Exploring the impacts of heterogeneity and stochasticity in air-conditioning behavior on urban building energy models

Abstract

Heterogeneity and stochasticity, two main aspects of uncertainty in occupant behavior (OB), at the urban scale are not featured in most current urban building energy modeling (UBEM) platforms, and their respective impacts on urban-scale building energy consumption remain unclear. We aimed to introduce OB uncertainty into the UBEM workflow and assess the differences in the impacts of heterogeneity and stochasticity on cooling demand. Different OB models were integrated into the cooling demand simulation of residential building stocks, considering the heterogeneity and stochasticity in both occupancy and energy-use behavior. The impacts of heterogeneity and stochasticity on urban-scale cooling demand and its applications for different purposes in UBEM are discussed. We found that stochasticity in occupancy decreased the peak cooling demand by 54%, whereas the uncertainty in air-conditioning (AC) behavior had little effect. Heterogeneity is the main reason for the diversity in cooling demand, whereas stochasticity better reflects the dynamics of cooling demand. Occupancy and AC behavior models with higher fidelity are required to obtain results with higher spatial or temporal resolution, which should be selected according to the UBEM applications. The proposed approach will contribute to the development of appropriate urban-scale occupant behavior models and bridge urban mobility with occupant-centric UBEMs.

Keywords: Urban building energy modeling, Occupant behavior, Uncertainty analysis, Residential buildings

1. Introduction

The urban environment is responsible for two-thirds of the energy consumption and 70% of carbon emissions worldwide (IEA, 2021). The building sector contributes to approximately 38%

and 35% of global carbon emissions and global energy consumption, respectively (United Nations Environment Programme, 2020). Urban building energy modeling (UBEM) is a technique for quantifying the operational energy demand of buildings at the urban scale (Reinhart & Davila, 2016; Hong et al., 2020) and has been widely used in the analyses of energy conservation measures (ECMs) (Deng et al., 2023) and renewable energy potential (Liu et al., 2023b; Perwez et al., 2023).

1.1. Significance of considering occupant behavior (OB) in urban building energy models

Despite the promising capacity of UBEM in assessing urban-scale energy demand, some sensitive parameters related to building physics, building systems, and energy-related occupant behavior (OB) are assessed only based on simple assumptions or representative values. Among the sources of uncertainty, OB is known to have a significant impact on building energy demand considering that occupants are served by the building and are the driving force of building energy usage (Yan et al., 2015). The heating and cooling demands can deviate by up to 30% when considering actual OB instead of the standard schedules (Eguaras-Martínez et al., 2014). Ferrando et al. (2022) found that randomized occupant schedules could introduce differences in energy demand owing to different temporal and spatial aggregation. Therefore, to accurately predict the building energy demand, a better understanding of the effects of OB on the intensity and temporal characteristics of building energy usage is required (Hou et al., 2022).

Notably, when expanding the perspective from individual buildings to the urban building stock, the OB of different buildings will have complex impacts on the entire building stock. From a temporal perspective, the load profiles of different buildings differ depending on the differences in occupancy and energy usage, even for buildings with the same usage (Ferrando et al., 2023). Thus, the peak load of each building will not occur simultaneously. Replicating a single-building approach for an entire building stock leads to the overestimation of peak loads (An et al., 2017) and the inaccurate estimation of the potential energy savings from ECMs related to occupancy-based sensors and controls (Tahmasebi & Mahdavi, 2015). From a spatial perspective, the energy consumption at different spatial scales exhibits different patterns owing to the asynchronous operational behavior of multiple agents. For high-density apartments with many units and with independent control of heating and cooling, the larger the scale, the more stable is the total energy consumption. This is because any uncertainty in the energy consumption of different households will be offset when aggregated (Hu & Xiao, 2020). Therefore, different OBs in buildings have more significant impacts on the energy consumption when a finer spatial/temporal resolution is employed, such as the building-level load profile at the urban scale.

Obtaining reliable estimates of energy consumption at finer spatiotemporal resolutions could expand the applications of UBEM in energy transition and decarbonization at the urban scale. First, the hourly and sub-hourly load profiles of each building in the stock play a fundamental role in the capacity design and optimal operation of photovoltaic (PV) systems (Feng et al., 2023; Luo et al., 2023), and optimizing them promotes the broader adoption of PV systems in a dense urban environment (Zhu et al., 2023). Second, the design of energy storage systems and vehicle-to-building (V2B) applications also depend on the load profiles of the buildings in the city (Kang et al., 2022). Third, load profiles with high spatiotemporal resolutions are crucial for accurately assessing the demand response potential and energy flexibility. In summary, improving the fidelity of building load profiles simulated by UBEM will facilitate its application at the urban scale. Hence, quantifying the uncertainty in OB is necessary.

1.2. Uncertainty in urban-scale OB: heterogeneity and stochasticity

The uncertainty in OB at the urban scale has garnered considerable attention from researchers. The scope of OB in building simulations, as summarized by Yan et al. (2015), includes movements and actions. Similarly, Dabirian et al. (2022) investigated the integration of the OB framework and UBEM from the two perspectives: occupancy and occupant energy-use behavior. Occupancy refers to the occupant's presence and absence schedule in a given space, which affects the internal heat gain and equipment control. The energy-use behavior refers to the occupant's interactions with appliances, including lighting and air-conditioning (AC), which further affect equipment operation based on occupancy.

Considering the characteristics of OB at the urban scale, the three characteristics of building occupancy schedules in commercial buildings are categorized as follows: stochasticity, seasonality, and building use-type diversity (Happle et al., 2020b). From the perspective of occupants in residential buildings, Chen et al. (2022) used heterogeneity and stochasticity to describe the diversity among occupants and variance in OB over time.

Based on the above categorization, the main aspects of uncertainty in urban-scale OB are illustrated in Fig. 1. Two dimensions of OB, namely, occupancy and energy-use behavior, are considered, and most energy-use behaviors are premised on occupancy. Additionally, for multiple agents in the building stock, the differing OBs among different occupants and those that change with time are both important, and the terms heterogeneity and stochasticity, respectively, are used to describe them. **Heterogeneity** is used to describe the differences between the occupants: different occupants have different daily routines, such as the waking time, working hours, and bedtime (Liu et al., 2023a). In terms of the energy-use behavior, different occupants have different interactions with appliances, such as different temperature ranges of the AC or keeping lights on whenever the room is occupied vs. adjusting according to the illumination (Hu et al., 2017). **Stochasticity** is used to describe the random variations over time; for example, the occupancy schedule may be slightly different on Mondays in different weeks owing to temporary arrangements or changes in the commute time, among other factors. Moreover, the energy-use behavior may also differ, even under similar conditions (same indoor temperature or illumination), owing to its intrinsic stochastic nature (Ren et al., 2014). Other characteristics, such as seasonality and spatial diversity, have also been investigated (Nejadshamsi et al., 2023). However, both these characteristics are inherently reflected in the differences among occupants and the variations in the behavior of individual occupants, which could be further reflected by differentiating the occupants at different locations and introducing more trends or variations of OB related to the weather or holidays (Happle et al., 2020b). Consequently, heterogeneity and stochasticity were selected as the focus of this study, and the uncertainty in OB is represented by the combined effect of stochasticity and heterogeneity.

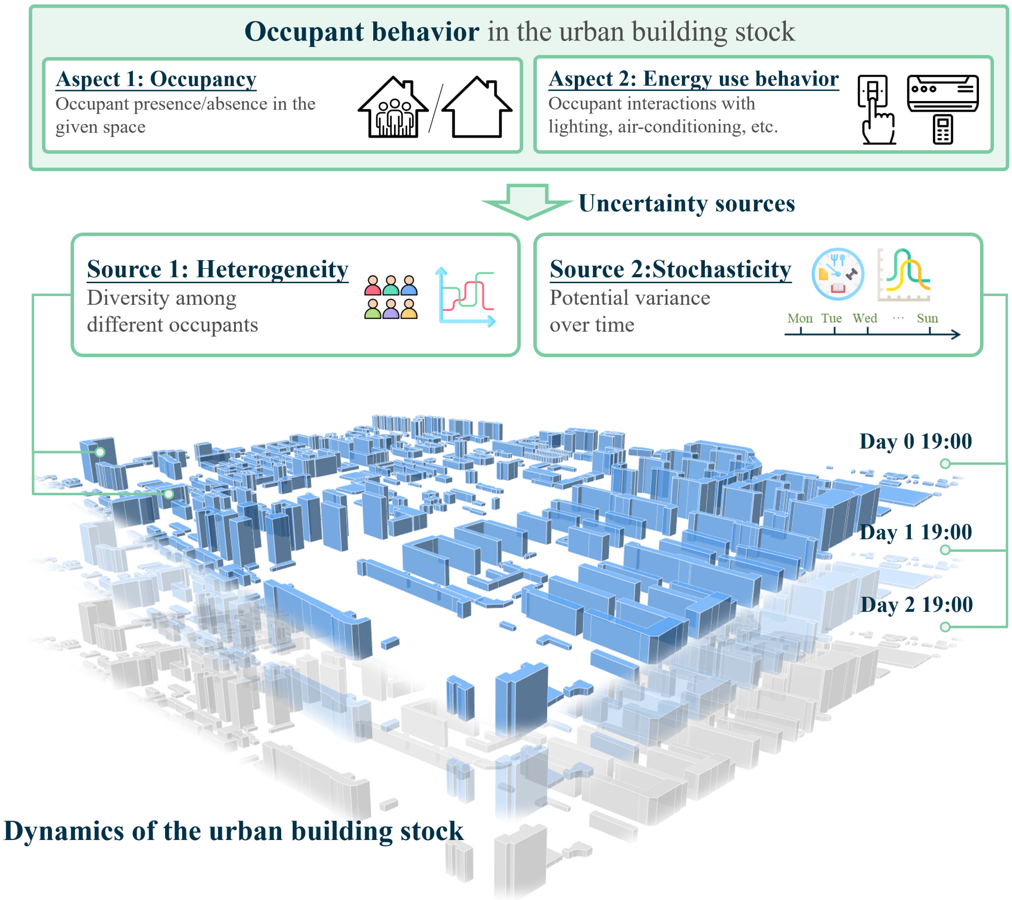

Figure 1: Uncertainty in occupant behavior (OB) in the urban building stock.

Attempts have been made to define the optimal amount of information or level of granularity required to systematically represent occupant information (O'Brien et al., 2020). Malik et al. (2022) proposed a novel framework to select the required details in representing occupants in agent-based models, based on the concept of level of detail (LoD). The structures of OB models were analyzed in terms of representation, heterogeneity, zoning, occupancy, and modeling formalism. Based on the framework, proper levels of detail in OB modeling were analyzed in the energy modeling of office buildings (Malik et al., 2023) or district cooling systems (Wu et al., 2023b).

1.3. OB models in current UBEM methods

Despite the heterogeneous and stochastic nature of urban-scale OB, most UBEM platforms only implement the description of occupants' presence and actions in a deterministic way (Ferrando et al., 2020), such as CitySim (Robinson et al., 2009), SimStadt (Nouvel et al., 2015), umi (Reinhart et al., 2013), CityBES (Chen et al., 2017), and URBANopt (El Kontar et al., 2020). Occupancy in buildings of the same type is set based on standard or deterministic schedules according to prototype building models (Dabirian et al., 2022). Occupants are assumed to leave and arrive according to a perfect and repeated schedule (Robinson et al., 2007). Additionally, the uncertainty in energy-use behavior is not considered. The AC operation and setpoint are also determined by preset schedules, ignoring the interaction between the occupants and indoor environment. To date, few UBEM platforms include heterogeneous or stochastic OB models, either completely or partially. One example is OpenIDEAS's StROBe module, which enables stochastic residential occupancy behavior modeling (Baetens et al., 2015). Moreover, SUNtool allows the stochastic modeling of occupancy presence, window opening, shading devices and lights, and electrical and water appliances (Robinson et al., 2007).

Probabilistic OB models are also being examined to properly consider the intrinsic heterogeneous or stochastic nature of occupants and investigate their impact on urban- or district-scale building energy consumption. In a study of public buildings, Bianchi et al. (2020) parametric schedules (derived from metered electric consumption data) were utilized to model the occupancy-driven schedules for large and diverse building stocks. Wu et al. (2020) developed a novel approach to derive urban-scale building occupant profiles from mobile position data, and quantified the difference in the heating or cooling demand at the urban scale. Moreover, based on location-based service (LBS) data, context-specific and data-driven occupancy schedules have been created to reflect the diversity in building occupancy (Happle et al., 2020a,b). An approach to generate agent-based models based on class and employee registers was also proposed and used to assess the impact of occupant presence modeling on district-scale energy demand simulations (Mosteiro-

Romero et al., 2020; Mosteiro-Romero & Schlueter, 2021).

Considering residential buildings, Martinez et al. (2022) investigated the flexibility potential of a district by diversifying occupancy based on time-use survey (TUS) data, and found that OB must be carefully considered when estimating the flexibility potential. In another study, Tanimoto & Hagishima (2010) a method was developed to calculate the stochastic load time-step by time-step in cases where the on/off state of the heating, ventilating, and air-conditioning (HVAC) varied. Time-varying and temperature-related behavior schedules were generated using Monte Carlo simulations. They found that deriving the dynamic state change of the HVAC system from the inhabitants' schedules was a significant factor in the peak heating or cooling loads. In another study, Chen et al. (2022) developed a novel stochastic OB model combining time-inhomogeneous Markov chains and probability sampling of event durations and magnitudes, which was also integrated with the building stock simulation platform. An et al. (2017) established OB models reflecting the spatial and temporal diversity and stochasticity based on a large-scale survey and applied this approach to district cooling. Table 1 summarizes the existing studies on the impact of uncertainty in OB on urban- or district-scale energy consumption, wherein considerations of the aspects of uncertainty in urban-scale OB are also specified.

As specified previously, the uncertainty in OB has not been featured in most current UBEM platforms, and the platforms that combine occupancy and AC behavior are even fewer, leading to the distortion of the load profiles. Although OB has garnered considerable attention in current UBEM research, few models reflect the heterogeneity and stochasticity in both occupancy and AC behavior. In urban-scale residential buildings, AC behavior has a more complex impact on energy consumption owing to the autonomous control of a large number of independent occupants (Dong et al., 2021).

Additionally, the focus of published studies has been the introduction of OB uncertainty into UBEM by utilizing different data sources or techniques; the systematic and comprehensive investigation of the mechanism of the heterogeneity and stochasticity of OB is lacking. In some studies,

Table 1: Summary of previous studies on the impact of uncertainty in OB on urban- or district-scale energy consumption.

Reference	Building function	Occupancy		AC behavior	
		Heterogeneity	Stochasticity	Heterogeneity	Stochasticity
Bianchi et al. (2020)	Public	✓			
Wu et al. (2020)	Public	✓			
Happle et al. (2020a)	Public	✓			
Mosteiro-Romero et al. (2020)	Public	✓	✓		
Happle et al. (2020b)	Mixed-use	✓			
Mosteiro-Romero & Schlueter (2021)	Mixed-use	✓	✓		
Martinez et al. (2022)	Residential	✓	✓		
Tanimoto & Hagishima (2010)	Residential		✓		✓
Chen et al. (2022)	Residential	✓	✓		
An et al. (2017)	Residential	✓	✓	✓	✓

such as An et al. (2017), although scholars have introduced heterogeneity and stochasticity in OB and achieved higher accuracy in assessing the district-level cooling demand, the respective impacts of heterogeneity and stochasticity on urban-scale cooling demand and methods to consider heterogeneity and stochasticity in UBEM practices require further study.

1.4. Aim and objectives

Considering these gaps in the current literature, we aimed to develop a novel framework to simulate urban-scale building cooling demand by incorporating the uncertainty in OB and systematically assessing the respective impacts of heterogeneity and stochasticity in OB on the cooling demand. Our results are expected to contribute to the literature by achieving the following three objectives:

- We aimed to develop an integrated approach to assess the cooling demand of residential building stocks, considering uncertainty in OB. The heterogeneity and stochasticity in both occupancy and AC behavior were comprehensively considered and integrated into the UBEM workflow.

- Based on the integrated approach, we aimed to assess the differences in the impacts of heterogeneity and stochasticity in OB on the urban-scale building cooling demand at different spatial (household level or urban scale) and temporal resolutions (annual, daily, or sub-hourly).
- We aimed to assess the fidelity of OB models for different UBEM applications and contexts. Based on the corresponding performance indicators, we aimed to determine the need to consider heterogeneity or stochasticity in occupancy and AC behavior.

The remainder of this paper is organized as follows. In Section 2, we describe the workflow of the proposed approach, AC behavior models, UBEM framework, comparison methods, and a case study. In Section 3, we present the results of the modeling in terms of the cooling demand at different spatial and temporal scales. In Section 4, we discuss the impact of occupancy and AC behavior on cooling demand, compare the heterogeneity and stochasticity in OB, and evaluate appropriate OB models for different UBEM purposes. Last, in Section 5, we summarize the contributions and significance of our results.

2. Methodology

The overall technical approach of our study is illustrated in Fig.2. In the proposed model, the OB with respect to AC was integrated with the bottom-up physics-based workflow of UBEM. Subsequently, different AC behavior models for UBEM were established, considering the heterogeneity in temperature preference and stochasticity in the AC operation. The cooling demand of each building was simulated based on an integrated approach, and the key performance indicators for UBEM obtained by different AC behavior models were compared. Based on the results, we discussed the impacts of heterogeneity and stochasticity on urban-scale cooling demand simulations and the application of UBEM for different purposes.

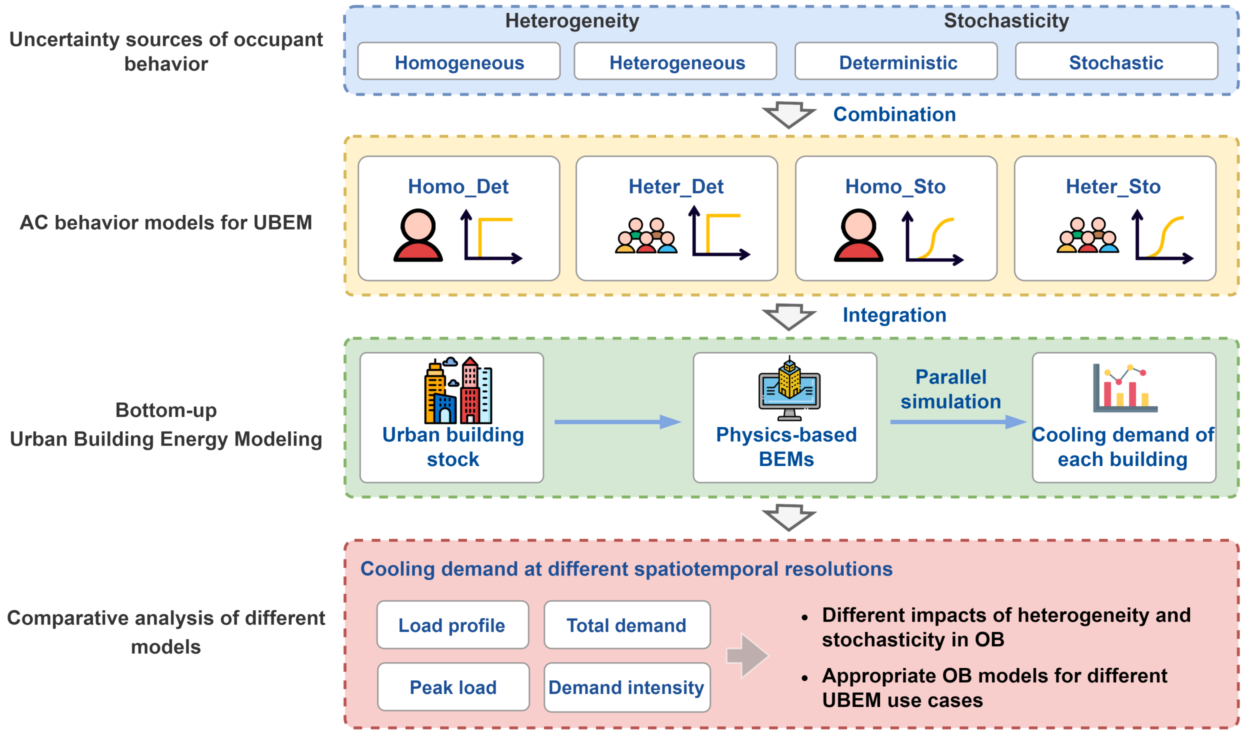

Figure 2: Technical approach of this study.

2.1. *Heterogeneity and stochasticity of AC behavior models*

As discussed in Section 1, heterogeneity and stochasticity are two main aspects of uncertainty in OB when simulating residential building loads. Based on the concept illustrated in Fig.1, heterogeneity in this study refers to the diversity of the tolerance threshold or the preference for indoor temperature. The term stochasticity represents the potential variance in the AC behavior at the same indoor temperature. As reported in previous studies, the thermal sensation of occupants is affected by many factors, making the relationship between AC behavior and indoor temperature non-deterministic (Lu et al., 2023; Ren et al., 2014). Accordingly, four different AC behavior models were proposed and compared in this study: Homo_Det, Heter_Det, Homo_Sto, and Heter_Sto. To better understand the model structures, the categorization of the proposed models under the framework of this study and the LoD framework proposed by Malik et al. (2022) is listed in Table 2.

Table 2: Model structures of the proposed AC behavior models.

Model	Uncertainty in AC behavior		Complicatedness attributes in the level-of-detail framework (Malik et al., 2022)			
	a. Heterogeneity	b. Stochasticity	a. Hetergeneity	b. Zoning	c. Occupancy	d. Model formalism
Homo_Det	None	None	None	Household	Static-deterministic or static-probabilistic	Dynamic-deterministic
Heter_Det	Yes	None	Yes	Household	Static-deterministic or static-probabilistic	Dynamic-deterministic
Homo_Sto	None	Yes	None	Household	Static-deterministic or static-probabilistic	Dynamic-probabilistic
Heter_Sto	Yes	Yes	Yes	Household	Static-deterministic or static-probabilistic	Dynamic-probabilistic

The Homo_Det model represents the status quo approach for simulating the AC behavior in UBEM. In most existing UBEM platforms, the AC behavior is static-deterministic; namely, the occupancy schedule is considered but not the indoor temperature (Prataviera et al., 2022), or the AC behavior is considered only when the room temperature exceeds the threshold (Liu et al., 2022). Homogeneous behavior of the occupants was assumed, and AC behavior was deterministically and instantly triggered. In particular, in the Homo_Det model, the AC behavior was triggered as soon as the indoor temperature exceeded the threshold temperature of 29.6 °C, as shown in Fig.3(a).

In the Heter_Det model, in contrast to the Homo_Det model, the heterogeneity of the occupants was considered. To reflect actual AC behavior and its heterogeneity, five typical AC behavior patterns and their proportions were considered in this model. Wu et al. (2023c) extracted five typical AC behavior patterns and established the stochastic model for each pattern from large-scale variable refrigerant flow (VRF) online monitoring data. The extracted typical OB models demonstrated that they can reflect differences in various population groups, and their effectiveness was validated by comparing the simulated and measured data. However, in the Heter_Det model, only heterogeneity in AC behavior was considered. Therefore, the assumption was made to ensure that the temperature preference was the same, as was the case in Wu et al. (2023c). We ignored the stochasticity, following the method in An et al. (2018): the AC was considered switched on when the probability of switching it on was greater than half; otherwise, it was considered switched off. Last, the temperature threshold in the Heter_Det model exhibited a wide range, from 20.0 to 32.9 °C, as shown in Fig.3(b).

The Homo_Sto model reflected the stochasticity of AC behavior. The probability associated with indoor temperature was considered, and the AC action was randomly determined based on the corresponding probability. However, the behavior pattern of the occupants was considered homogeneous. The stochastic AC behavior model was based on a widely used discrete three-parameter Weibull cumulative function (Du & Pan, 2022; Sun & Hong, 2017; Li et al., 2022). The model was formalized according to Eq. 1 based on the indoor temperature.

$$p(\tau) = \begin{cases} 0, & T(\tau) < u \\ 1 - \exp\{-[\frac{T(\tau)-u}{l}]^k (\frac{\Delta\tau}{\tau_c})\}, & T(\tau) \geq u. \end{cases} \tag{1}$$

Here, u is the threshold temperature (°C), which represents the lowest temperature when there is a probability that occupants will switch on the AC. l is the scale parameter (°C) used to non-dimensionalize the temperature. k is a shape parameter that describes the sensitivity to the environment (Ren et al., 2014). $\Delta\tau$ refers to the time step of the data and τ_c is the time constant. The parameters ($u = 25.5$, $l = 6.5$, $k = 6.5$) were selected for this model, as shown in Fig. 3 (c).

The Heter_Sto model comprehensively reflected heterogeneity and stochasticity and was found to have the highest fidelity among the models assessed in this study. The five typical AC behavior patterns and their proportions were the same as those in the Heter_Det model. Additionally, the stochastic AC behavior models were the same as the discrete three-parameter Weibull cumulative models described in Wu et al. (2023c), as shown in Fig. 3(d). Owing to the adequate reflection of both heterogeneity and stochasticity, the Heter_Sto model was used as the reference model with respect to the effects of heterogeneity and stochasticity in OB on urban-scale cooling demand.

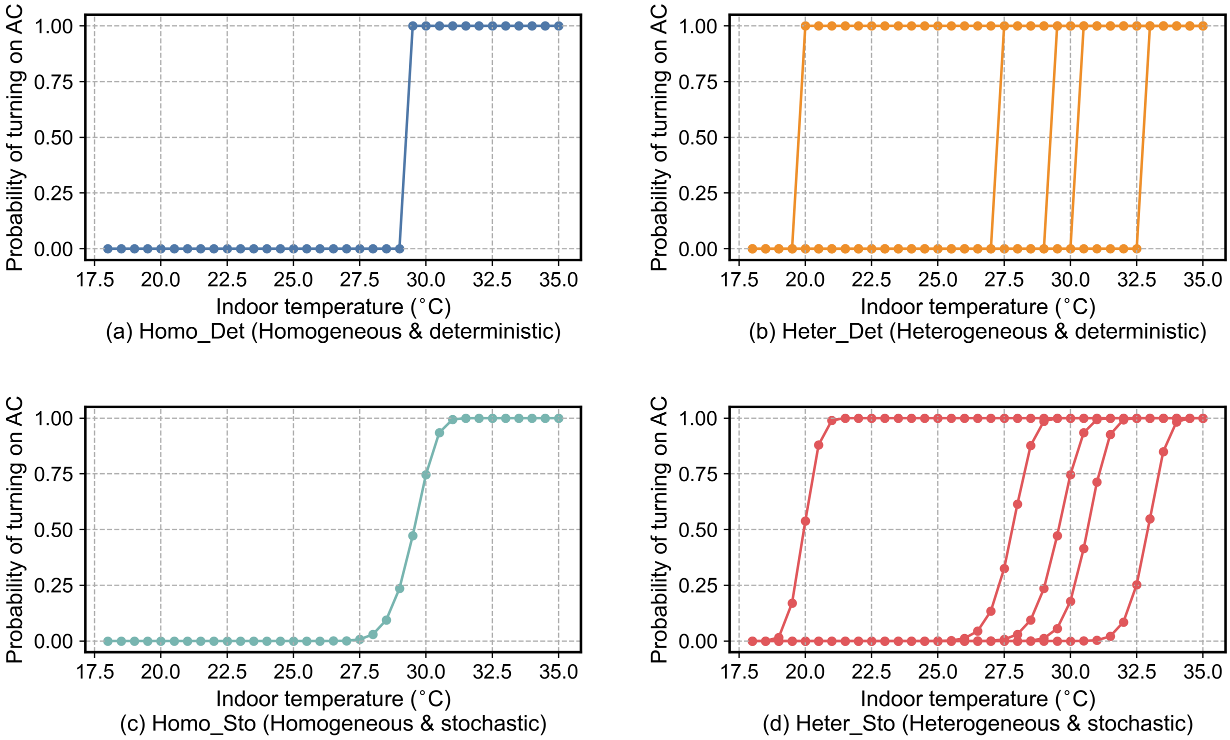

Figure 3: Relationship between indoor temperature and the probability of switching on the AC: comparison of different AC behavior models.

More details, such as the model parameters and the proportions of different patterns are specified in Appendix.

2.2. Modeling framework of UBEM integrated with OB

The integration of the OB model into the current workflow of UBEM is illustrated in Fig. 4. After the generation by UBEM, the single-building model was split into household models. Subsequently, OB parameters were configured, including the occupant movement and AC behavior parameters. Stochastic occupancy was generated and the AC operation state was determined for each time step based on the occupant state and zone temperature. The cooling demand was calculated when the AC was switched on.

DeST-urban, a platform for urban building energy modeling, was used for UBEM simulations.

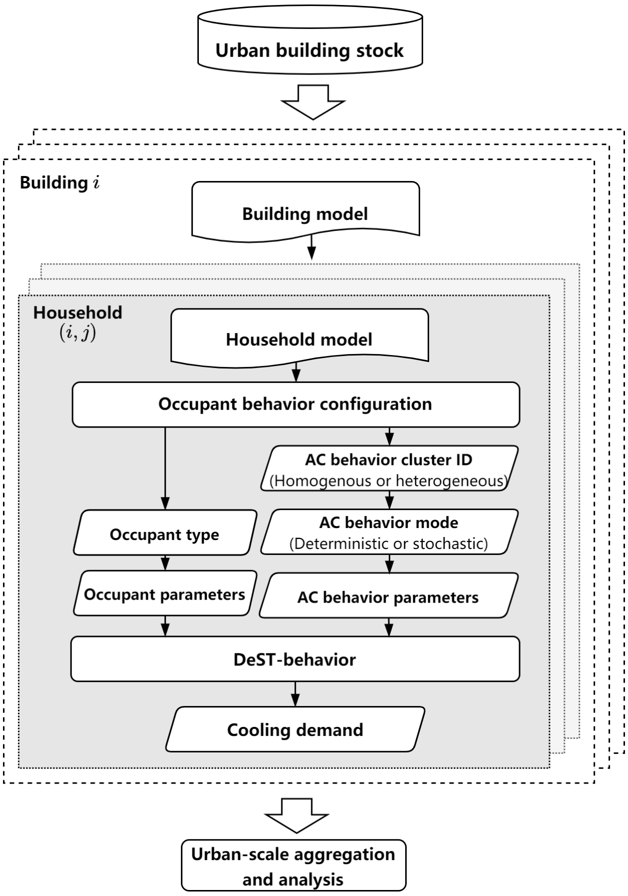

Figure 4: Integration of the OB model into the workflow of UBEM.

DeST-urban uses a physics-based bottom-up approach for urban building energy modeling (Liu et al., 2022). Physics-based building energy models (BEMs) were automatically generated and simulated in parallel using multiprocessor servers. DeST, a whole-building energy modeling program developed by Tsinghua University, China, based on a state-space multi-zone heat balance calculation method (Hong & Jiang, 1997; Hong et al., 1997), was used as the building energy simulation engine (Yan et al., 2022, 2008). The cooling demand driven by OB within a household was simulated using the OB module embedded in DeST (Feng et al., 2015; Hong et al., 2016).

2.3. Comparison of the models

To explore the impact of heterogeneity and stochasticity of OB, the cooling demands of the building stocks calculated using the different models were compared in different dimensions of time and space, as well as for different application scenarios.

The 15-min profiles of the cooling demand were analyzed to understand the impact of uncertainty on the temporal patterns. Moreover, the annual total cooling demand at the urban scale was chosen as a metric for evaluating the stock-level energy efficiency and carbon emissions. The 15-min, diurnal, and annual cooling demands at the urban scale were aggregated by the 15-minute cooling demand of each household. As shown in Eqs. (2), $c_k^i(j)$ is the cooling demand of household k at time step i on day j; $C_{\mathrm{hour}}^i(j)$ is the cooling demand at the urban scale at time step j on day i; C_{di}^i is the diurnal cooling demand on day i at the urban scale; C_{ann} is the annual cooling demand at the urban scale; and N is the total number of households.

$$C_{\mathrm{ann}} = \sum_{i=1}^{365} C_{\mathrm{di}}^i = \sum_{i=1}^{365} \sum_{j=1}^{96} C_{\mathrm{15min}}^i(j) = \sum_{i=1}^{365} \sum_{j=1}^{96} \sum_{k=1}^{N} c_k^i(j) \tag{2}$$

The peak load is an important metric in terms of the district-level system design. The peak loads over the entire cooling period $C_{\mathrm{ann}}^{\mathrm{max}}$ and within each day $C_{\mathrm{di}}^{i,\mathrm{max}}$ at the urban scale were calculated using Eqs. (3) and (4), respectively.

$$C_{\mathrm{ann}}^{\mathrm{max}} = \max_{1\le i\le 365,\ 1\le j\le 96} C_{\mathrm{15min}}^i(j) \tag{3}$$

$$C_{\mathrm{di}}^{i,\mathrm{max}} = \max_{1\le j\le 96} C_{\mathrm{15min}}^i(j) \tag{4}$$

The variability of cooling demands of individual households has garnered increasing concern owing to its significant impact on policy and technology deployment. The annual cooling demand per unit floor area of each household was calculated to indicate the demand intensity, as expressed in Eqs. (5), where CI_k is the annual cooling intensity of household k, and A_k is the floor area of household k:

$$CI_k = \frac{\sum_{i=1}^{365} \sum_{j=1}^{96} c_k^i(j)}{A_k} \tag{5}$$

2.4. Case study

The methodology was applied to a residential building stock comprising 1,000 households in Hangzhou (30.3 N, 120.2 E), eastern China. Hangzhou belongs to the hot-summer and cold-winter (HSCW) climate zone. In the simulations, we used the actual meteorological year (AMY) of 2019 for Hangzhou based on ERA5 weather data (Hersbach et al., 2020; Wu et al., 2023a).

The layouts of the different households were assumed to be typical, as shown in Fig. 5. Differences in the orientation and size of households and the inter-building shading were not considered because the focus of our study was the impact of different AC behaviors on UBEM. However, the generation of diverse household geometry models required further research. The building stock comprising 1,000 households, which referred to the common scale in the studies on UBEM, was selected (Prataviera et al., 2022; Zeng et al., 2022). The building parameter settings are listed in Table 3. Ten simulations were repeated to ensure stability of the results and obtain a favorable estimation of the mean value of the distribution, as recommended by Feng et al. (2017).

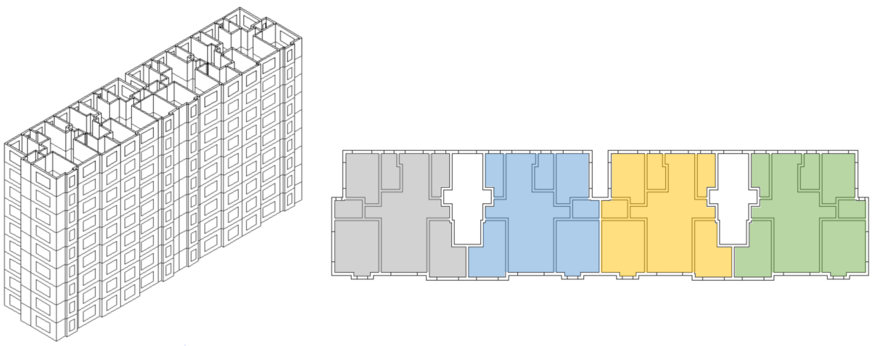

Figure 5: Typical layout of households.

Table 3: Parameters of building energy models.

Parameters	Values	Parameters	Values
Wall U-value [W/m^2· K]	1	Roof U-value [W/m^2· K]	1
Window U-value [W/m^2· K]	1	Window solar heat gain coefficient (SHGC)	1
Simulation period	2019.6-2019.9	Time step (min)	15

3. Results

3.1. Impact of stochasticity in occupancy on cooling demand

The stochastic nature of occupancy has a significant impact on the urban-scale energy consumption at fine time resolutions. However, most UBEM platforms use deterministic and typical occupancy schedules; these perform well for annual energy consumption simulations but may lead to unrealistic hourly or sub-hourly load profiles with huge coincident peaks or steep ramp-ups and ramp-downs (Bianchi et al., 2020). To parse out the impact of the uncertainty in occupancy and operational behavior and quantify the improvement in the results of the traditional method of UBEM in a step-wise manner, we conducted a preliminary comparison between deterministic occupancy (fixed occupancy schedule for each household cluster) and stochastic occupancy (based on the Markov Chain model). The details on deterministic and stochastic occupancy are specified in Appendix. The AC behavior model is Homo_Det.

The results are shown in Fig.6. The total cooling demand of stochastic occupancy was almost the same as that of deterministic occupancy, whereas deterministic occupancy overestimated the peak load by more than 117%. The load profile was smoother when stochastic occupancy was considered as the occupied periods of the dwellings were staggered. However, when the stochasticity in occupancy was neglected, air conditioners tended to operate coincidentally, resulting in a steep increase in the load profile. Therefore, stochasticity in occupancy is necessary when high time-resolution profiles or peak loads are required.

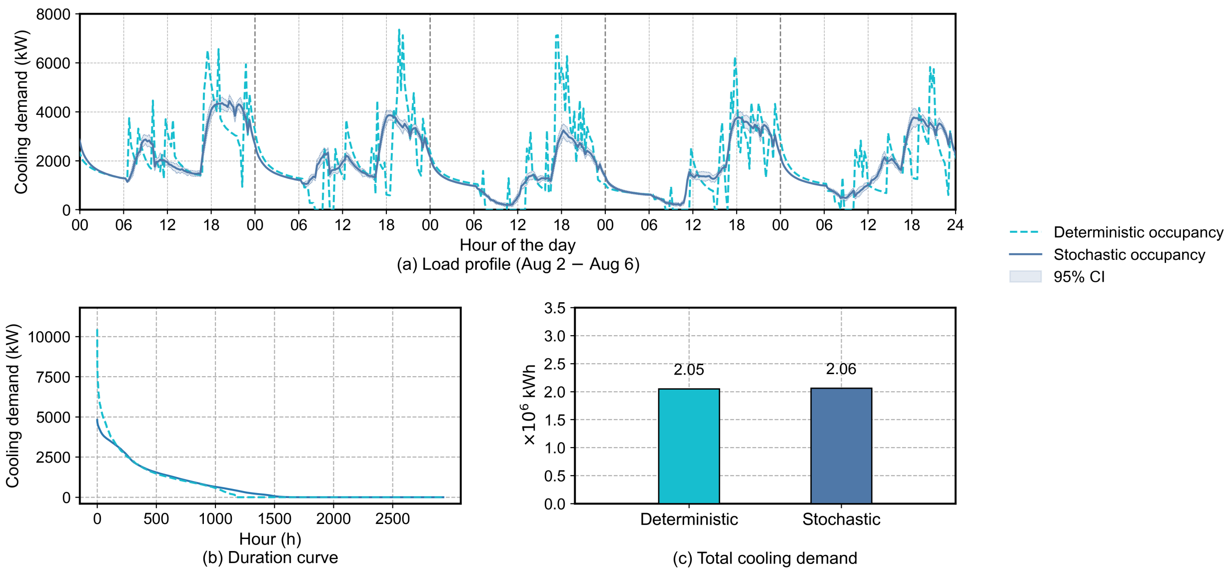

Figure 6: Comparisons of (a) load profile, (b) duration curve, and (c) total cooling demand, as determined by deterministic and stochastic occupancy. The shaded areas represent the 95% confidence regions based on ten repeated simulations.

3.2. *Impact of different AC behavior models on cooling demand*

As described in Section 3.1, the heterogeneity and stochasticity of occupancy are important for simulating the cooling demands of residential buildings at the urban scale. Therefore, the four AC behavior models considering heterogeneity and stochasticity were further compared based on the stochastic occupancy of all typical occupant clusters.

3.2.1. *Load profiles*

The aggregated 15-min load profile is shown in Fig.7. Two representative periods were selected to better compare the differences in the results. On days with a high cooling demand, as shown in Fig.7(a), two peaks were observed in the cooling load profile, one appearing in the morning, when occupants start their daily activities, and the other appearing in the evening when most occupants stay home. The peak in the evening was higher than that in the morning, because in the case of employed occupants, the unoccupied room accumulates a large amount of heat in the afternoon, which needs to be removed in the evening. On comparing the four models, the load profiles during the evening peak were quite similar as almost all occupants turned on their air conditioners on the hottest days. Switching on the air conditioners was inevitable in all AC behavior models. However, the morning peaks of the Heter_Sto and Heter_Det models were smaller than those of the Homo_Sto and Homo _Det models. This is because occupants with high temperature thresholds will delay the operation of the AC when heterogeneity is considered, causing some employed occupants to leave their homes before they feel hot. Additionally, the two models considering heterogeneity could better describe the temperature preferences of the occupants and reflect the tendency of people to use AC at different times. Moreover, the profile of the Heter_Det model had greater curve volatility than that of the Heter_Sto model as the stochastic model will also cause varying degrees of delay in AC use, which will smooth out the aggregated profile. This indicates that accounting for both heterogeneity and stochasticity in AC behavior has important implications for the cooling load profile, especially during short occupancy periods.

For the days with moderate cooling demand, as shown in Fig.7(b), the differences in the load profiles were significant. The load profiles of the Homo_Det and Homo_Sto models were significantly higher than those of the other two models, which illustrates that selecting only one OB model to represent all the occupants at the urban scale was inadequate to accurately reflect the temporal characteristics of the load profiles. In the moderate cooling load period, only a portion of the occupants had cooling demands, and the heterogeneity in AC behavior was important in reflecting the different responses of occupants with different preferences. However, the load profiles of the Homo_Det and Heter_Det models exhibited larger fluctuations than those of the two stochastic models. In the two deterministic models, the AC systems were switched on as soon as the indoor temperature reached a certain threshold. AC behavior was still an immediate and deterministic response to the indoor temperature, leading to frequent fluctuations in the cooling load profiles. In contrast, the load profile of the Heter_Sto model better reflected changes in the AC turn-on rate with weather changes and the stochastic nature of AC operation. Therefore, quantifying both the heterogeneity and stochasticity of AC behavior can improve the fidelity of cooling load profiles during moderately hot days when AC systems are partially switched on.

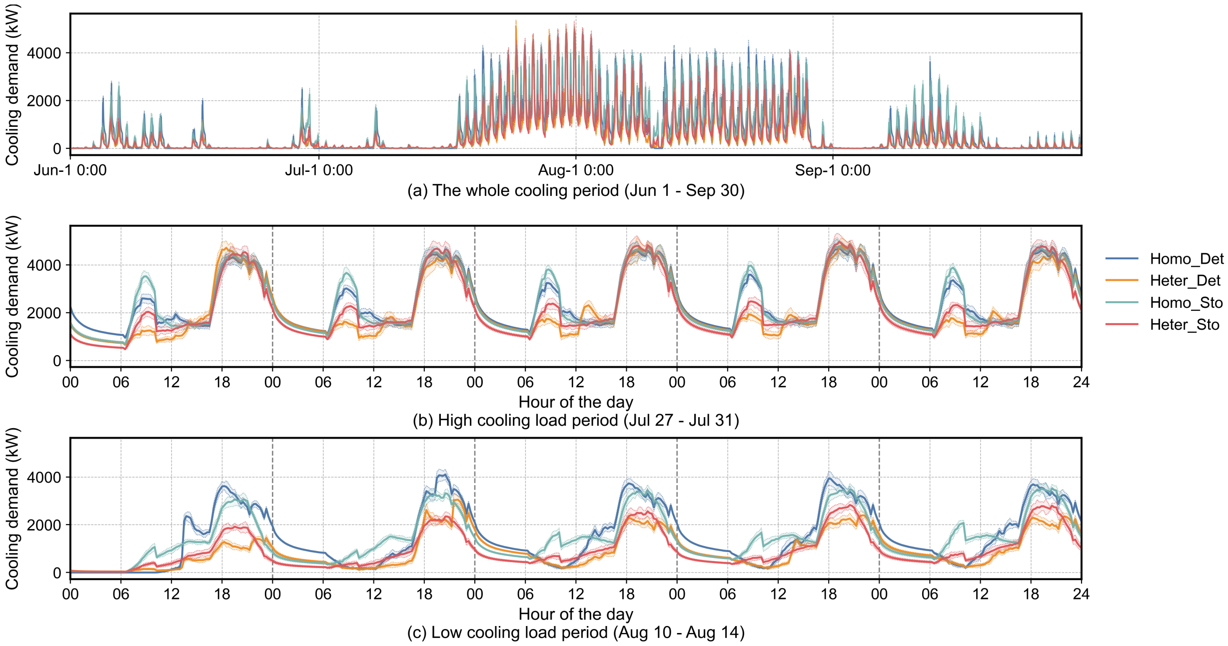

Figure 7: Load profiles of different AC behavior models: (a) the whole cooling period (Jun 1 - Sep 30), (b) days with high cooling demands, and (c) days with moderate cooling demands. The shaded areas represent the 95% confidence regions based on 10 repeated simulations.

Table 4: Overall errors of the three low level-of-detail models compared with those of the Heter_Sto model (ground truth). The maximum and minimum errors are marked.

	Homo_Det (Homogeneous & deterministic)	Heter_Det (Heterogeneous & deterministic)	Homo_Sto (Homogeneous & stochastic)
MAE (kW)	253 (max)	147 (min)	225
CVMAE	47.9% (max)	27.8% (min)	42.6%
RMSE (kW)	426 (max)	248 (min)	386
CVRMSE	80.5% (max)	46.9% (min)	73.0%

Table 4 presents the overall errors of the Homo_Det, Heter_Det, and Homo_Sto models compared with that of Heter_Sto model. Four metrics were used to evaluate discrepancies relative to the Heter_Sto model: mean absolute error (MAE), coefficient of variation of mean absolute error (CVMAE), root mean square error (RMSE), and coefficient of variation of the root mean square error (CVRMSE). The outputs of all three models showed significant discrepancies compared with that of the Heter_Sto model, which considered both heterogeneity and stochasticity. The Heter_Det model showed the highest accuracy, with CVMAE and CVRMSE of 27.8 and 46.9%, respectively, whereas the highest CVMAE and CVRMSE obtained by the Homo_Det model were 47.9 and 80.5%, respectively. The results indicate that both heterogeneity and stochasticity have significant impacts on the load profiles, neither of which can be neglected to accurately reflect the cooling load dynamics.

3.2.2. Total cooling demand

The results of the total annual cooling demand at the district level are presented in Table 5. Heterogeneity and stochasticity had different effects on the total cooling demand during the cooling period. The heterogeneous model diversified the temperature preferences and accurately reflected the cooling demands of different people. In this case, the total cooling demands of the Heter_Det and Heter_Sto models differed by only 5%, indicating that considering only heterogeneity provided a good estimate of the total cooling demand. However, both deterministic models overestimated the total cooling demand. The Homo_Det and Homo _Sto models overestimated the total cooling demand by 33% and 39%, respectively, emphasizing the importance of representativeness in AC behavior models. Quantifying the differences in temperature preferences based on a detailed population segmentation was required to accurately assess the total cooling demand. Furthermore, stochasticity in AC behavior had a smaller impact on the total cooling demand than did heterogeneity in AC behavior. Once stochasticity was considered, the variation in total cooling demand was minor. The stochastic model described the probabilistic response of occupants, whereas the uncertainty in AC behavior in the time dimension was hidden during the aggregation process. Therefore, when focusing on the annual total cooling demand at the urban scale, considering the heterogeneity of OB is necessary to obtain a representative AC behavior model. However, the stochastic nature of AC behavior may not be considered.

Table 5: Total cooling demand of different models (the average of ten repeated simulations). The values in parentheses are normalized to the results of the Heter_Sto approach.

Methods	Homo_Det	Heter_Det	Homo_Sto	Heter_Sto
Cooling demand ($\times 10^6$ kWh)	2.06	1.47	2.16	1.55
	(1.33)	(0.95)	(1.39)	(1)

3.2.3. Peak loads

Peak loads at different temporal scales are important indicators for the reliable planning of energy distribution systems; the annual peak load is important for sizing the power grid infrastructure, and the daily peak load is also important for power plant capacity allocation and demand response analysis. Fig.8 shows the values for the daily peak load of the four models, sorted in ascending order to better visualize the performance of different models in terms of the daily and annual peak loads. As shown in the far-right side of Fig.8, the annual peak loads calculated by all four models were similar. In particular, the lowest and highest peak cooling loads of 4,707.9 and 5,127.6 kW were obtained by the Homo_Det and Heter_Det models, respectively. The coefficient of variation (CV) of the peak load for the four models was only 3.86%. This suggests that heterogeneous and stochastic AC behaviors have little impact on the peak load as it occurred when most occupants were at home and required urgent cooling. Under these circumstances, the uncertainty in the stochastic and heterogeneous AC usage diminished and became more deterministic.

The ± 10% region of the daily peak load results for the Heter_Sto model is shown in Fig.8, as indicated by the dashed lines. For the hottest eight days, the daily peak loads calculated by the different models were within the ± 10% range of the Heter_Sto model. In addition to the annual peak load, the heterogeneity and stochasticity of AC behavior had little impact on the daily peak load on the hottest days of the year, such as during heatwaves. Therefore, the key to assessing the peak cooling loads of residential buildings at the urban scale was the estimation of occupancy rather than AC behavior.

Apart from those during the hottest days, the differences in daily peak loads for other days obtained from the different models were significant, and the models' characterization of AC behavior became important. The homogeneous models (Homo_Det and Homo_Sto models) overestimated the daily peak load when the cooling demand was moderate and a wide range of daily peak loads was not reflected. This implies that the heterogeneous distribution of AC behavior at the urban scale plays an important role in assessing daily peak loads, and that simply selecting one AC behavior pattern to represent all occupants would introduce large errors. Therefore, although the four models predicted similar annual peak loads, both heterogeneity and stochasticity were important for accurately simulating the daily peak load.

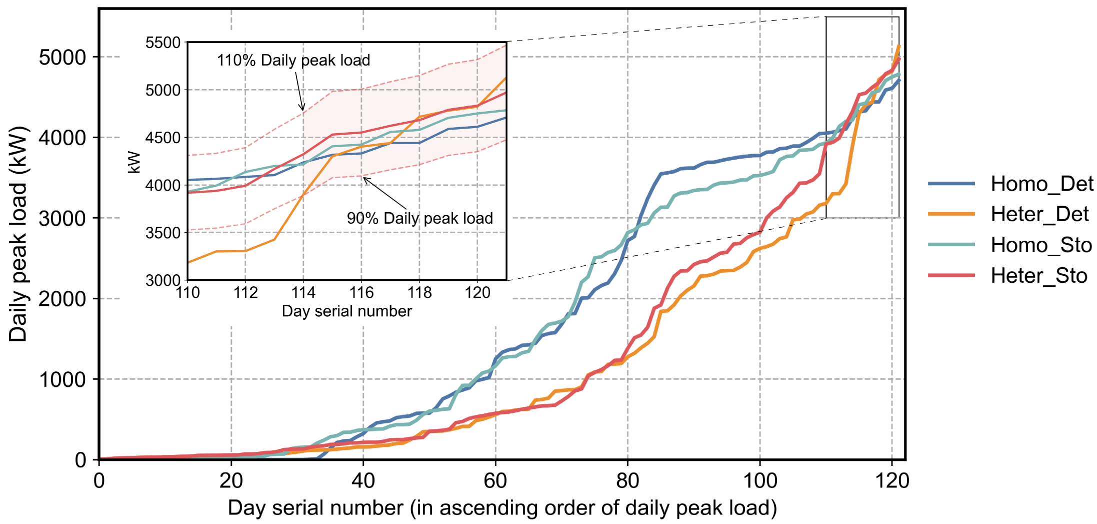

Figure 8: Daily peak cooling loads of different models. The daily peak loads are sorted in ascending order and those during the hottest days are shown separately.

3.2.4. Cooling demand distribution

The cooling demand intensity at the household level is shown in Fig.9. Four occupancy types were categorized in this study to represent the different occupancy patterns, as shown in Appendix. Different occupancy types exhibit different cooling demand intensities because the duration at home determines the average level of the cooling demand. As shown in Fig. 9, the dispersion of the cooling load intensity by the heterogeneous models (Heter_Det and Heter_Sto models) was much greater than that by the homogeneous models (Homo_Det and Heter_Sto models). Considering the cooling load intensities using the Homo_Sto model, although the stochasticity in the AC behavior of each occupant was considered, the calculated distribution was overly concentrated as the AC-usage patterns among different occupants were not differentiated. As presented in Table 6, the CVs of the cooling demand intensity in the Homo_Sto and Heter_Sto models were more than 10-fold larger than those in the Homo_Det or Heter_Det models. In particular, the CVs of the heterogeneous models were greater than 40%, whereas those of the homogeneous models were all within 5%. The CVs of the cooling demand intensity in the stochastic models were similar to those in the corresponding deterministic models as the stochasticity in AC behavior had little impact on the diversity of cooling demand intensity; this affected the variation in AC behavior with time but did not reflect the diversity among different occupants. Thus, when analyzing the cooling demand intensity of different households through UBEM, the diversity in cooling demand intensity can be better reflected by considering the heterogeneity in AC behavior, which cannot be achieved by considering stochasticity only.

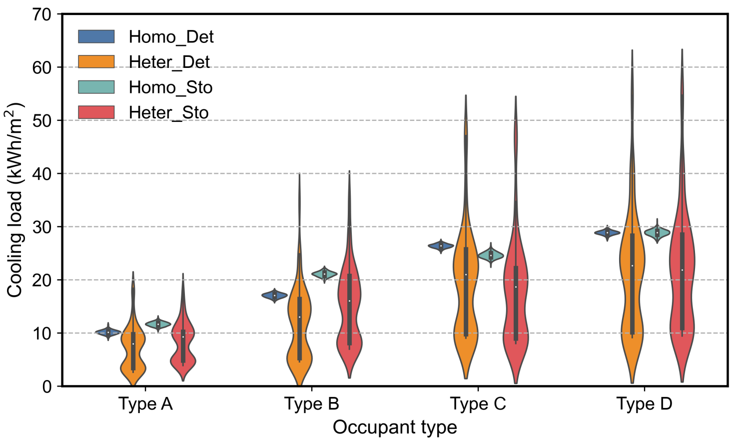

Figure 9: Cooling demand intensity of each household, categorized by the occupant clusters.

Table 6: Coefficient of variation of cooling demand intensity of each household.

	Homo_Det	Heter_Det	Homo_Sto	Heter_Sto
Type A	0.040	**0.541**	0.035	**0.429**
Type B	0.024	**0.556**	0.022	**0.452**
Type C	0.014	**0.495**	0.023	**0.534**
Type D	0.014	**0.505**	0.020	**0.500**

4. Discussion

4.1. Impact of occupancy and AC behavior on the cooling demand

As revealed by many studies, occupant presence and energy-related action are two main aspects of OB (Yan et al., 2015; Dabirian et al., 2022). As most existing studies have neglected the uncertainty in AC behavior, the differences between the impact of uncertainty in occupancy and AC behavior require further investigation.

A comparison of the results is shown in Figs. 6(b) and 8; notably, the uncertainties in occupancy and AC behavior had different magnitudes of peak load reduction. Assuming identical schedules for generating the stochastic schedules for each occupancy type, the total peak load was reduced by 54%. However, based on the stochastic occupancy schedules, the variation in the peak cooling loads owing to the heterogeneity and stochasticity of the AC behavior was less than 9%. We found that occupancy uncertainty was the prime reason for the reduction in peak demand at the urban scale. Therefore, accurate modeling of building occupancy at the urban scale was more important for the accuracy of peak loads than for AC behaviors. This reduction effect on the peak load has also been discussed in existing studies, wherein the uncertainty in occupancy was introduced into UBEM (Liao et al., 2022; Happle et al., 2020b). Some nascent multidisciplinary approachesfor example, widespread urban sensing, technologies based on the Internet of things (IoT), and big data obtained from cities could help better capture urban dynamics and reflect realistic occupancy (Salim et al., 2020; Dong et al., 2021).

The uncertainty in AC behavior is important in terms of the daily peak load, especially on days with moderate cooling loads. When the annual peak cooling load occurs, the unconditioned temperature is substantially above the comfort zone, and less uncertainty is observed in AC operation. However, when the cooling load is low, the heterogeneous and stochastic nature of AC behavior is necessary to reflect the actual dynamics of the cooling demand.

4.2. Comparison of heterogeneity and stochasticity

The different effects of heterogeneity and stochasticity, as the two main sources of uncertainty in urban-scale OB, on cooling demand must be distinguished. Heterogeneity captures the diversity among various occupants, including the different levels of occupancy rate and AC usage intensity. Therefore, heterogeneity affects the cooling demand at the urban scale by changing the intrinsic composition of the population characteristics, which can more accurately capture the distribution of the cooling demand intensity.

However, the stochasticity of OB introduces variability in occupancy schedules and AC behaviors; thus, unrealistic coincidences and determinacy of behavior are avoided. In our model, the time series were staggered between different occupants and different days owing to stochasticity. Therefore, stochasticity was important for accurately quantifying the peak loads as well as the stochastic and dynamic behaviors when AC systems were only partially used.

Both heterogeneity and stochasticity must be considered when simulating the sub-hourly cooling load profiles at the urban scale. Considering heterogeneous OB, the distribution of occupant characteristics could be obtained more precisely. Stochastic behavior affects the temporal characteristics of each occupant. When aggregating the load profiles at the urban scale, both the composition of the population and time series of each occupant can have a significant impact.

4.3. Appropriate OB models for different UBEM purposes

As indicated by our findings, the importance of uncertainty in OB depends on the performance indicators of UBEM. UBEM approaches can provide a multidimensional assessment of the building energy consumption, whereas users focus only on the output corresponding to an application (Ang et al., 2020). Table 7 summarizes the appropriate OB models for different UBEM applications in terms of the heterogeneity and stochasticity in occupancy and AC behavior.

Table 7: Appropriate OB models for different performance indicators.

Indicators	Spatiotemporal resolution	Occupancy		AC behavior		Use cases
		Heterogeneity	Stochasticity	Heterogeneity	Stochasticity	
Total cooling demand	urban, annual	✓		✓		(a) Energy policy interventions (b) Carbon reduction strategies
Peak cooling load	urban, annual	✓	✓			(a) District cooling system design (b) Transmission/distribution system design
	urban, daily	✓	✓	✓	✓	(a) Demand response analysis (b) Day-ahead scheduling of grid
Cooling demand intensity	household, annual	✓		✓		(a) Adaptability of ECMs (b) Energy sufficiency analysis (c) Energy inequality analysis
Cooling load profile	urban, sub-hourly	✓	✓	✓	✓	(a) Renewable energy potential (b) Load-modifying interventions (c) Energy flexibility analysis

The commonly used cases of UBEM and the corresponding performance indicators are reviewed as follows: (1) total cooling demand, (2) peak cooling load, (3) distribution of cooling demand intensity, and (4) cooling load profile.

The total cooling demand supports energy policy interventions and carbon reduction strategies that provide guidance for stakeholders in formulating an energy transition plan at the building stock level. In evaluating the total cooling demand, heterogeneous AC behavior should be modeled or considered when calibrating the representative usage patterns for modeling. This is because the diversity in the occupant's indoor environment preference affects the hours of AC usage of different groups of occupants during the cooling period and further affects the annual total cooling demand. However, the stochasticity of occupancy and AC behavior can be simplified as the temporal characteristics of OB are less crucial than typical OB patterns when aggregating the annual cooling demand.

The annual peak cooling load aids in the system design of district cooling systems or transmission/distribution systems. The daily peak cooling load reflects the peak cooling-induced electricity load and becomes more important for demand response analysis and day-ahead scheduling of the grid. The annual peak cooling loads were mainly affected by the heterogeneity and stochasticity of occupancy. Different occupancy patterns at the urban scale must be considered, and the stochasticity of occupancy is crucial and the main reason for the sharp drop in annual peak loads. The daily peak load had higher model requirements than did the annual peak load. The daily peak load depends on the high-fidelity AC behavior model as both the heterogeneity and stochasticity in OB affect the overall cooling demand when AC systems are used by a part of the population. Heterogeneity in AC behavior determines which occupants will use AC systems in a given current situation, and stochasticity influences the dynamics and temporal characteristics of AC usage. Therefore, both the heterogeneity and stochasticity in OB are important in terms of the daily peak cooling load.

The household cooling demand intensity reflects the level of household energy demand. Owing to the attention of all individuals, household cooling load intensity can be used to comprehensively analyze the adaptability of ECMs, energy sufficiency, and energy inequality. Characterizing the heterogeneity of occupancy and AC behavior is important because an accurate characterization of the diversity among occupants is required to obtain an accurate distribution of the cooling load intensity among different households. However, stochasticity in OB can be neglected as it has little effect on the cooling demand intensity because the dynamic variations in the cooling load over time do not manifest when aggregating over the entire year.

The cooling load profile reflects the dynamics of the cooling period and is used in the potential analysis of renewable energy, load-modifying interventions, and energy flexibility analysis. In terms of the load profiles with high temporal resolution, heterogeneity reflects the spatial scale of the cooling demand, and stochasticity affects the temporal dynamics of the aggregated cooling loads. Both heterogeneity and stochasticity influences the cooling load profile, which should be considered for accurate simulations.

Moreover, by comparing the model requirements of different indicators, we found that the requirement for the fidelity of heterogeneity and stochasticity increased with increasing spatiotemporal resolution of the focused results. Indicators with a higher spatiotemporal resolution require a heterogeneous and stochastic model of both occupancy and AC behavior, such as the sub-hourly cooling load profile and daily peak load. Considering the total cooling demand, annual peak cooling load at the urban scale, or cooling load intensity, which are low-dimensional results of aggregation, only some of the uncertainty sources could reflect the characteristics of the cooling demand with sufficient fidelity.

4.4. Limitations and potential avenues for future research

There are some limitations in our study. First, more types of buildings need to be studied, such as commercial buildings. In contrast to residential buildings where people can control their own air conditioners, most HVAC systems in commercial buildings are centrally controlled, where the impact of OB on cooling demand may be different.

Second, only AC behavior in HSCW climate zones was analyzed in this study. Studying the impact of uncertainty in more OB types could further improve the representation of OB in UBEM, such as the usage of space heating, lighting, among others. Moreover, the analysis of different climate zones would facilitate a more comprehensive study of the effects of OB uncertainty on UBEM.

Third, the OB modeling approach should be integrated into UBEM workflows that consider the orientation, distance, and inter-building shading of real buildings. Based on the impact of OB heterogeneity and stochasticity determined in our study, appropriate OB models should be used to characterize building energy models of UBEM to better reflect specific building characteristics and inter-building effects.

Fourth, the simulation results should be validated against metered data even though the Heter_Sto model comprehensively reflected the features of OB. Smart meter data have been proven to be a good data source for capturing operational characteristics and energy demand (Zhan et al., 2020).

Finally, studying complexity attributes of OB uncertainty apart from heterogeneity and stochasticity, such as the seasonality and spatial diversity, is necessary. Such attributes could be related to contextual factors, such as urban planning, holidays or events, and the local microclimate (Hou et al., 2020).

5. Conclusion

In this study, we proposed a modeling approach for occupant air-conditioning behavior integrated with a bottom-up physics-based UBEM workflow. Based on this approach, the two main sources of uncertainty in OB, namely, heterogeneity and stochasticity, can be quantified to evaluate the cooling demand at different spatial and temporal scales.

Heterogeneity and stochasticity can affect the urban-scale cooling demand in different ways. The stochasticity in occupancy was found to decrease the peak cooling load by 54% but had little effect on the total cooling demand. Considering the AC behavior, neither heterogeneity nor stochasticity affected the annual peak cooling load as little uncertainty was observed in the AC behavior when the peak load occurred. However, the heterogeneity and stochasticity of AC behavior had significant impacts on the cooling load profiles and daily peak cooling load when the cooling load was moderate. A comparison between heterogeneity and stochasticity indicated that heterogeneity is the main reason for the diversity of cooling demand. The CVs of the cooling demand intensity were more than 10-fold larger after considering the heterogeneity in AC behavior. Stochasticity plays an important role in reflecting the temporal characteristics of cooling demand and reduces unrealistic fluctuations in the load profiles. Therefore, both the heterogeneity and stochasticity of OB are necessary to reflect the distribution and dynamics of the urban-scale cooling demand.

The sources of uncertainty reflected in the model should be selected according to the applications of UBEM. In particular, for results with higher spatial or temporal resolutions, occupancy and AC behavior models with higher fidelity are required. The proposed modeling framework can be used to quantify the impacts of the heterogeneity and stochasticity of OB on UBEM. Overall, our results can provide insights into developing appropriate urban-scale OB models and bridging urban mobility with occupant-centric UBEM.

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Appendix. Details on the occupancy and AC behavior modeling

The typical occupancy of residential buildings was set according to Wu et al. (2023c). Four types of occupants were considered, and the occupancy schedules and the AC probability for the average state are shown in Fig. A.1. We considered occupancy in bedrooms and living rooms, which are the main rooms for occupant activities. For occupant schedules, types A and B represented the commuters who are away from home during the day and were home at night, whereas types C and D represented the occupants who were mostly home. Considering the preference of using AC when sleeping, types A and C did not use AC when sleeping, whereas types B and D used AC when sleeping. Each of the four types of occupants accounted for 25% of the total.

The typical schedules for the average state were used when neglecting stochasticity in occupancy, as discussed in Section 3.1. To reflect the stochasticity in occupancy, the Markov Chain model was used to generate stochasticity occupant profiles according to the method proposed by Wang et al. (2011) and Feng et al. (2015). Different households were simulated by different random seeds to generate the diversified and stochastic occupant schedules.

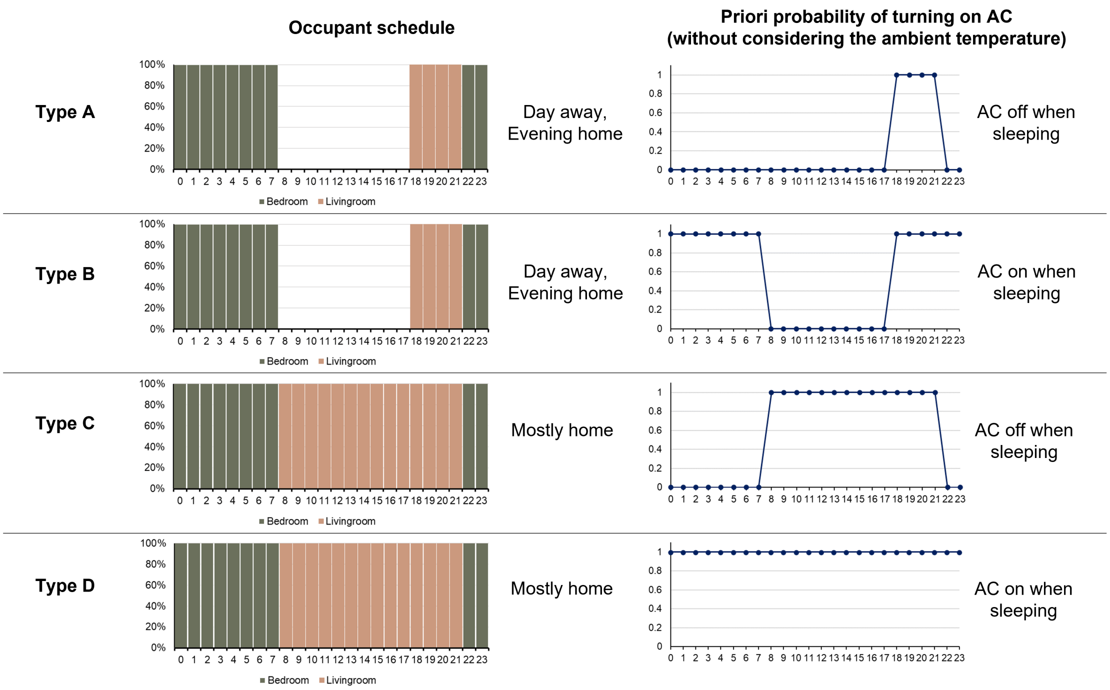

Figure A.1: Occupancy profiles and AC probability for the average state. The stochastic occupant schedules were generated based on the average state, and the AC probabilities only represented the AC preference when sleeping; the actual probabilities were further calculated based on the presence of occupants and indoor temperature.

Table A.1 presents the detailed parameters of the four different AC behavior models. The percentage of occupants with different AC usage patterns was estimated based on a previous study (Wu et al., 2023c). In the case study, when heterogeneity in OB was considered, each household model was randomly assigned to one type of AC usage pattern according to the proportion. When heterogeneity was not considered, the AC usage pattern representing the medium level of cooling demand was selected as the typical AC behavior pattern for all the households. The AC behavior models were applied to both the bedrooms and living rooms.

Table A.1: Detailed parameters of the different AC behavior models.

Model	Temperature threshold	Parameters in Weibull model	Proportion
Homo_Det	29.6°C	/	100%
Heter_Det	20.0°C	/	3.3%
	27.8°C	/	4.9%
	29.6°C	/	18.7%
	30.6°C	/	32.1%
	32.9°C	/	41.0%
Homo_Sto	/	$u = 25.5°C, l = 6.5°C, k = 6.5$	100%
Heter_Sto	/	$u = 18.5°C, l = 3.5°C, k = 3.5$	3.3%
	/	$u = 23.5°C, l = 6.5°C, k = 7.5$	4.9%
	/	$u = 25.5°C, l = 6.5°C, k = 6.5$	18.7%
	/	$u = 27.5°C, l = 5.5°C, k = 5.5$	32.1%
	/	$u = 29.5°C, l = 5.5°C, k = 6.5$	41.0%

To determine the AC on/off states, the stochastic occupant schedules were generated first and the sleeping hours were marked. Subsequently, the AC on/off state was determined based on the occupant presence, AC preference when sleeping, and the indoor temperature.

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