevance or connection to the simulation's aim. In parallel, using simple aggregated models that overlook important agents' features (e.g., behavioral repertoire) could fail to achieve the desired simulation results. A suitable LoD to represent OB in ABM while supporting diverse use cases in building performance simulation is a subject matter worthy of investigation.

Previous efforts on selecting OB models at an appropriate granularity for building simulation have been focused on the spatial and temporal dimension or occupant actions, presence, and movement. For instance, Mahdavi and Tahmasebi [10] explored the deployment of occupancy-related models in relevance to the use cases of BPS. They developed a multidimensional conceptual framework incorporating building lifecycle, domain, performance indicators, and temporal resolution, among others, to assist practitioners in choosing an appropriate occupancy model. While Mahdavi and Tahmasebi explicitly focused on the occupancy-related model selection, Gaetani et al. [11] also considered occupant actions when selecting OB models in BPS. Later, Gaetani et al. [12] developed a fit-for-purpose approach that offers a choice of representing occupants' actions and presence through schedules, rule-based equations, probabilistic expressions, or agent-based models, to suit the specific use case. However, there are attributes of OB beyond occupants' actions and presence that can significantly impact the simulation outcomes. Mahdavi [13] emphasizes the inclusion of occupants' perceptual and behavioral processes in the computational representation of occupant agents for BPS. A fit-for-purpose approach may help assess whether ABM is required for a specific use case or not. However, to determine the level of semantic richness required to represent OB in an ABM, we need a holistic framework that integrates occupant actions and presence with the occupant's behavioral repertoire. In summary, the fit-for-purpose approach helps users select the appropriate technique of OB modeling, among which ABM is one. However, the current study dives deeper into the OB modeling aspects within the agent-based method—especially in the occupant/agent's decision making—that involves learning, reflecting, and inter-agent interactions and influencing.

This paper attempts to address the following fundamental question: At what LoD should building occupants' behavior be represented in agent-based occupant modeling? This study proposes a novel framework, grounded on the concept of LoD, for selecting an appropriate representation of OB in ABM. The study intends to formalize the LoD of OB in agent-based building models. The broader goal is to support the international research community by formulating modeling guidance for ABM of occupants in BPS.

The paper is organized as follows. First, it reviews the literature on the OB representation in agent-based models within BPS. Then it provides an overview of the concept of LoD and how it relates to the built environment and occupant modeling. In Section 3, we develop a conceptual framework for selecting an appropriate LoD to model human behavior in ABM and describe the applicability of the proposed framework. Section 4 discusses the associated challenges in adopting the LoDs, limitations, and future scope of work. Lastly, a summary highlights this paper's major contributions. The framework development and demonstration with use cases is a cross-task activity of Annex 79 [14] on "Occupant-centric building design and operation," an international collaborative project under the IEA's Energy in Buildings and Communities Programme.

2. Agent-based Modeling Literature Review

This section presents a review of studies using agent-based approaches for occupant modeling in the built environment. The objective of conducting a literature search is to explore ABM applications in building performance assessment, identify key features of OB representation, and comprehend the amount of information and the level of granularity adopted for occupant modeling processes. It is important to note that this review is limited to the OB representation in agent-based models for BPS. The behavioral theories or implementation approaches adopted for OB modeling in agent-based environments are not within the scope of this work and have been reviewed elsewhere [5]. Specifically, studies related to the energy and environmental performance in the built environment are covered.

The literature search process comprises developing a search strategy, conducting database search and final screening for identification of relevant studies. Three bibliographic databases: Scopus, Web of Science, and Science Direct were utilized for the search. The inclusion criteria were set to studies published in English and those related to categories- Energy, Environmental Science and Engineering. A combination of keywords involving ("agent-based modeling" OR "agent-based simulation") AND ("occupant behavior" OR "human building interaction" OR "human behavior") AND ("building energy simulation" OR "indoor environment" OR "thermal comfort" OR "indoor environment") were selected for the inquiry. The database search involved scanning the title, abstracts and keywords of the articles according to the search strategy defined above. This keyword-based inquiry returned a total of 89 non-duplicate articles. A preliminary examination of the abstracts of the selected 89 studies was carried out to identify their suitability for exploring OB representation in agent-based models for BPS. Studies that were not relevant to OB modeling or representation were excluded. 45 studies were then selected for further evaluation that involved a thorough read of the full-text to ascertain their relevance to the objective of this review. During this final screening, 11 articles were excluded because 10 of them did not include any building performance analysis and one of the articles was a review study. The rest (34 studies) were reviewed for detailed analysis.

The selected studies were conducted within the past 10 years (2011–2021), which seems appropriate because research on OB modeling gained momentum during the past decade. The studies span various building lifecycle phases, support varied modeling purposes, and include diverse sophistication of occupant modeling approaches. The spatial extent of these studies ranged from a single office zone investigating clothing and activity behavior [15] to a residential community evaluating heat pump usage behavior [16]. Table 1 shows the use case characteristics, OB actions and their modeling approaches, and the data sources for the 34 selected studies.

In this study, we adopted the terminology of occupant modeling approaches from Gilani et al. [17], given the absence of a consistent language describing different OB modeling methods among researchers. The selected studies are categorized into four occupant modeling approaches: (1) static-deterministic, (2) dynamic-deterministic, (3) static-probabilistic, and (4) dynamic-probabilistic. Note that, in our adaptation of this terminology, the expression "deterministic" is not intended to carry any philosophical connotations [13]. As such, our use of this term does not imply that those using schedules and rules in occupant modeling assume that occupants behave in a strictly predictable manner. Rather, the term "deterministic" is used here to simply and exclusively denote the application of fixed schedules and rules for the representation of occupants' presence and actions in buildings. The static-deterministic approach considers fixed schedules assuming an occupant's behavior is not affected by their surroundings; for instance, a fixed window schedule may assume that windows are always open or closed. The dynamic-deterministic approach considers that occupants are affected by and respond to the building and conditions [18]. An example of such an approach is a rule-based model for window adjustment that assumes an occupant closes windows when the outdoor temperature exceeds a certain threshold. In static-probabilistic approaches, stochasticity is introduced into static behavior through a probabilistic manner; for instance, a conditional probability model depicting the likelihood of a window being open during occupied and unoccupied hours. A dynamic-probabilistic approach adds randomness to the dynamic OB, such as a logistic regression model where the probability of window opening ranges from zero to one over a wide range of outdoor temperatures.

Table 1: Review of ABM studies concerning energy and environmental performance of buildings

Ref.	Objective	Building Typology	OB Actions and Modeling Approaches									Cognitive or Social Factors	Data Sources	Level of Detail Adopted* (based on the authors' proposed framework)
			Occupant Movement and Presence	**Window**	**Blinds**	**Thermostat**	**Light**	**HVAC**	**Plug Loads**	**Clothing Level**	**Others**			
[15]	To assess the effect of thermal adaptation in different seasons on annual thermal comfort	University office	Not mentioned							Dynamic-probabilistic			Simulated data	O-2.5
[16]	To predict dynamic energy consumption by estimating dynamic heat pump behavior in residential communities	Residential	Dynamic-probabilistic					Dynamic-probabilistic				Social interactions	Measured data and survey	O-2.5
[19]	To develop an ABM using Performance Moderated Functions Server for commercial buildings and propose a method for validation	University Office		Dynamic-deterministic	Dynamic-deterministic							Thermal, visual comfort, and air quality perceptions	Measured data and survey	O-1.5
[29]	To analyze the impact of occupant behaviors on BPS using a co-simulation approach													
[20]	To estimate the energy consumption in commercial buildings by using the ABM approach	Office			Dynamic-deterministic		Dynamic-deterministic		Dynamic-deterministic		Hot water: Static-deterministic	Word of mouth	Simulated data	O-1
[21]	To develop a program for co-simulating building occupant behavior in performance simulation	Office	Static-probabilistic	Static-probabilistic		Static-probabilistic				Dynamic-deterministic	Personal heater/fan: Static-probabilistic	Thermal comfort perception	Simulated data	O-1.5
[30]														
[51]	To develop an ABM of thermally adaptive office occupant behavior and validate it against one year of behavior field data													
[22]	To develop an ABM approach for simulating multiple thermal behaviors and linking building energy simulators	Office		Dynamic-deterministic	Dynamic-deterministic					Dynamic-deterministic	Local fan/heater: Dynamic-deterministic	Behavioral, control, and normative beliefs.	Simulated data	O-1.5

[23]	To evaluate the impact of load shedding on occupants' heterogenous comfort and adaptive behavior	Office			Dynamic-deterministic		Dynamic-deterministic			Dynamic-deterministic	Local fan/heater: Dynamic-deterministic	Thermal and lighting perception	Measured data and survey	O-1.5
[24]	To develop an agent-based occupancy simulation model to accurately simulate stochastic occupancy schedules	Office	Dynamic-probabilistic				Static-probabilistic						Simulated data	O-2.5
[52]	To study the feasibility of installing lighting occupancy sensors in building renovation through the ABM approach													
[25]	To assess the usability of building designs using a human-centered ABM framework	Office					Static-probabilistic				Shading control: Static-probabilistic	Lighting perception and preferences	Survey	O-2.5
[26]	To develop an ABM framework capable of testing and optimizing occupancy interventions (namely, energy feedback methods) for any building stock	Office				Static-probabilistic	Static-probabilistic		Static-probabilistic			Energy feedback and peer effect	Historical data and survey	O-2
[27]	To investigate the diffusion of energy-saving policies among the occupants and its impact on energy use	Office										Peer feedback and word-of-mouth	Simulated data	O-1.5
[28]	To investigate human-building-appliance interactions and estimate determinants of energy waste in buildings	Office	Static-deterministic				Dynamic-deterministic	Dynamic-deterministic	Dynamic-deterministic			Energy literacy levels	Simulated data	O-2
[32]	To quantify the impact of uncertainties in human behavior on BPS using an ABM approach	Office				Static-deterministic	Dynamic-deterministic		Dynamic-deterministic				Simulated data	O-1.5
[33]	To develop an agent-based occupancy simulator for co-simulation	Office	Dynamic-probabilistic										Simulated data	O-3
[35]	To evaluate the performance of an agent-based building occupancy simulation model using the occupancy simulator	University Office											Field observations	
[34]	To simulate and visualize occupant	Office	Dynamic-probabilistic	Static-probabilistic		Dynamic-deterministic	Static-probabilistic	Static-probabilistic	Dynamic-deterministic				Simulated data	Varies O-2 to O-3

	behavior in a new detailed and visual way to assess its impact on energy use in buildings					and Static-probabilistic			and Static-probabilistic					
[36]	To develop a stochastic agent-based model for estimating the number of people present in a building	Office	Dynamic-probabilistic										Field data (Video image data)	O-3
[37]	To propose a co-simulation ABM environment for accounting for occupants' actions in smart homes for energy management.	Residential	Static-deterministic	Dynamic-deterministic		Dynamic-deterministic	Dynamic-deterministic	Dynamic-deterministic	Dynamic-deterministic			Psychological state and perceived environmental values	Simulated data	O-1.5
[38]	To propose an ABM interacting with the building information modeling (BIM) accounting for multiple residents' attributes	Residential		Dynamic-deterministic	Dynamic-deterministic		Dynamic-deterministic	Dynamic-deterministic	Dynamic-deterministic			Environmental awareness, awareness about building systems, comfort priority, social behavior	Measured data and interviews	O-1.5
[39]	To model occupants' interactions with thermostats in residential buildings in the heating season for demand response management	Residential	Static-probabilistic										Historical data	O-2
[40]	To assess the impact of occupant behavior and occupants' interactions with building systems in response to overheating	Residential	Static-probabilistic	Static-probabilistic				Static-probabilistic				Hierarchical negotiation	Simulated data	O-2.5
[41]	To identify energy-saving strategies for reducing energy consumption in student residences	Student Dormitories	Static-probabilistic				Static-probabilistic	Static-probabilistic	Static-probabilistic			Energy habits, awareness, and willingness to save	Measured data and survey	O-2.5
[42]	To evaluate the influence of household habits on household energy consumption (HEC) for clean energy promotion policies	Residential district							Dynamic-deterministic			Behavioral change	Historical data	O-1
[43]	To assess a household- and urban-scale load curve using multi-agent simulation of human activity	Residential district	Dynamic-probabilistic						Dynamic-probabilistic			Energy knowledge and preferences	Historical data	O-1.5

[44]	To couple realistic occupant behaviors with building energy simulation through a Functional Mockup Interface	Residential	Dynamic-probabilistic								Not specified: general household activities	Thermal comfort perception	Simulated data	O-1.5
[46]	To couple a pedestrian flow model with energy simulation to predict the HVAC energy demands in transitional environments	Airport	Dynamic-probabilistic										Simulated data	O-3
[47]	To incorporate dynamic spatial and social factors in occupant movement patterns within hospitals	Hospital	Dynamic-probabilistic										Measured data and interviews	O-2.5
[48]	To integrate organizational issues of energy management into office energy consumption	University Office	Static-probabilistic						Static-probabilistic			Energy saving intentions and awareness	Measured data and survey	O-2.5
[49]	To evaluate the performance of a built environment using an ABM framework	University campus	Dynamic-probabilistic			Dynamic-deterministic	Dynamic-deterministic		Dynamic-deterministic	Dynamic-deterministic			Simulated data	O-1.5
[50]	To analyze the impact of occupant behaviors and crowd effect on the lighting energy usage in different sized office buildings	Office	Not mentioned				Static-probabilistic						Simulated data, Lighting model adopted from previous research	O-1.5
*Refer to Section 4.2 for the definition of different levels of detail and the OB attributes covered.														

Among the 34 articles, 20 studies were conducted within office environments for applications within the building design, operation, and retrofit stages. Researchers adopted ABM approaches to study the impact of office OB on energy use and occupant comfort [15], [19]–[22], load shedding events [23], the performance of lighting occupancy sensors [24], and the assessment of building design performance [25]. ABMs in office environments also have been applied to assess the influence of occupant interactions for evaluating energy feedback methods [26], diffusion of energy-saving policies [27], and estimating determinants of energy waste in buildings [28]. In addition, some studies in office environments introduced novel implementation approaches to couple ABM with BPS [29]–[31]. Papadopoulos and Azar [32] evaluated the impact of uncertainty in OB in building operations through a co-simulation framework, while Jia and Srinivasan [29] and Langevin et al. [30] proposed different coupling approaches to integrate occupant-centric ABMs with building performance simulation. Table 1 depicts the commonly considered occupant actions in ABMs that include window use, blind adjustment, thermostat adjustments, lighting operations, and heating or cooling operations. A few ABM studies also have looked into personal heater or fan use, shading controls, and hot water use. In addition to occupant actions, agent-based approaches to model stochasticity in occupants' presence and movement have been introduced. For instance, Chen et al. [33], [34] developed an agent-based occupancy simulator and demonstrated its application in simulating and visualizing office occupant behavior. Later, Luo et al. [35] evaluated its performance in a prototype office building using a co-simulation approach. Liao et al. [36] proposed an agent-based method with graphical modeling for simulating building occupancy. The authors acknowledged the need for different resolutions of occupancy models for different aims, hinting towards the various levels of detail in occupant modeling.

Ten studies were conducted in a residential environment, and most focused on evaluating the influence of OB during building design and operation phases. Kashif et al. [37] simulated the dynamic OB in smart homes to predict energy trends and reduce energy waste. They considered multiple occupant activities, social elements of interactions, and negotiations to optimize power savings while maintaining inhabitants' comfort levels. Micolier et al. [38] integrated an agent-based occupant model, Li-BIM, with a building information model to quantify the impact of occupants' social and cognitive behavior on energy consumption and comfort. The Li-BIM model integrates the occupant dimension in evaluating early building design choices.

ABMs have also been used in residential use cases to evaluate thermostat adjustment behavior for demand response analysis [39], analyze heat pump usage behavior to predict regional dynamic electricity loads [16], incorporate dynamic OB for estimating energy consumption during summer overheating [40], and evaluate energy management strategies in student residences [41]. Urban-scale residential applications of ABM include assessing the impact of increased income and technological advancements on household behavior for clean energy policy planning [42] and simulating household activities to generate household and urban-scale load curves [43]. Vellei et al. [39] considered diversity in occupant presence and activity behavior, as well as dynamic thermal perceptions to develop a stochastic model of occupant-thermostats interactions for informing the design and control of setpoint modulations. Chen et al. [16] incorporated interactions among household members and dynamic occupancy profiles for simulating stochastic heating behavior in residential buildings. Most of the ABMs concerning residential studies include single or multiple occupant actions related to window opening, household appliance usage, lighting usage, and air-conditioner usage. Unlike office buildings, studies in residential environments that demonstrate novel ABM implementation approaches are scarce. Plessis et al. [44] demonstrated a co-simulation framework to couple an OB model implemented in the agent-based tool SMACH with a single-family building energy model to determine heating, ventilation, and air conditioning (HVAC) energy demand. Later, a multi-agent model of occupant activities and decision making using the SMACH platform was developed along with a validation approach [43], [45]. In addition to office and residential building settings, agent-based occupant models have been applied in an airport for estimating cooling energy demand [46], a hospital for estimating energy consumption [47], administrative offices within schools to account for the impact of organizational issues on energy consumption [48], and a university campus for identifying an optimal HVAC strategy [49].

The sophistication in modeling occupant actions within agent-based environments varies significantly across the reviewed studies. For instance, Azar and Menassa [20] adopted fixed light use profiles based on occupancy for simulating energy use in offices. In contrast, Wang et al. [50] modeled individual-light switch behavior using a conditional probability model based on workplane illuminance and occupancy events. A detailed light-use model enabled Wang to identify a phenomenon of crowd effect in energy usage. At the same time, Azar and Menassa's fixed schedule served their purpose of comparing occupant archetypes having different energy consumption habits. Langevin et al. [51] and Lee and Malkawi [22] both considered the predicted mean vote model as the behavioral trigger driving OB actions in their respective ABMs. However, the choice of the model representing occupant clothing levels varied, and was primarily driven by the availability of data. Langevin et al. developed a logistic regression model involving morning outdoor temperature and thermal preference of occupants for determining initial clothing insulation based on the data collected from a longitudinal office field study. In contrast, and in the absence of occupant data, Lee and Malkawi [22] adopted standard clothing values for different seasons from ASHRAE's thermal comfort standard to estimate occupants' initial clothing value.

In addition to occupant actions, occupants' presence and movements are also represented with varying degrees of detail in agent-based models. Most ABMs intended for energy demand estimation typically consider a high-resolution occupancy model to capture randomness in movement and presence. For instance, Vellei et al. [39] adopted stochastic occupancy models to capture occupant diversity in thermostat behavior in residential buildings. Likewise, Sinha et al. [46] implemented an agent-based passenger flow model for estimating HVAC demand in a terminal building. Azar et al. [49] also introduced stochasticity in their occupancy model to identify energy management strategies for a university campus. Aggregated probabilistic occupancy models have also been implemented for other purposes. For instance, Norouziasl et al. [52] developed a probabilistic occupancy model for analyzing the feasibility of different lighting occupancy sensors in offices. Zhang et al. [48] implemented a random normal distribution for modeling occupant presence to identify energy management strategies. While the choice of OB model representation appears to be influenced by factors such as the objective of the simulation or data availability, there is no consensus or justification regarding the level of representation for modeling occupants' presence, movement, or actions in agent-based models.

Another significant aspect of ABM is the underlying behavioral characteristics that define how an occupant interacts with building systems and other occupants. Researchers have adopted various factors to depict occupants' behavior in ABMs, such as the perception of comfort, peer interaction and word of mouth effects, energy literacy, or perceived environmental values (see Table 1). For instance, Ding et al. [41] developed a full ABM based on students' motivations and intentions gathered from an occupant survey to analyze energy behavior in student residences. Langevin et al. [51] developed an ABM to depict thermally adaptive office OB based on the indoor environment, adaptive actions, and thermal comfort perceptions data collected from a longitudinal field study. However, due to the unavailability of subjective occupant data related to the psychological, social, and cognitive determinants of OB, most ABM studies either adopt certain assumptions or rely on historical data to develop ABMs. For instance, in the absence of relevant occupant data related to perception and value systems, Jia et al. [19] presumed a decision-making model for occupants' actions. The authors later validated the model using data collected by sensor nodes and a paper-based survey [27]. While investigating the application of Bass diffusion theory on office occupants' behavior, Bastani et al. [27] assumed certain procedures/parameters for simulating the word-of-mouth effect in the absence of real data. Similarly, Lee and Malkawi [22] proposed an ABM based on behavioral, control, and normative beliefs. The authors assumed weight coefficients to represent the agent's beliefs and developed a cost function that drives their decision making.

The findings of the review show that ABM of OB supports diverse use cases spanning across different building typologies and lifecycle stages. The OB representation in agent-based models varies across different studies and is influenced by the simulation objective, desired performance indicator, or the availability of reliable data. However, little is known about the optimal degree of details required in representing OB in ABMs to optimize the modeling effort and accuracy of simulation results. This study attempts to bridge this knowledge gap by formulating a guiding framework for selecting OB representational details in ABM applications for supporting building performance assessment.

3. The level of detail concept

A level of detail (LoD) technique essentially permits different representations of an object at various resolutions [53]. The concept was first proposed in the field of computer graphics by Clark (1976) to regulate the amount of detail required in geometric modeling to represent the virtual world [54]. The selection of a particular LoD was based on factors such as mesh simplification and specification of the number of polygons per LoD to reduce the geometrical complexity [55]. Since then, the concept of LoD has been adapted by researchers for various domains such as software development [56], [57] virtual reality systems [58], geoinformatics [59], and building information modeling (BIM) [60]. It is important to mention that the LoD should not be confused with a similar concept of "Level of Development" in BIM that determines the degree to which the element's geometry and attached information should be delivered by the various stakeholders during the design and construction stages [61].

The LoD technique has been extensively implemented in built environment studies, such as 3D city modeling or urban building energy modeling (UBEM) [62]. The City Geography Markup Language (CityGML) standard defines five LoDs that principally indicate the geometric detail of the buildings for virtual 3D city models [63]. The simplified granularity within CityGML is represented at LoD 0, comprising the 2D footprint of the building, while the finest LoD 4 encompasses an architecturally detailed model with windows and doors and indoor features. Biljecki et al. [64] redefined these levels to overcome the generic nature of LoDs that fall short in defining the complexity of the city models. A set of 16 refined LoDs were put forward that indicate the spatial-semantic complexity, and they could be applied to any 3D building modeling format. Biljecki et al. [65] formalized the concept of LoD in 3D city models and defined LoD as the degree of its adherence to its corresponding subset of reality. An application-driven LoD approach also has been developed to help derive specific LoDs suited for particular applications of 3D building models [66]. Recently, Mathur et al. [67] extended the concept of LoD from 3D city modeling to UBEM and considered characteristics such as occupancy, geometry, context, modeling methodology, and calibration for defining the LoDs. However, to the authors' knowledge, the LoD technique has not yet been used in the

OB domain despite researchers highlighting the substantial influence of OB representation at various resolutions and complexity on building performance results [68].

An important concern while adopting the LoD technique is determining the suitable resolution. Biljecki et al. [64] argue that a higher LoD is not a universal solution for improving accuracy in spatial analysis. Similarly, for UBEMs, Strzalka et al. [69] recommended a low geometric detail for urban modeling to forecast energy demand. Johari et al. [70] suggest that the importance of having a higher LoD in UBEM is secondary because the error due to a coarse LoD can be compensated by using some data as nongeometrical attributes of the geometry. Mathur et al. [67] further recommended that the selection of LoD for UBEM should be based on the use case, building location, and desired accuracy, as well as data and computing resources. Researchers quantifying the impact of LoDs suggest that the intended results may vary depending on the LoD attributes such as geometric details, modeling approaches, and the specific use case. For example, Nouvel et al. [71] examined the influence of geometric LoDs on the annual heating demand of a German district and observed a difference of 7.3% in mean error. In parallel, Strzalka et al. [72] found a deviation in heating demand of up to 12% at two LoDs in six different building configurations. Cerezo et al. [73] compared the influence of LoDs regarding modeling approaches on urban energy use and observed a variation of 15% in mean error. The results from these studies highlight that there is no universal rule to choose a specific LoD within built environment applications, and it rather depends on the specific use case.

To sum up, LoD is an effective technique for representing model information at various levels of granularity, but the selection of LoD must be carefully done to balance practicality with accuracy. In the present study, we borrow and adapt the LoD concept, already established in 3D city modeling and UBEM, to describe the OB representation in ABM. We define the LoD of an agent-based model as the degree of details used to represent complex human behavior for accurate simulation in building performance assessment. The formalized LoDs emphasize the level of behavioral dynamics and semantic richness of occupant behavior.

4. Occupant Behavior Representation Framework

4.1. Representation Framework

A framework underlying the concept of LoD is proposed to formalize the LoDs in occupant representation in ABM. It is important to clearly define the terminology adopted in this framework since terms such as "complicatedness" and "complexity" are often used interchangeably in ABM domains. We adopt the nomenclature proposed by Sun et al. [6] to describe the *model complicatedness* and *model complexity* in agent-based models. *Model complicatedness* denotes the details of model structure related to the spatial and temporal resolution, number and types of agents, representation of processes, and interactions via logical rules and/or quantitative relationships. *Model complexity*, on the other hand, relates to the model behavior and describes how agent interactions at a micro level affect their actions and produce emergent effects at the macro level [74],[75]. The purpose of this framework is to capture the level of complicatedness and complexity in ABMs, collectively referred to as the "Level of Detail" for simulating OB in building performance assessment.

The model structure of the proposed framework is described using the parameters concerning occupant presence and actions, such as occupant type and spatial location, or the modeling approach. Five such influential attributes demonstrating *model complicatedness* are identified from OB modeling research under the IEA's Annex 66 and Annex 79 projects [14], [76], [77], such as the fit-for-purpose modeling approach [12]. The model behavior is described using the widely accepted overview, design concepts, and details (ODD) protocol that provides a standardized way for describing ABM [78]. We borrow the *model complexity* attributes from the 'Design Concepts' elements of the ODD protocol that describe the principles and rationale underlying the design of the ABM. Five such elements pertaining to occupant processes such as interactions, learning or sensing are selected for depicting the model behavior in the proposed framework. Other elements of the 'design concepts' such as observation, basic principles or emergence that do not relate specifically to occupants or agents modeling are not considered.

In brief, the LoD for OB representation comprises of 10 occupant-centric attributes related to ABM. We classify these attributes according to their impact on the model outcomes. The first five attributes relate to model structure and represent the complicatedness of the model. The other five attributes are related to model behavior and reflect the complexity. Each of the attributes is described below:

i. Representation: The occupants may be represented in simpler models at an aggregated level depicting average user behavior, at a group of occupants sharing specific characteristics, or at an individual level with distinct characteristics.
ii. Heterogeneity: The occupant's characteristics such as preferences, attitudes, or hierarchical levels that affect their decision-making behavior can be modeled by introducing occupant heterogeneity. A model may or may not have heterogeneity among the occupants.
iii. Zoning: The location of occupants in the environment could be represented at the whole building level for simpler models, or based on floor levels such as core or perimeter for commercial buildings. A complicated model can have internal space or sub-space level zoning, for example, at desk level in an open office.
iv. Occupant presence and movement (Occupancy): Occupancy representation could range from schedules or rule-based models for simpler models to stochastic processes reflecting the randomness and uncertainty for complicated models.
v. Modeling formalism: The choice of an occupant to perform a particular action is determined by the decision-making process. The representation of such a process could be as simple as a set of logical rules or as detailed as an elaborate model based on the planned behavior theory reflecting the underlying intentions of occupants and their perceived controls.
vi. Interactions: The local interactions among the occupants affecting their behavior could be modeled as direct processes (such as encounters or communications) or indirect processes (such as approaching a mediator). A simpler model may not assume any occupant-occupant interaction effects.
vii. Learning: Occupants or a group of occupants may learn from previous experience and change their decision-making rules over time. For instance, an occupant may shift towards passive energy-saving measures over a period of time after learning about their efficacy.
viii. Sensing: This is the occupants' capability to sense internal and environmental variables for consideration in decision making. For instance, the occupants sense their indoor environmental parameters to determine if they are thermally comfortable or not, which may eventually dictate their decision to use spacing conditioning devices.
ix. Prediction: Occupants often need to anticipate future consequences of their decisions for successful decision making. A model may or may not assume the prediction characteristic in occupant behavior.
x. Collectives: The aggregation of agents may lead to a group that exhibits a specific behavior or performs a particular action. Such a behavioral attribute is characterized as *collectives,* which may lead to emergent effects. Collectives should not be confused with heterogeneity, as the agents

constituting the group do not exhibit such behavior at the individual level. In simpler models, the collectives may not be defined.

A novel framework is put forward to select suitable LoDs to represent OB in ABM for building performance. The conceptual framework presented in Figure 1 comprises different use case parameters that collectively guide the choice of ABM attributes and their degree of details for formulating OB LoDs. The classification of occupancy and modeling formalism is done according to the four OB modeling approaches discussed in Section 2. The framework allows the combination of ABM attributes at different granularities to suit the specific use cases. For instance, dynamic-deterministic models of occupant actions could be combined with group-level agent representation, along with learning and sensing capabilities. However, the framework must be adopted with caution because it considers model complexity and complicatedness concurrently. In reality, the model complexity has a nonlinear relationship with the complicatedness of model structure. In other words, a slight increase in the degree of detail of model complexity may lead to a drastic change in simulation results at the same level of complicatedness in the model structure. Additionally, the cross mixing of attributes should be carefully done to avoid overloading the model structure or behavior without any significant improvements to the outcomes. For example, representing individual agents at whole building level with fixed lighting schedules may not be useful because individual actions would be aggregated, reflecting average OB. In addition, the increased complicatedness may not improve the accuracy of model outcomes while still increasing the time and effort needed for model creation and initialization. The hybrid approach of selecting varying granularity of ABM attributes is particularly useful for use cases where different sub-models (such as occupancy, window use, and thermostat operations) require different degrees of details to suit the aim of the simulation. Overall, the choice of optimal LoD is case and context-specific. The following section defines four distinct LoDs that can guide the work of researchers applying the proposed framework.

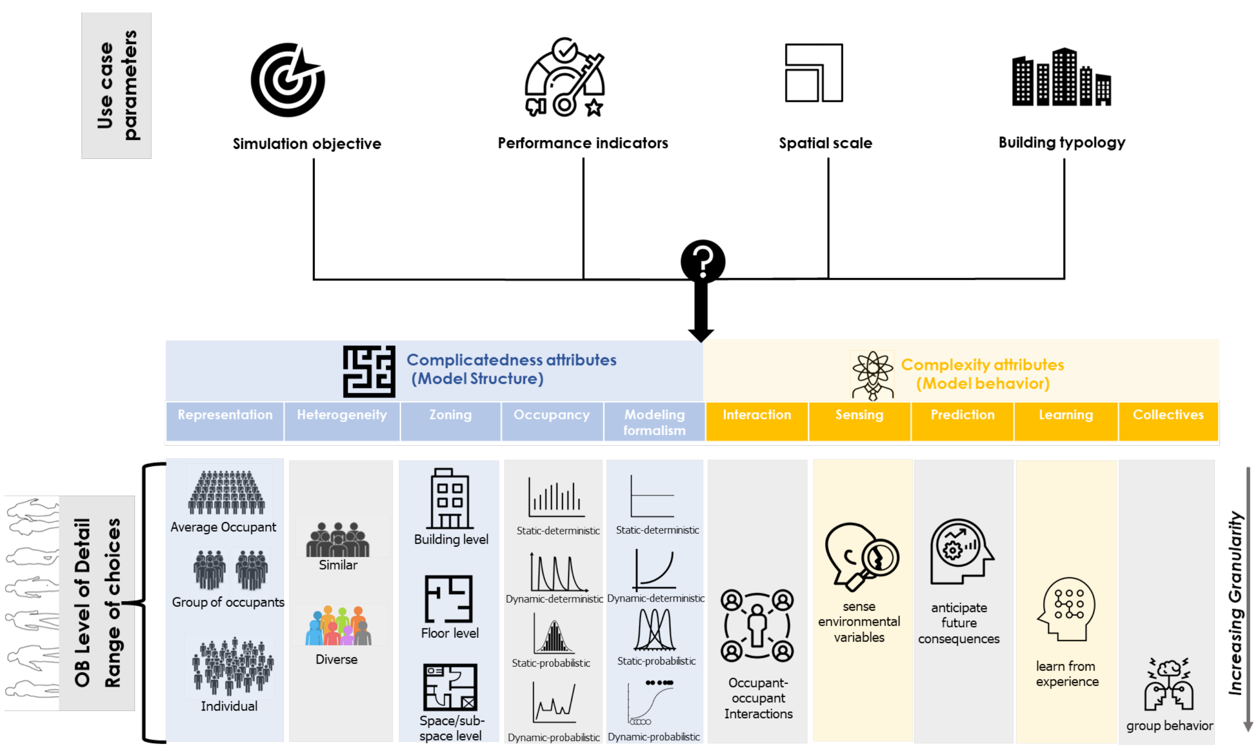

Figure 1: Framework on Level of Details for occupant behavior representation in ABM

4.2. Defining the Levels of Detail

Agent-based models representing OB in existing literature could be classified according to varying levels of granularity In this subsection, we define four LoDs for OB representation consisting of ABM attributes discussed in the previous section. The naming convention adopted here contains the abbreviation "LoD" followed by the occupant information level represented as "O-X" where "O" denotes the occupant information and "X" denotes the degree of detail. For instance, LoD O-1 represents the LoD for occupant representation at a granularity of level 1. This naming convention ensures that the OB LoDs are not confused with the standardized BIM LoDs [79]. We chose to organize OB LoDs into four categories primarily because the OB representation in traditional BPS models is guided by four modeling approaches as discussed in Section 2. Additionally, the four OB LoDs are comprehensible and distinctive enough to make it easier for modelers to choose the desired model attributes and their degree of detail. Furthermore, instead of defining a more detailed LoDs system, we introduce a hybrid approach to capture the varied combinations of model structure and model behavior elements adopted in existing OB literature (see Table 1). The cross-mixing of OB attributes through the hybrid approach imparts flexibility for practical applications in different use cases. However, this LoD classification may be expanded or refined in the future to accommodate new use cases.

The proposed LoDs range from the simplest level of representation at LoD O-0 to a comprehensive level corresponding to LoD O-3, as shown in Table 2. LoD O-0 comprises homogeneous user behavior represented through static-deterministic models such as fixed schedules with no elements of model complexity such as sensing, learning, or prediction. Nutkiewicz et al. [80] adopted such a model for exploring design parameters for optimal thermal comfort in informal settlements. The authors incorporated building level zoning with fixed occupancy schedule, and the other OB influences were not considered. In principle, LoD O-0 does not require any ABM because behavior is not considered dynamic, nor does it involve any complex systems. However, some LoD O-0 attributes can serve in combination with higher LoDs using the hybrid approach.

Table 2: Four levels of detail for representing occupant behavior

Levels of Detail	**Representation**	**Heterogeneity**	**Zoning**	**Occupancy**	**Modeling Formalism**	**Interaction**	**Learning**	**Sensing**	**Prediction**	**Collectives**
LoD O-0	Average Occupant	None	Building Level	Static-deterministic	Static-deterministic	No	No	No	No	No
LoD O-1	Average Occupant	None	Floor Level	Dynamic-deterministic	Dynamic-deterministic	No	No	Yes	Yes	No
LoD O-2	Group of Occupants	Yes	Detailed Space Type	Static-probabilistic	Static-probabilistic	Yes	Yes	Yes	Yes	No
LoD O-3	Individual Occupant	Yes	Individual Space	Dynamic-probabilistic	Dynamic-probabilistic	Yes	Yes	Yes	Yes	Yes

LoD O-1 is an aggregated level of ABM representing average OB and human building interactions using dynamic-deterministic models such as rule-based schedules or simple equations. Occupants are structured as homogeneous agents similar to LoD O-0, however complexity in model structure is introduced by considering that the agents have capabilities to sense environmental parameters and predict the future consequences of their actions. LoD O-1 is particularly useful for studies on decision making at a macro level, such as policy making at the urban scale, where a typical user behavior with basic complexity attributes would be sufficient for fulfilling the objective of the simulation. LoD O-1 can also be applied for exploratory studies on OB, such as the application of certain behavioral theories or methods. Bastani et al. [27] adopted a similar LoD to investigate the applicability of Bass diffusion theory for energy-saving policies.

LoD O-2 offers a relatively detailed approach for OB representation by introducing agent heterogeneity, static-probabilistic models for modeling occupancy, and decision-making process. The interaction among occupants is also incorporated in this LoD scheme. At LoD O-2, the occupants' complex behavior system reflects learning and capabilities to model the emergent effects. The purpose of this LoD is to serve use cases where the focus is on the different types of agents, their interactions effects, and/or the representation of their dynamics. An example of such a case is the ABM developed by Carmenate et al.[81] , to capture the human-building-appliance interactions among office building occupants. The purpose of the model was to investigate the impacts of energy literate and illiterate occupants' behavior on the total energy expenditure.

LoD O-3 represents complicated models with individual-level behavioral granularity and a detailed representation of complex systems influencing OB. At LoD O-3, dynamic-probabilistic models such as Markov chain or survival models are employed to simulate occupant presence, movement, and actions. Moreover, model behavior reflects occupants as collectives that have aggregated effects on the built environment. LoD O-3 is useful for developing case-specific models supported by empirical data and where the detailing of agent behavior would make a difference to the outcomes of the model's objective. The empirically rich and complicated models can also be utilized for validation and verification. It is important to note that the implementation of LoD O-3 must be carried out with utmost attention, since the complicated models may be difficult to initialize and lack transparency and completeness [51]. An example of a relatively complicated ABM in the BPS domain was developed by Sinha et al. [46] to estimate HVAC energy demand in an airport terminal building. The model features individual-level granularity, detailed internal zoning, and stochastic decision-making models (LoD O-3) that affect passenger density and, in turn, the zones' HVAC demand. However, the mentioned model only focuses on the occupants' presence and movement, while other attributes, such as occupant interactions or learning, are muted.

4.3. Use case parameters influencing the choice of OB LoD

The choice of LoD for occupant behavioral representation is primarily guided by the desired objective of the model and the quantitative metrics or key performance indicators (KPIs) measuring its attainment. In addition to the model's objective, building typology and spatial scale of the simulation may also affect the selection of an LoD or a particular attribute within the LoD scheme. Figure 2 entails a few examples illustrating the influence of use case parameters on the choice of OB LoD. A discussion on how each use case parameter impacts the choice of OB LoD is presented below:

- *Objectives and KPIs:* The guiding principle for adopting a particular LoD must be linked primarily to the purpose of the simulation model. As identified from the literature review presented in Section 2, ABM could support a variety of use cases in the building lifecycle, such as design, building controls and operations, or retrofit. LoD O-1, which depicts average OB, would be suited for ABM applications related to building design and retrofit requiring an aggregate level analysis. For instance, while comparing design options during the design stage analysis, a coarser level, such as LoD O-1, would suffice to estimate and compare relative energy performance for different design options using KPIs such as energy use intensity or ENERGY STAR score, which is based on annual aggregated energy performance. Implementing a higher LoD by simulating individual-level behavior may unnecessarily burden the model because the individual contribution to whole-building level performance indicators is likely to be negligible. However, if occupant-centric KPIs, such as peak kilowatts (kW)/person or annual kWh/person, are expected from the simulation output, a relatively higher LoD, such as LoD O-2 or a hybrid LoD O-1.5 may be appropriate because of the sensitivity of occupant representation and their behavioral repertoire on the desired performance metric.

Finer LoDs may be suited for building operation applications, such as demand response management in an office building, to simulate individual-level or group-level behavior with some model complicatedness (e.g., to estimate peak in energy demand). For system-level KPIs, such as lighting energy use or HVAC energy use on the basis of per occupant or per occupied hours, simulating stochasticity in occupant actions at LoD O-2 or O-2.5 would serve the simulation's purpose. In contrast, for aggregated analysis in demand response management, such as load shape analysis, a hybrid LoD O-1.5 would be suitable to depict group-level behavior and interaction among occupants with limited learning and sensing capabilities.

LoD O-2.5 or O-3, which comprise semantically rich ABMs in terms of both model complexity and model structure, may be useful for operations or control stages where occupant presence and behavioral repertoire have a significant impact on building performance. An example of such application could be the development, implementation, and evaluation of occupant-centric controls for improving comfort and reducing energy use. A relatively high LoD would aid in capturing the random appearance of individual-level actions and behavioral complexity aspects, such as learning, adaptation, or prediction, which are essential for occupant-centric controls studies. The usefulness of higher LoDs in design, operation, and control of low or net-zero energy buildings, where technology solutions alone may not achieve the desired energy-saving goals, cannot be overstated. The energy performance of such buildings is known to be influenced by occupants' lifestyles, awareness, or expectations. Translating such behavioral aspects into occupant models for building performance assessment requires a greater LoD. The highest LoDs may also support use cases that require occupant-centric KPIs, such as the degree-occupant-hour criterion partial occupancy demand performance. In addition, finer LoDs can be advantageous for use cases relating to interdisciplinary studies that integrate human values or norms such as occupants' energy saving intentions with behavioral actions for building performance.

- *Building typology and spatial scale:* The type of building serving the use case may also affect the selection of OB LoD or a particular attribute within the LoD scheme. Each building typology offers different levels of human–building interaction and underlying factors affecting occupant actions, which the OB LoD must consider. For instance, personal choices are known to be a major driver of energy use in residential buildings, which offer more options for personalization than in commercial buildings (e.g., by allowing occupants to adjust their indoor environment) [82]. Moreover, most residents pay their own energy bills and perceive building energy consumption differently than occupants within commercial buildings [83]. Therefore, an ABM at LoD O-1 without occupant behavioral complexity may be inadequate for estimating the energy demand or peak loads in residential buildings. In comparison, the same model may suffice for retail or restaurant building types, where occupants have limited control over their indoor environment. Use cases such as senior living or disadvantaged community housing that focus on a specific user group may have nuances in OB that are crucial to the simulation objective. The LoD selection in such cases should be intended at capturing the key behavioral attributes of the target population. We take an example of comparing retrofit strategies for improving energy efficiency in resource-constrained residential communities. Though a coarse LoD may suit the purpose of comparing options for retrofit, the peculiarity in resource-constrained user behavior towards the acceptance of a certain retrofit strategy would require the ABM to include model complexity elements corresponding to LoD O-1.5 or O-2.

For educational facilities, such as schools or university buildings, profiling students and defining patterns may be easier, and thus occupant heterogeneity may be an aspect to focus on. In contrast, for hospital buildings, simulating zone-level OB may not have a significant impact given the process-driven environment and specialized needs. In transient buildings, such as airports, the occupants' presence and movement patterns may be a crucial attribute that influences the heating and cooling demands. A finer occupancy model at LoD O-2 or above would improve the desired results, while model complexity attributes such as learning or interaction may not be important for this particular use case. Along with the building type, building systems and user interfaces also influence the choice of LoD for developing an agent-based model. Detailed OB representation may be required in environments offering a higher degree of human-building interaction. One such example is a naturally ventilated residential or office building where occupants undertake passive measures to maximize their comfort, driven by underlying behavioral processes. In contrast, for controlled environments, such as auditoriums or retail stores, where occupants' interaction with buildings is minimal, a simpler ABM would be suitable.

The choice of OB LoD may also be governed by the model's spatial scale. For urban-scale use cases aiming at estimating yearly or monthly energy use or carbon emissions for an urban area, a lower LoD (e.g., LoD O-1) may be adequate because the detailed OB may not be significant due to the averaging effects. However, if the desired outcome of urban-scale ABM requires a higher temporal resolution, such as one that enables estimation of thermal resilience during extreme weather events, LoD O-1.5 or O-2 may be suitable to incorporate improved schedules for occupant presence, movement, and actions. Finer urban-scale agent-based models may be useful for incorporating changes in population demographics, shifts in behavior over time, and occupants' adaptation to economic or environmental changes [84]. Moreover, utmost attention should be paid while selecting higher OB LoD for urban-scale ABMs since the computational burdens at such a scale may be excessive [85]. Though a detailed ABM corresponding to LoD O-2 or O-3 may be conceivable for simulating a neighborhood or a district, overloading the model with occupant attributes that do not add value to the model objective must be avoided.

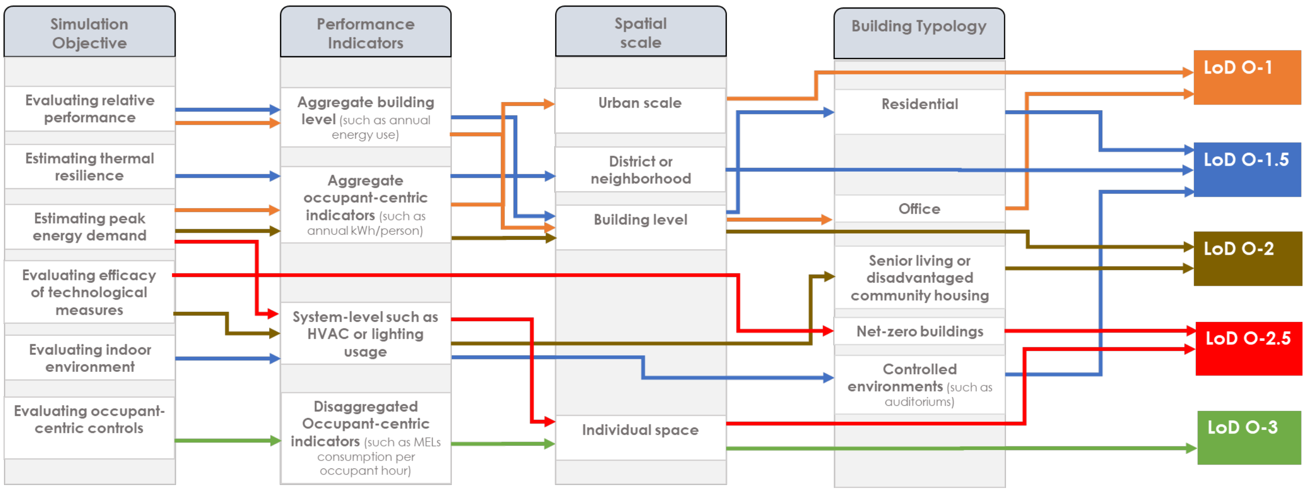

Figure 2: Use case parameters influencing the choice of OB LoD

5. Discussion

This work is a first step towards formalizing OB representation in agent-based models. It is intended to support the international research community by providing modeling guidance for selecting adequate OB LoD in ABMs for building simulation. However, it is not suggested that the proposed approach can be readily implemented in terms of an automated LoD selection algorithm. Rather, the intention is to raise the level of awareness concerning the factors influencing the proper choice of an LoD for a specific computational inquiry that employs ABM. As such, the conceptual framework may require further refinement and advancements for use by practitioners to determine which occupant attributes meet the project goals and at what LoD they need to be developed. An effort is underway to demonstrate the proposed framework to reflect upon the overall impact of ABM LoDs on BPS. Several case studies implementing the ABM LoD for occupant modeling are being designed and will be conducted as part of follow-up work under the related IEA EBC Annex 79 activities [14]. Results from these case studies will be reported in the future and used to fine-tune the ABM LoDs and the proposed framework to make them clearer and more usable. The incremental impact of LoD attributes on the BPS results is also a subject worthy of investigation since the model structure and model complexity are known to have a nonlinear relationship. Developing an OB schema and a corresponding ontology to standardize occupant modeling in agent-based environments is also an area of future development that could offer a customized approach for researchers that suits their specific needs or use cases.

The proposed LoD framework sets the purpose of the simulation as the guiding principle to identify the optimal LoD comprising 10 occupant-centric ABM attributes for OB representation. However, apart from the use case parameters, the selection of OB LoD may also be influenced by data availability, computational requirements, or time required for model development. A parsimonious modeling approach [86] that involves finding a compromise between the available data, the different modeling levels of detail, the expected output, and the computation time must be applied to select the most relevant and adequate OB LoD. This of course requires a certain level of expertise and experience from the user.

One of the major challenges in implementing finer OB LoDs is the paucity of sufficiently detailed and representative empirical data [13]. ABMs may require high-resolution measured data to quantify occupant actions and program occupants' behavioral repertoire from sources such as post-occupancy evaluation surveys or behavioral programs. It is imperative to map the data requirements and the required level of resolution for each LoD. The existing efforts to improve data availability for OB modeling, such as the recently developed ASHRAE Global Occupant Database under the IEA's Annex 79 project [14] and the ASHRAE Global Thermal Comfort Database [87], could be leveraged for this purpose. Moreover, balancing the data acquisition efforts required for any particular LoD scheme and the extent to which LoD can improve a model's performance is critical. An additional level of complicatedness or complexity that would require a larger dataset and higher computation time should only be incorporated to the model if there is a significant incremental change in the simulation outcomes. Adequate attention also must be paid to the errors resulting from the simulation at a particular LoD and the influence of those errors on the consistency of KPI values.

Mapping the formalized OB LoDs presented in this paper to building information modeling (BIM) and building energy modeling (BEM) frameworks is required. BIMForum, the U.S. chapter of buildingSMART International, defines the LoD for BIM by relating it with the progression of a model's graphic representation and the various building phases such as design, construction, or operations [79]. The LoDs for BEM are not as standardized as the BIM LoDs, and as discussed previously, the existing body of research that relates the concept of LoD with energy modeling is focused upon the urban scale [67]. These BEM LoDs are essentially linked with the geometrical representation of buildings and elements such as windows, roofs, and ducts. The matching of ABM LoDs with BIM and/or BEM tools can improve interoperability among the three environments and assist in the better integration of OB. This process can be implemented through various methods of coupling or co-simulation and could reduce model development time by reusing the data stored in BIM and BEM. Furthermore, the choice of ABM LoD for occupant modeling must be consistent with the considerations of LoDs for BIMs and LoDs of BEM, as the final simulation results depend on the integrated representation of details and how they exchange information across the spatial, temporal, and occupant scales.

6. Conclusions

Agent-based modeling (ABM) has received increasing attention in the building performance domain because of its formal potential to represent complex occupant behavior (OB). However, an important question that needs to be addressed for advancing agent-based occupant modeling is the appropriate level of granularity at which OB should be represented within such models. This present contribution is an attempt to formalize the levels of detail (LoD) to describe OB within ABM environments for building performance simulation. A detailed literature review on previous studies adopting the ABM approach laid the foundation for the study. A novel conceptual framework was developed to determine the degree of details required to represent human behavior in agent-based environments. The framework comprises 10 occupant-centric attributes related to the *model structure* (spatial and temporal resolution, number and types of agents, and representation of processes and interactions) and *model complexity* (occupant behavioral repertoire). Four LoDs of OB comprising varying degrees of model structure and complexity were defined to support diverse ABM use cases in BPS. A hybrid LoD approach was put forward to offer guidance in adopting the adequate OB LoD depending on the purpose of the simulation model, desired performance indicator, spatial scale, or building typology. Furthermore, a discussion on the applicability of the framework and its related challenges, such as data availability, is presented, and the importance of parsimony of principle, which considers the trade-offs between model complexity/complicatedness and accuracy is discussed. This study directly contributes to the OB research community by providing modeling guidance towards optimal levels of occupant representation. The proposed framework is scalable and could be expanded easily to finer LoD classifications involving significantly more complex behavioral rules or more detailed model structures. However, the pragmatism and need for such a framework remains questionable. Other relevant aspects of ABMs that were not within the scope of the current study and present important opportunities for future research include calibration and validation approaches, implementation methods, and the computational resources required for each LoD.

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 Programme.

References

[1] H. Yoshino, T. Hong, and N. Nord, "IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods," Energy and Buildings, vol. 152, pp. 124–136, Oct. 2017, doi: 10.1016/j.enbuild.2017.07.038.

[2] E. Bonabeau, "Agent-based modeling: methods and techniques for simulating human systems.," Proceedings of the National Academy of Sciences of the United States of America, vol. 99, pp. 7280–7287, May 2002, doi: 10.1073/pnas.082080899.

[3] S. Abar, G. K. Theodoropoulos, P. Lemarinier, and G. M. P. O'Hare, "Agent Based Modelling and Simulation tools: A review of the state-of-art software," Computer Science Review, vol. 24. Elsevier Ireland Ltd, pp. 13–33, May 01, 2017. doi: 10.1016/j.cosrev.2017.03.001.

[4] A. Mahdavi, V. Bochukova, and C. Berger, "Occupant-centric ontology as a bridge between domain knowledge and computational applications," in European Conference on Product and Process Modeling 2021 – eWork and eBusiness in Architecture, Engineering and Construction, CRC Press, pp. 106–112, 2021. doi: 10.1201/9781003191476-14.

[5] 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, Apr. 2020, doi: 10.1016/j.buildenv.2020.106726.

[6] Z. Sun, I. Lorscheid, J. D. Millington, S. Lauf, N. R. Magliocca, J. Groeneveld, S. Balbi, H. Nolzen, B. Müller, J. Schulze, and C. M. Buchmann, "Simple or complicated agent-based models? A complicated issue," Environmental Modelling & Software, vol. 86, pp. 56–67, Dec. 2016, doi: 10.1016/j.envsoft.2016.09.006.

[7] M. Abdou, L. Hamill, and N. Gilbert, "Designing and Building an Agent-Based Model," in Agent-Based Models of Geographical Systems, A. J. Heppenstall, A. T. Crooks, L. M. See, and M. Batty, Eds. Dordrecht: Springer Netherlands, pp. 141–165, 2012 . doi: 10.1007/978-90-481-8927-4_5.

[8] H. Couclelis, "Modeling frameworks, paradigms, and approaches," in Geographic information systems and environmental modelling, K.C. Clarke, B.E. Parks, and M.P. Crane, Eds., Prentice Hall , pp.36-50, 2002.

[9] F. Stazi, F. Naspi, and M. D’Orazio, “A literature review on driving factors and contextual events influencing occupants’ behaviours in buildings,” Building and Environment, vol. 118, pp. 40–66, Jun. 2017, doi: 10.1016/j.buildenv.2017.03.021.

[10] A. Mahdavi and F. Tahmasebi, “The deployment-dependence of occupancy-related models in building performance simulation,” Energy and Buildings, vol. 117, pp. 313–320, Apr. 2016, doi: 10.1016/j.enbuild.2015.09.065.

[11] I. Gaetani, P. J. Hoes, and J. L. M. Hensen, “On the sensitivity to different aspects of occupant behaviour for selecting the appropriate modelling complexity in building performance predictions,” Journal of Building Performance Simulation, vol. 10, no. 5–6, pp. 601–611, Nov. 2017, doi: 10.1080/19401493.2016.1260159.

[12] I. Gaetani, P.-J. Hoes, and J. L. M. Hensen, “A stepwise approach for assessing the appropriate occupant behaviour modelling in building performance simulation,” Journal of Building Performance Simulation, vol. 13, no. 3, pp. 362–377, May 2020, doi: 10.1080/19401493.2020.1734660.

[13] A. Mahdavi, “The trouble with ‘HIM’: new challenges and old misconceptions in human information modelling,” Journal of Building Performance Simulation, vol. 14, no. 5, pp. 611–618, Sep. 2021, doi: 10.1080/19401493.2021.1990410.

[14] W. O’Brien, A. Wagner, M. Schweiker, A. Mahdavi, J. Day, M. B. Kjærgaard, S. Carlucci, B. Dong, F. Tahmasebi, D. Yan, T. Hong, H. B. Gunay, Z. Nagy, C. Miller, and C. Berger, “Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation,” Building and Environment, vol. 178, p. 106738, Jul. 2020, doi: 10.1016/j.buildenv.2020.106738.

[15] A. Zhang, Q. Huang, Y. Du, Q. Zhen, and Q. Zhang, “Agent-based modelling of occupants’ clothing and activity behaviour and their impact on thermal comfort in buildings,” in IOP Conference Series: Earth and Environmental Science, vol. 329, no. 1, Oct. 2019. doi: 10.1088/1755-1315/329/1/012022.

[16] S. Chen, H. Zhang, J. Guan, and Z. Rao, “Agent-based modeling and simulation of stochastic heat pump usage behavior in residential communities,” Building Simulation, vol. 13, no. 4, pp. 803–821, Aug. 2020, doi: 10.1007/s12273-020-0625-2.

[17] S. Gilani, W. O’Brien, and H. B. Gunay, “Simulating occupants’ impact on building energy performance at different spatial scales,” Building and Environment, vol. 132, pp. 327–337, Mar. 2018, doi: 10.1016/j.buildenv.2018.01.040.

[18] W. O’Brien, A. Abdelalim, T. Abuimara, I. Beausoleil-Morrison, J. Sebastián Carrizo, R. Danks, S. Gilani, B. Gunay, T. Kesik, and M. Ouf, “Roadmap for Occupant Modelling in Building Codes and Standards.” In ESim2018-Building Simulation to Support Building Sustainability, pp. 259-268, 2018. http://www.ibpsa.org/proceedings/eSimPapers/2018/1-4-A-3.pdf (accessed September 11, 2021).

[19] M. Jia, R. S. Srinivasan, R. Ries, N. Weyer, and G. Bharathy, “A systematic development and validation approach to a novel agent-based modeling of occupant behaviors in commercial buildings,” Energy and Buildings, vol. 199, pp. 352–367, Sep. 2019, doi: 10.1016/j.enbuild.2019.07.009.

[20] E. Azar and C. C. Menassa, “Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings,” Journal of Computing in Civil Engineering, vol. 26, no. 4, pp. 506–518, Jul. 2012, doi: 10.1061/(asce)cp.1943-5487.0000158.

[21] J. Langevin, J. Wen, and P. L. Gurian, “Quantifying the human-building interaction: Considering the active, adaptive occupant in building performance simulation,” Energy and Buildings, vol. 117, pp. 372–386, Apr. 2016, doi: 10.1016/j.enbuild.2015.09.026.

[22] Y. S. Lee and A. M. Malkawi, “Simulating multiple occupant behaviors in buildings: An agent-based modeling approach,” Energy and Buildings, vol. 69, pp. 407–416, Feb. 2014, doi: 10.1016/j.enbuild.2013.11.020.

[23] H. C. 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.

[24] S. Norouziasl, A. Jafari, and C. Wang, “An agent-based simulation of occupancy schedule in office buildings,” Building and Environment, vol. 186, p. 107352, Dec. 2020, doi: 10.1016/j.buildenv.2020.107352.

[25] C. J. Andrews, D. Yi, U. Krogmann, J. A. Senick, and R. E. Wener, “Designing buildings for real occupants: An agent-based approach,” Institute of Electrical and Electronics Engineers Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, vol. 41, no. 6, pp. 1077–1091, Nov. 2011, doi: 10.1109/tsmca.2011.2116116.

[26] E. Azar and H. al Ansari, “Multilayer Agent-Based Modeling and Social Network Framework to Evaluate Energy Feedback Methods for Groups of Buildings,” Journal of Computing in Civil Engineering, vol. 31, no. 4, Jul. 2017, doi: 10.1061/(asce)cp.1943-5487.0000651.

[27] M. S. Bastani, S. Asadi, and C. J. Anumba, “Application of Bass Diffusion Theory to Simulate the Impact of Feedback and Word of Mouth on Occupants’ Behavior in Commercial Buildings: An Agent-Based Approach,” Journal of Architectural Engineering, vol. 22, no. 4, Dec. 2016, doi: 10.1061/(asce)ae.1943-5568.0000223.

[28] T. Carmenate, P. Inyim, N. Pachekar, G. Chauhan, L. Bobadilla, M. Batouli, and A. Mostafavi, “Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis,” in Procedia Engineering, vol. 145, pp. 42–49, 2016. doi: 10.1016/j.proeng.2016.04.012.

[29] M. Jia and R. Srinivasan, “Building performance evaluation using coupled simulation of energyplus and an occupant behavior model,” Sustainability, vol. 12, no. 10: 4086, May 2020, doi: 10.3390/su12104086.

[30] J. Langevin, J. Wen, and P. L. Gurian, “Including occupants in building performance simulation: integration of an agent-based occupant behavior algorithm with Energyplus,” in proceedings of 2014 Building Simulation Conference, pp. 417–424, 2014. doi: 10.13140/2.1.2551.4244

[31] E. Azar and C. Menassa, “A conceptual framework to energy estimation in buildings using agent based modeling,” in Proceedings of the 2010 Winter Simulation Conference, pp. 3145–3156, 2010. doi: 10.1109/WSC.2010.5679007.

[32] S. Papadopoulos and E. Azar, “Integrating building performance simulation in agent-based modeling using regression surrogate models: A novel human-in-the-loop energy modeling approach,” Energy and Buildings, vol. 128, pp. 214–223, Sep. 2016, doi: 10.1016/j.enbuild.2016.06.079.

[33] 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.

[34] Y. Chen, X. Liang, T. Hong, and X. Luo, "Simulation and visualization of energy-related occupant behavior in office buildings," Building Simulation, vol. 10, no. 6, pp. 785–798, Dec. 2017, doi: 10.1007/s12273-017-0355-2.

[35] 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.

[36] C. Liao, Y. Lin, and P. Barooah, "Agent-based and graphical modelling of building occupancy," Journal of Building Performance Simulation, vol. 5, no. 1, pp. 5–25, Jan. 2012, doi: 10.1080/19401493.2010.531143.

[37] A. Kashif, S. Ploix, J. Dugdale, and X. H. B. Le, "Simulating the dynamics of occupant behaviour for power management in residential buildings," Energy and Buildings, vol. 56, pp. 85–93, Jan. 2013, doi: 10.1016/j.enbuild.2012.09.042.

[38] A. Micolier, F. Taillandier, P. Taillandier, and F. Bos, "Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling," Engineering Applications of Artificial Intelligence, vol. 82, pp. 44–59, Jun. 2019, doi: 10.1016/j.engappai.2019.03.008.

[39] M. Vellei, S. Martinez, and J. le Dréau, "Agent-based stochastic model of thermostat adjustments: A demand response application," Energy and Buildings, vol. 238, May 2021, doi: 10.1016/j.enbuild.2021.110846.

[40] A. Alfakara, and B. Croxford, "Understanding occupants' behaviours using detailed agent-based modelling," in proceedings of Building Simulation and Optimization 2014. https://www.researchgate.net/publication/266673688_Understanding_occupants'_behaviours_using_detailed_agent-_based_modelling (accessed September 10, 2021).

[41] Z. Ding, T. Hu, M. Li, X. Xu, and P. X. W. Zou, "Agent-based model for simulating building energy management in student residences," Energy and Buildings, vol. 198, pp. 11–27, Sep. 2019, doi: 10.1016/j.enbuild.2019.05.053.

[42] S. Tian and S. Chang, "An agent-based model of household energy consumption," Journal of Cleaner Production, vol. 242, Jan. 2020, doi: 10.1016/j.jclepro.2019.118378.

[43] M. Schumann, Q. Reynaud, N. Sabouret, F. Sempé, Y. Haradji, B. Charrier, J. Albouys, and C.Inard ,"Multi-Agent based simulation of human activity for building and urban scale assessment of residential load curves and energy use." In Proceedings of Building Simulation 2021: 17th Conference of IBPSA, Sep 1. 2021. https://hal.archives-ouvertes.fr/hal-03505242/file/BS2021.pdf (accessed September 8, 2021).

[44] G. Plessis, E. Amouroux, and Y. Haradji, "Coupling occupant behaviour with a building energy model - A FMI application," in Proceedings of the 10th International Modelica Conference, vol. 96, pp. 321–326, Mar. 2014. doi: 10.3384/ecp14096321.

[45] J. Albouys, N. Sabouret, Y. Haradji, M. Schumann, and C. Inard, "SMACH: Multi-agent Simulation of Human Activity in the Household," in Advances in Practical Applications of Survivable Agents and Multi-Agent Systems: The PAAMS Collection, Lecture Notes in Computer Science, vol 11523., pp. 227–231, Springer, Cham., 2019. doi:10.1007/978-3-030-24209-1_19 .

[46] K. Sinha, N. Ali, and E. Rajasekar, "An agent-based dynamic occupancy schedule model for prediction of HVAC energy demand in an airport terminal building," in Proceedings of 2019 Building Simulation Conference, vol. 3, pp. 2063–2070, 2019. doi: 10.26868/25222708.2019.211133.

[47] D. Schaumann, S. Breslav, R. Goldstein, A. Khan, and Y. E. Kalay, "Simulating use scenarios in hospitals using multi-agent narratives," Journal of Building Performance Simulation, vol. 10, no. 5–6, pp. 636–652, Nov. 2017, doi: 10.1080/19401493.2017.1332687.

[48] T. Zhang, P.-O. Siebers, and U. Aickelin, "Modelling electricity consumption in office buildings: An agent based approach," Energy and Buildings, 43(10), 2882–2892. https://doi.org/10.1016/j.enbuild.2011.07.007

[49] E. Azar, C. Nikolopoulou, and S. Papadopoulos, "Integrating and optimizing metrics of sustainable building performance using human-focused agent-based modeling," Applied Energy, vol. 183, pp. 926–937, Dec. 2016, doi: 10.1016/j.apenergy.2016.09.022.

[50] C. Wang, D. Yan, and X. Ren, "Modeling individual's light switching behavior to understand lighting energy use of office building," in Energy Procedia, vol. 88, pp. 781–787, Jun. 2016. doi: 10.1016/j.egypro.2016.06.128.

[51] J. Langevin, J. Wen, and P. L. Gurian, "Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors," Building and Environment, vol. 88, pp. 27–45, Jun. 2015, doi: 10.1016/j.buildenv.2014.11.037.

[52] S. Norouziasl, A. Jafari, and C. Wang, "Analysis of Lighting Occupancy Sensor Installation in Building Renovation Using Agent-Based Modeling of Occupant Behavior." In Proceedings of the ASCE International Conference on Computing in Civil Engineering 2019 ; pp. 593–601, June 2019. doi: 10.1061/9780784482421.075

[53] L. de Floriani, L. Kobbelt, and E. Puppo, "A Survey on Data Structures for Level-of-Detail Models," in Advances in Multiresolution for Geometric Modelling, pp. 49–74. Springer, Berlin, 2005. doi:10.1007/3-540-26808-1_3.

[54] J. H. Clark, "Hierarchical Geometric Models for Visible Surface Algorithms," Communications of the ACM, vol. 19, no. 10, pp. 547–554, 1976. https://doi.org/https://doi.org/10.1145/360349.360354.

[55] D. Luebke, M. Reddy, J. Cohen, Varshney Amitabh, B. Watson, and R. Huebner, "Chapter 1 – Introduction" In D. Luebke, M. Reddy, J. D. Cohen, A. Varshney, B. Watson, & R. Huebner (Eds.), Level of Detail for 3D Graphics, Morgan Kauffman, pp. 3-17, 2002. doi: 10.1016/B978-155860838-2/50002-9

[56] A. Nugroho, "Level of detail in UML models and its impact on model comprehension: A controlled experiment," Information and Software Technology, vol. 51, no. 12, pp. 1670–1685, Dec. 2009, doi: 10.1016/j.infsof.2009.04.007.

[57] A. M. Fernández-Sáez, M. Genero, and M. R. v Chaudron, "Does the Level of Detail of UML Models Affect the Maintainability of Source Code?," in Models in Software Engineering, Lecture Notes in Computer Science, Springer, Berlin, vol. 7167, pp. 134–148, 2012. doi: 0.1007/978-3-642-29645-1_15

[58] M. Reddy, "A survey of level of detail support in current virtual reality solutions," Virtual Reality, vol. 1, no. 2, pp. 95–98, 1995, doi: 10.1007/bf02009725.

[59] M. Lemmens, "Quality of Geo-information," in Geo-information: Technologies, Applications and the Environment, M. Lemmens, Ed. Springer Netherlands, 2011, pp. 211–227. doi: 10.1007/978-94-007-1667-4_11.

[60] P. Uusitalo, O. Seppänen, E. Lappalainen, A. Peltokorpi, and H. Olivieri, "Applying Level of Detail in a BIM-Based Project: An Overall Process for Lean Design Management," Buildings, vol. 9, no. 5, 2019, doi: 10.3390/buildings9050109.

[61] L. Tang, L. Li, S. Ying, and Y. Lei, “A full level-of-detail specification for 3D building models combining indoor and outdoor scenes,” ISPRS International Journal of Geo-Information, vol. 7, no. 11, Nov. 2018, doi: 10.3390/ijgi7110419.

[62] T. Hong, Y. Chen, X. Luo, N. Luo, and S. H. Lee, “Ten questions on urban building energy modeling,” Building and Environment, vol. 168, p. 106508, Jan. 2020, doi: 10.1016/j.buildenv.2019.106508.

[63] T. Kutzner, K. Chaturvedi, and T. H. Kolbe, “CityGML 3.0: New Functions Open Up New Applications,” PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, vol. 88, no. 1, pp. 43–61, 2020, doi: 10.1007/s41064-020-00095-z.

[64] F. Biljecki, H. Ledoux, and J. Stoter, “An improved LOD specification for 3D building models,” Computers, Environment and Urban Systems, vol. 59, pp. 25–37, Sep. 2016, doi: 10.1016/j.compenvurbsys.2016.04.005.

[65] F. Biljecki, H. Ledoux, J. Stoter, and J. Zhao, “Formalisation of the level of detail in 3D city modelling,” Computers, Environment and Urban Systems, vol. 48, pp. 1–15, 2014, doi: 10.1016/j.compenvurbsys.2014.05.004.

[66] L. Tang, S. Ying, L.Li, F. Biljecki, H. Zhu, Y. Zhu, F. Yang, and F. Su, “An application-driven LOD modeling paradigm for 3D building models,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 161, pp. 194–207, Mar. 2020, doi: 10.1016/j.isprsjprs.2020.01.019.

[67] A. Mathur, P. Fennell, R. Rawal, and I. Korolija, “Assessing a fit-for-purpose urban building energy modelling framework with reference to Ahmedabad,” Science and Technology for the Built Environment, vol. 27, no. 8, pp. 1075–1103, 2021, doi: 10.1080/23744731.2021.1941248.

[68] S. Chen, W. Yang, H. Yoshino, M. D. Levine, K. Newhouse, and A. Hinge, “Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies,” Energy and Buildings, vol. 104, pp. 1–13, Jul. 2015, doi: 10.1016/j.enbuild.2015.06.075.

[69] A. Strzalka, J. Bogdahn, V. Coors, and U. Eicker, “3D City modeling for urban scale heating energy demand forecasting,” HVAC&R Research, vol. 17, no. 4, pp. 526–539, Aug. 2011, doi: 10.1080/10789669.2011.582920.

[70] F. Johari, G. Peronato, P. Sadeghian, X. Zhao, and J. Widén, “Urban building energy modeling: State of the art and future prospects,” Renewable and Sustainable Energy Reviews, vol. 128, p. 109902, Aug. 2020, doi: 10.1016/j.rser.2020.109902.

[71] R. Nouvel, M. Zirak, V. Coors, and U. Eicker, “The influence of data quality on urban heating demand modeling using 3D city models,” Computers, Environment and Urban Systems, vol. 64, pp. 68–80, Jul. 2017, doi: 10.1016/j.compenvurbsys.2016.12.005.

[72] A. Stzalka, D. Monien, A. Koukofikis, and U. Eicker, “Sensitivity analysis for minimization of input data for urban scale heat demand forecasting,” in proceedings of 14th International Conference on Sustainable Energy Technologies - SET 2015, Nottingham, UK, 2015. http://www.researchgate.net/profile/Aneta_Strzalka/publication/279527274_Sensitivity_analysis_for_minimization_of_input_data_for_urban_scale_heat_demand_forecasting/links/55cc587d08aebc967dfe2346.pdf. (accessed October 14, 2021)

[73] C. Cerezo, J. Sokol, S. AlKhaled, C. Reinhart, A. Al-Mumin, and A. Hajiah, “Comparison of four building archetype characterization methods in urban building energy modeling (UBEM): A residential case study

in Kuwait City," Energy and Buildings, vol. 154, pp. 321–334, Nov. 2017, doi: 10.1016/j.enbuild.2017.08.029.

[74] S. M. Manson, S. Sun, and D. Bonsal, "Agent-Based Modeling and Complexity," in Agent-Based Models of Geographical Systems, A. J. Heppenstall, A. T. Crooks, L. M. See, and M. Batty, Eds. Springer Netherlands, 2012, pp. 125–139. doi: 10.1007/978-90-481-8927-4_7.

[75] M. Gallegati and A. Kirman, "Reconstructing economics: Agent based models and complexity," Complexity Economics, vol. 1, pp. 31-35, 2012. doi: http://dx.doi.org/10.7564/12-COEC2.

[76] S. Carlucci, M. De Simone, S.K. Firth, M. B. Kjærgaard, R. Markovic, M. S. Rahaman, M.K. Annaqeeb, S. Biandrate, A. Das, J.W. Dziedzic, G. Fajilla, M. Favero, M. Ferrando, J. Hahn, M. Han, Y. Peng, F. Salim, A.Schlüter, and C. van Treeck,., "Modeling occupant behavior in buildings," Building and Environment, vol. 174, p. 106768, May 2020, doi: 10.1016/j.buildenv.2020.106768.

[77] D. Yan, W. O'Brien, T. Hong, X. Feng, H. B. Gunay, F. Tahmasebi, and A. Mahdavi, "Occupant behavior modeling for building performance simulation: Current state and future challenges," Energy and Buildings, vol. 107, pp. 264–278, Nov. 2015, doi: 10.1016/j.enbuild.2015.08.032.

[78] V. Grimm, U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, T. Grand, S. K. Heinz, G. Huse, A. Huth, J. U. Jepsen, C. Jørgensen, W. M. Mooij, B. Müller, G. Pe'er, C. Piou, S. F. Railsback, A.M. Robbins, M. M. Robbins, E. Rossmanith, N. Rüger, E. Strand, S. Souissi, R. A. Stillman, R. Vabø, U. Visser, and D. L. DeAngelis,., "A standard protocol for describing individual-based and agent-based models," Ecological Modelling, vol. 198, no. 1–2, pp. 115–126, Sep. 2006, doi: 10.1016/j.ecolmodel.2006.04.023.

[79] BIMForum, Level of Development Specification, 2021. https://bimforum.org/lod/ (accessed November 3, 2021)

[80] A. Nutkiewicz, R. K. Jain, and R. Bardhan, "Energy modeling of urban informal settlement redevelopment: Exploring design parameters for optimal thermal comfort in Dharavi, Mumbai, India," Applied Energy, vol. 231, pp. 433–445, Dec. 2018, doi: 10.1016/j.apenergy.2018.09.002.

[81] T. Carmenate, P. Inyim, N. Pachekar, G. Chauhan, L. Bobadilla, M.Batouli, and A.Mostafavi,., "Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis," in Procedia Engineering, 2016, vol. 145, pp. 42–49. doi: 10.1016/j.proeng.2016.04.012.

[82] O. Guerra Santin, L. Itard, and H. Visscher, "The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock," Energy and Buildings, vol. 41, no. 11, pp. 1223–1232, Nov. 2009, doi: 10.1016/j.enbuild.2009.07.002.

[83] T. Harputlugil and P. de Wilde, "The interaction between humans and buildings for energy efficiency: A critical review," Energy Research & Social Science, vol. 71, p. 101828, Jan. 2021, doi: 10.1016/j.erss.2020.101828.

[84] G. Happle, J. A. Fonseca, and A. Schlueter, "A review on occupant behavior in urban building energy models," Energy and Buildings, vol. 174, pp. 276–292, Sep. 2018, doi: 10.1016/j.enbuild.2018.06.030.

[85] K. Zhao, P. Fennell, and J. Tomei, "Representations of people in Urban Building Energy Models," In Proceedings of Building Simulation 2021: 17th Conference of IBPSA, Sep 1. 2021. https://discovery.ucl.ac.uk/id/eprint/10129393/1/BS2021-People%20in%20models%20final%20upload.pdf (accessed November 8, 2021).

[86] E. Garreau, T. Berthou, B. Duplessis, V. Partenay, and D. Marchio, “Solar shading and multi-zone thermal simulation: Parsimonious modelling at urban scale,” Energy and Buildings, vol. 249, p. 111176, Oct. 2021, doi: 10.1016/j.enbuild.2021.111176.

[87] V. Földváry Ličina, T. Cheung, H. Zhang, R. de Dear, T. Parkinson, E. Arens, and 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.