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A data-driven agent-based model of occupants' thermal comfort behaviors for the planning of district-scale flexible work arrangements

Martín Mosteiro-Romero [a,b,*], Matias Quintana [c], Rudi Stouffs [a], Clayton Miller [d]

[a] Department of Architecture, National University of Singapore, SDE1 #03-01, Singapore, 117566, Singapore
[b] Department of Architectural Engineering and Technology, Delft University of Technology, Julianalaan 134, Delft, 2628BL, Netherlands
[c] Singapore-ETH Centre, Future Cities Laboratory Global, 1 CREATE Way, #06-01 CREATE Tower, Singapore, 138602, Singapore
[d] Department of the Built Environment, National University of Singapore, 4 Architecture Drive, SDE1 #03-04, Singapore, 117566, Singapore

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ABSTRACT

In a global context of increasing flexibility in the way workplaces and the districts in which they are located are used, there is a need for occupant-driven approaches to plan urban energy systems. Several authors have suggested the use of agent-based models (ABM) of building occupants in urban building energy simulations due to their ability to reproduce emergent behaviors from individual agents' actions. However, few works in the literature take full advantage of the ABM paradigm, accounting for both occupant presence and energy-relevant behaviors at the district scale. In this work, we propose a methodology to develop a data-driven, agent-based model of building occupants' activities and thermal comfort in an urban district. Our methodology combines the use of campus-scale Wi-Fi data to derive feasible occupant activity and location plans, along with thermal preference profiles derived from a longitudinal field study where off-the-shelf, non-intrusive sensors were used to capture the right-here-right-now thermal preference of 35 participants in the same case study district. Our model is then used to explore how different district operation strategies could affect building energy performance in the context of increased workspace flexibility. Our results show that by providing a diversity of building operation conditions, with different buildings having different set point temperatures, occupants' thermal comfort hours could be improved by an average of about 10% with little effect on district energy performance. Meanwhile, a 6%–15% average decrease in space cooling energy use intensity was observed when implementing occupant-driven ventilation and setpoint controls, regardless of location choice scenario.

1. Introduction

Planning highly efficient urban energy systems and other decarbonization initiatives that are resilient to the changing needs of urban districts requires a detailed characterization of urban energy use at high spatial and temporal resolution. This entails an understanding of not only historical and present demand patterns but also how future scenarios might affect the future needs of urban districts [1]. In order to improve our understanding of urban energy use and how it might change in the future, mathematical modeling or computer simulations are typically used [2].

Urban Building Energy Modeling (UBEM) seeks to provide quantitative insights (e.g., annual or seasonal energy use and potential of renewable power generation) to inform urban building design and operation, as well as energy policy-making [3]. UBEM are physics-based computational models that aim to predict the energy consumption contributed by buildings in the urban context [4]. While data acquisition is a significant and challenging issue in UBEM [5], in recent years, open-access data for model calibration and validation has become increasingly available. For example, Roth et al. [6] propose an *Augmented* Urban Building Energy Model (A-UBEM) combining data-driven and physics-based simulation approaches using publicly available data.

Due to their inherently stochastic nature, building occupant behavior nevertheless continues to be a major source of uncertainty in building energy modeling [7]. Occupant behavior can significantly influence simulation results not only for individual buildings but also for a group of buildings in an urban district [3]. For example, in the context of increasing workplace flexibility, the choice to work from home or from the office affects the energy demands of both the occupants' place of residence as well as their workplace.

The idea of remote working has been proposed for over 50 years [8], although flexible work arrangements have become increasingly common over the past two decades [9]. In particular, the COVID-19 pandemic resulted in the restriction of movement of people worldwide in

* Corresponding author at: Department of Architectural Engineering and Technology, Delft University of Technology, Julianalaan 134, Delft, 2628BL, Netherlands.
E-mail address: m.a.mosteiroromero@tudelft.nl (M. Mosteiro-Romero).

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early 2020, leading to remote working becoming the norm for all non-essential workers. However, the increased reliance on remote working did not necessarily lead to a proportional decrease in the energy demand for space conditioning in traditional workspaces [10,11], possibly due to the use of fixed HVAC operation schedules [12].

Given that the push for workspace flexibility precedes the pandemic, remote working arrangements are expected to continue to be prevalent moving forward: 25% of workers in high-income countries are expected to continue remote working either part-time or full-time after the pandemic [13]. This means that office occupancy might further decrease moving forward, but at the same time, as more and more occupants in offices adopt flexible work hours, the total scheduled operating time of HVAC systems may increase in duration in order to satisfy occupants of future commercial buildings [14].

Workplace flexibility implies occupant behaviors and choices (such as whether to work from home or from the office on any given day), which affect both building occupancy and the associated energy demands in residential and office buildings. Furthermore, flexible working styles such as hot-desking allow employees more freedom to choose their work location, and at the same time, desks may be shared by different occupants [15]. The touted benefits for occupants include increasing overall comfort, choice, and control [16]. For example, Sood et al. [17] propose a platform that improves indoor environmental satisfaction by allocating occupants to spaces that are the best match for their needs.

In a global context of increased flexibility in the way workplaces and the districts in which they are located are used, there is a need for occupant-driven approaches to planning urban energy systems. Occupant comfort behaviors could, therefore, affect building occupancy at the district to urban scale. Thus, it is important for UBEM to account for not only occupant presence but also comfort and energy-related behaviors.

With the growing availability of big data and high-performance computing resources, there has been an increasing interest in the development of detailed agent-based models (ABM) to model occupant behavior in buildings [18]. ABM is a bottom-up simulation technique that allows for the modeling of people (e.g., occupants) as individual agents, giving them attributes, letting them interact with their environments, and observing how the macro behavior of the system emerges from the micro-interactions of these agents [19]. ABMs assign each individual in the building personal attributes and behavioral possibilities [20] to simulate not only user behavior but also how occupants react and adapt to their environment and other occupants [21]. Thereby, as compared to more conventional occupant representation methods, agent-based modeling has a richer potential to capture the dynamic and complex presence and behavior patterns of building users [22].

In this work, we propose a methodology to develop a data-driven, agent-based model of building occupants' activities and thermal comfort in an urban district. This methodology is used to explore how different district operation strategies could affect building energy performance in the context of increased workspace flexibility. Our methodology is based on the use of Wi-Fi data at the campus scale to derive feasible occupant activity and location plans. In order to protect the privacy of individual users, generic activity plans for synthetic occupants are created using a Bayesian network approach. The occupants are also given thermal comfort preferences based on a dataset from a longitudinal field study where off-the-shelf, non-intrusive sensors are used to capture a wide array of data from 35 participants alongside their right-here-right-now thermal preference [23,24]. A similar experimental dataset on 17 participants' thermal comfort preference subjective feedback, along with indoor and outdoor sensor networks and building information modeling (BIM), have been merged into an "Internet-of-Buildings" platform for a case study within the university campus [25]. This work expands the scope of that study to the campus scale, as well as incorporating building energy simulations along with occupants' thermal comfort preferences.

Occupants' activity and location choices within the urban district are modeled in the agent-based model, assuming three different location choice scenarios: a "business-as-usual" case, where occupants carry out their primary activities in predefined locations; one where occupants are allowed to choose their location in order to minimize the distance traveled between activities; and one in which occupants are allowed to flexibly change their location in order to maximize their thermal comfort. The effects of these operation strategies on building energy demand at the district scale are assessed by using these occupant schedules in a calibrated model of an urban campus [1] and simulating demands on the UBEM City Energy Analyst (CEA) [26]. Three building system operation strategies are considered: a status-quo *centralized* scenario, in which buildings are controlled based on fixed operation schedules; a demand-driven *ventilation* control scenario, in which buildings' ventilation rates are adjusted based on occupant sensing; and a demand-driven ventilation and *temperature* control scenario, in which buildings' setpoint temperature is also adjusted according to occupant presence.

The rest of the paper is organized as follows. Section 2 summarizes the literature on occupant modeling in UBEM and discusses data sources for occupant modeling at this scale. Section 3 presents our methodology for our district-scale agent-based model of building occupants. Section 4 presents our results and the impact of different location choice models on building occupancy, occupant comfort, and energy performance. The implications of these results for the operation of districts with flexible work arrangements are discussed in Section 5, while Section 6 summarizes our conclusions.

2. Background

2.1. Occupant modeling in UBEM

Urban energy forecasts require an understanding of urban dwellers, as it is their activities that create the demands for energy in buildings. However, a review of occupant modeling approaches in UBEM [27] found that a majority of the works in the literature relied on deterministic space-based occupant modeling approaches, *i.e.*, the use of standard schedules that associate building occupancy to the building use type, with some stochastic approaches being used to add diversity to daily profiles. Such standard-based assumptions provide a simple input for simulations in the absence of data.

Standard schedules have, however, often been demonstrated to overpredict actual occupancy in buildings. For example, in one study [28], the actual occupancy of an office building (obtained through passive infrared motion sensors) was found to peak at 50% as compared to 95% as indicated by standards. Similarly, previous studies have found significantly lower peak occupancy in buildings when comparing standard-based assumptions to student and employee registers in a university campus [29], and commercial buildings were found to have five times lower occupancy when using mobile phone data to estimate building occupancy [30]. Such discrepancies can have an impact on the sizing and performance of district energy systems. In a case study in China, oversimplified assumptions were found to lead to an overestimation of the peak cooling loads, which would result in oversized, inefficient district cooling systems [31].

In addition to the observed discrepancy in assumed and observed occupant density, the lack of diversity in occupancy profiles is another issue with standard-based occupant schedule assumptions [32]. Different buildings of the same use type may have different occupancy profiles over a given day or on different days of the year. Some of these variations could furthermore be traced back to differences between individual occupants' schedules, energy-related behaviors, and comfort preferences. However, there is limited study regarding occupant behavior modeling for urban building design and operation [33].

Current occupant behavior studies are often isolated and only research individual behavior, such as presence or interactions in a single space or building [34].

Several authors have suggested the use of agent-based models (ABM) of building occupants in urban energy systems [5,27,29,35]. The main benefit of ABM over other modeling techniques is their ability to deal with emergent phenomena [36]. This is particularly useful at the urban scale, where the decisions of individuals can lead to large-scale effects. Thus, use cases concerning energy and environmental performance of buildings at higher spatial extents can take particular advantage of the ABM approach [37]. For example, ABMs have been a staple in land use and transportation for years [35]. A review of data sources for UBEM [5] found agent-based occupancy modeling approaches to be “recommendable” due to the fact that these methods have been proven in the field of transportation and their use of real data.

Existing applications of ABMs at the building scale include modeling occupants’ movement within buildings, their thermally adaptive behavior, their interaction with lighting and shading devices, as well as the change in occupants’ energy characteristics through their peers’ influence [29]. Applications in UBEM, however, remain limited. The aforementioned review, for example, found only two papers using ABM-inspired approaches. In both cases, researchers used agents generated by transportation models as inputs to building energy simulations. Barbour et al. [30] used call detail records and the TimeGeo framework to estimate urban-scale building occupancy in Boston, U.S. Mosteiro-Romero et al. [29], on the other hand, used agents generated from student and employee register data for the agent-based transportation simulation MATSim to model a district in Zurich, Switzerland. Both of these cases, however, were limited to studying the effects of building occupancy on urban building energy demand, but neither looked at the behaviors of individual occupants.

Azar et al. [19], on the other hand, propose a district-scale ABM framework to model the movements and actions of people within buildings in a university, calculate key performance metrics such as thermal comfort and energy consumption levels, and test strategies to optimize building operation. The model assumed daily schedules for students and employees, and estimated occupants’ outdoor and indoor thermal comfort through the predicted percentage of dissatisfied index. However, occupant behaviors were limited to random changes in occupant schedules; that is, the study again focused solely on occupant presence, not behavior.

Yu et al. [38] created a “community occupant agent model” and used it as part of a community-scale building energy model. Occupant activity chains and energy use habits were collected through an online questionnaire distributed to the community’s occupants, with 2528 valid questionnaires collected. Based on this data, three types of occupants (students, commuters, and home-based occupants) and ten types of agents with their corresponding characteristics and behaviors were defined. Using this model, they analyzed different heating modes and their effects on the 19-building community’s energy performance.

Zhu et al. [39] modeled occupant inter-building movement at a university campus scale through a Bayesian network approach. Occupant location data was collected through an application installed in the smartphones of 193 volunteers. This data source was combined with data from building automation systems and field counting of occupants in seven buildings on campus. The smartphone dataset was used for model development, while the field data was used for model validation. The effects of agent-based modeling on the simulated building energy performance compared to the use of standard-based schedules were then analyzed by modeling the demand of a library building on the winter and summer design days, and a difference of −15% to 20% was observed.

A systematic and coherent representation of occupants’ presence and actions via the deployment of ABM techniques can provide a powerful virtual test bed for the examination and evaluation of multi-domain occupant comfort and behavior models [40]. Such techniques can allow testing of the effects of different building and district operation strategies to maximize occupant comfort while improving the overall efficiency of urban districts. However, few works in the literature take full advantage of the ABM paradigm, accounting for both occupant presence and energy-relevant behaviors. In particular, no works incorporating comfort-related behaviors are observed. Few works (e.g., [39]) seek to model inter-building displacement, and few [19] include thermal comfort preferences as part of their agent definition. One reason for this might be the huge amount of data required about individual occupants in order to create an ABM [41], making data collection at scales larger than single rooms cumbersome [42].

2.2. Data sources for occupant modeling in UBEM

The increasingly widespread availability of open datasets in urban areas is transforming the way urban areas are planned, simulated, and visualized. In particular, digital twin platforms enable informed decisions and avoid costly ad-hoc problem-solving by facilitating the inclusion of stakeholders because everyone can be updated to have the same and the latest information [43]. Such platforms have been used for a variety of applications, including energy forecasting, emergency planning, operational optimization, participatory planning, policy development, and scenario modeling [44].

In the energy field, urban-scale data on building geometries, construction years, energy demands, and building systems is facilitating the development of urban information models that can provide reliable estimates of demands for planning applications. However, building occupant data is typically not openly available for a myriad of reasons, including the difficulty of tracking individuals at the urban scale, as well as privacy and safety concerns. As a result, authors frequently rely on either fairly general (e.g., code-based) information on assumed occupants’ preferences and requirements or limited surveys or interviews with a limited number of occupants [45].

In the past, occupants’ daily patterns of presence and activities have been collected using questionnaires such as Time Use Surveys (TUS) [33]. Wilke et al. [46] used French TUS data from 1998/99 to calibrate a model of occupants’ time-dependent activities for use in dynamic building simulations based on three types of time-dependent quantities: the probability to be at home, the conditional probability to start an activity whilst being at home, and the probability distribution function for the duration of that activity. Similarly, Aerts et al. [47] used data from a 2005 Belgian TUS to develop a probabilistic model to generate realistic occupancy sequences that include three possible states: at home and awake, sleeping, or absent. One of the limitations of these approaches is that they typically require access to large TUS and behavior questionnaire survey data in the relevant context [27]. Another key limitation of the survey methodology is the inconsistency between actual and self-reported behaviors [48].

Hence, there has been a tendency in recent years towards the use of alternative data sources. The proliferation of occupant-centric big data such as internet-of-things (IoT), sensor-based, and mobility data has paved the way to model occupant behavior at a neighborhood, district, or city scale [33]. Such data sources are already being used at the building scale for opportunistic occupant detection to develop more energy-efficient lighting and HVAC controls (e.g., [49,50]).

Aggregated, anonymized telecommunications data is increasingly being used to analyze urban inhabitants’ activity and location patterns for the development of agent-based transportation models [51] as well as planning renewable energy systems and electric vehicle charging infrastructure [52]. Happle et al. [53] used location-based service data from Google Maps to create context-specific, data-driven occupancy schedules for commercial buildings in 13 different U.S. cities. While their methodology relied on openly available data, allowing replicability in other case studies, only publicly accessible buildings such as retail and restaurants were included.

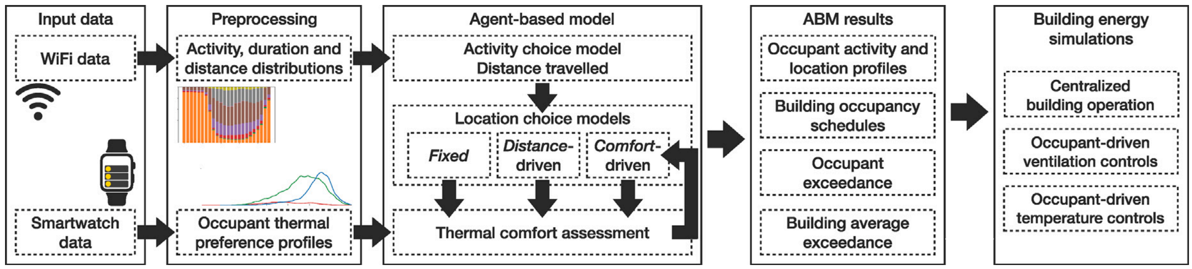

Fig. 1. Workflow for the creation of the agent-based model (including the activity choice and distance traveled model, location choice model, and thermal comfort assessment module) and its use to generate building occupancy schedules for building energy simulations (including different building system operation strategies).

Other location-based service data can similarly provide valuable occupancy information in public buildings. Kang et al. [54] used data on active positioning requests of social network software from Tencent on mobile devices. They used clustering methods to extract building occupancy patterns for three different building typologies (railway station, commercial building, and hospital) in China. Similarly, Gu et al. [55] used location services data from the same mobile social network company to develop typical occupancy schedules for seven different building typologies (office, shopping area, transportation, hospital, hotel, education, and restaurant).

Mobile positioning data from telecommunications companies has been used to extract urban-scale building occupancy profiles for three different building use types at the urban scale [30]. Wu et al. [56] used mobility data collected from over 100 smartphone apps that provide location-based services to derive occupancy profiles for 998 buildings in San Antonio, Texas, USA. Both of these studies compared the derived occupancy profiles to Department of Energy (DOE) reference models for each of these building use types and compared the energy demands under each occupancy assumption, showing significant reductions in simulated demand for the data-driven profiles.

In the absence of geolocation data, other authors have proposed deriving occupancy schedules from building meter data. For example, Miller and Meggers [57] presented a framework to infer information such as building use type, performance class and operational behavior of buildings based on electric meter data, and tested it on a dataset of 507 buildings with five different use types (office, university laboratory, university classroom, university dormitory, and school). In the UBEM field, Bianchi et al. [58] developed parametric schedules for occupancy modeling in large and diverse building stocks based on electric meter data collected for 24 982 buildings in Los Angeles comprising 22 different building use types. Their methodology consisted of extracting probability distributions for the daily start and stop time for each building use type based on the meter data and then parametrizing Database of Energy Efficiency Resources (DEER) schedules for each use type by shifting their hours of operation and occupancy fraction. Their methodology improved the performance of their calibrated UBEM by 1%.

Another popular avenue for implicit occupant detection is the use of Wi-Fi device counts to estimate building occupancy. Wang et al. [59] proposed a Markov-based feedback recurrent neural network algorithm to model and predict the occupancy profiles based on Wi-Fi connection requests and responses between access points and network devices in a graduate student office in Hong Kong. They validated their model by collecting ground truth using camera-based video analysis and found their methods reached accuracies of 81%–94% over a 9-day period. However, their limited scale demonstrates the difficulty of validating the number of occupants detected based on Wi-Fi signals.

Given the difficulty of discerning the number of occupants present based solely on the number of Wi-Fi-connected devices, a number of authors have pursued methods to estimate building occupancy without collecting ground-truth occupancy counts. Hou et al. [60] tracked occupant location within a four-story administrative building in the United Kingdom, considering the building's urban context. They proposed a framework for occupancy modeling relying on a competing hazard risk formulation and compared it to a conventional discrete-time Markov chain model, using the number of Wi-Fi-connected devices to benchmark both models' performance.

Park et al. [61] developed a methodology to estimate the number of occupants in buildings based on the number of Wi-Fi-connected mobile devices using a capture and recapture methodology inspired by ecology. Their methodology was found to estimate the number of mobile devices in a building with reasonable accuracy, though the margin of error varied by building scale, thus affecting the applicability of the results to different use cases. For small buildings with small estimation errors, the methodology could be used for demand-driven controls, whereas for larger buildings, the authors propose the use of the methodology to understand the dynamic of occupants' traffic and/or crowd density in a space.

Other authors use clustering approaches to define occupancy profiles based on Wi-Fi connection profiles without considering the number of devices detected. Zhan and Chong [62] used this approach to analyze occupancy and energy demand profiles for four building use types in a university campus in Singapore. Mosteiro-Romero et al. [1] created occupancy profiles for 35 buildings using the same methodology and used them to assess the effects of different occupant scenarios on district energy performance. Nweye and Nagy [63] used clustering techniques to derive typical building occupancy schedules based on Wi-Fi device counts for five buildings in Texas, USA, over a period of seven months. They used these schedules to estimate potential energy savings by shifting the ramp-up and setback times observed in typical load profiles obtained by clustering smart meter data.

3. Methodology

The methodology presented in this paper consists of three main steps (Fig. 1): data collection and preprocessing, agent-based modeling of occupant activities and locations, and building energy simulation. At the same time, the agent-based model consists of three main components: an activity and distance traveled module, a location choice module, and a thermal comfort assessment module.

The agent-based model is based on two main data sources: campus-scale Wi-Fi logs, which are used to infer occupant activity and location patterns on a typical week during the semester, and subjective thermal comfort feedback data collected through a smartwatch application, which is used to identify typical thermal comfort profiles for the occupants of the campus. At the start of each simulation run, each occupant is assigned a thermal comfort profile along with a randomly chosen initial activity, duration, and location. Subsequently, at each time step, occupants who have finished an activity are assigned a new activity, duration, and maximum distance traveled based on the activity choice model. Occupants who finish an activity furthermore evaluate their thermal comfort in their previous location. Depending on the location choice model used, they might use this assessment for future location choices. Occupants' personal thermal comfort throughout the

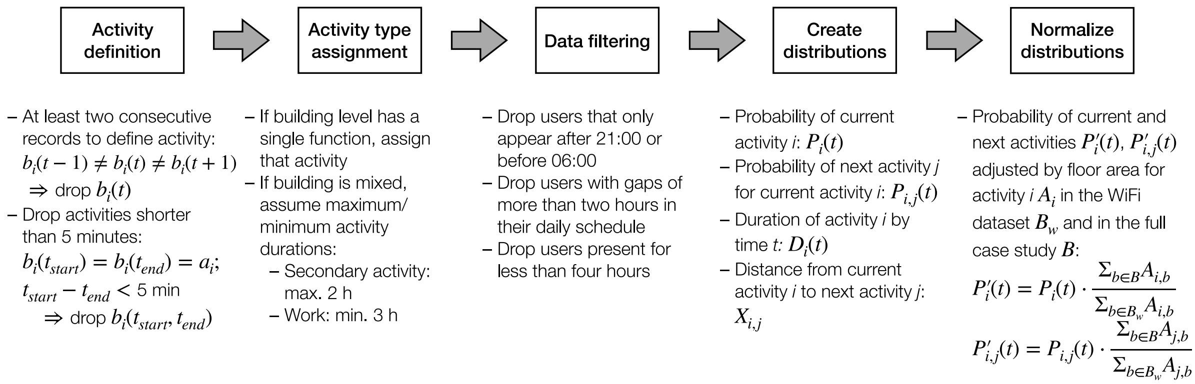

Fig. 2. Wi-Fi data preprocessing to generate distributions.

Table 1
Occupant types and their different home locations and exclusive activities.

Occupant type	Number	Home locations	Exclusive activities
Undergraduate Student	27 604	Student dorms Off-campus	"class" "homework"
Graduate Student	8 304	Student dorms Off-campus	"work: office" "work: lab"
University Employee	2 094	Faculty apartments Off-campus	"work: office" "work: lab"

simulation is evaluated by their *exceedance*, which is the percentage of time spent outside of the expected occupant comfort range [64].

The agent-based model produces individual activity and location plans over a week for each occupant in a case study district. These are then aggregated into building occupancy schedules, which are used in a campus-scale building energy simulation. The building energy demand model is developed using the National University of Singapore (NUS) campus as a district-scale case study. The campus-scale model comprises 169 buildings with a variety of building use types: residential, office, lab, classroom, library, restaurant, gym, museum, supermarket, and hospital. Although Wi-Fi data was only available for 104 of those buildings, in the simulation phase, the entire building stock was assumed to be available for occupants to choose from.

Three different types of occupants were considered and were differentiated by their available home locations and primary activities. The number of occupants of each type and their differences are summarized in Table 1. Students and employees are differentiated by their available home locations, as faculty apartments are only available to staff and dorms are only available to students. Undergraduate and graduate students are differentiated by their main activities, as undergraduates are assumed to mostly focus on coursework, while graduate students focus mostly on research. The number of each type of occupant was obtained from university records [65].

In order to assess the effects of flexible work arrangements on campus operation and performance, three different location assignment cases are considered. In the *fixed* location assignment case, which represents a status quo district operation strategy, each occupant has an assigned location for each of the primary activities ("work: office", "work: lab" and "class"). For the other two cases, an elastic space allocation strategy [11] is assumed, meaning that occupants are given the freedom to select the location for both their primary and secondary activities. We subsequently defined two scenarios focused on different driving factors behind an occupant choosing one location over another. The first factor we considered was the distance between locations. In the *distance*-driven case, occupants choose an adequate location for their next activity within a maximum distance they are willing to travel, which is based on the dataset defined from the Wi-Fi logs (Section 3.1). The second factor we considered was thermal comfort, which has been proposed as one of the potential advantages of flexible work arrangements [16,17]. In the third, *comfort*-driven case, each time an occupant finishes an activity, they assess their comfort in their current location and keep track of their assessment for future location choices. Other factors that might affect occupant choices (e.g., social network, aesthetics, indoor air quality, etc.) are beyond the scope of this study (see in Section 5).

Given that different occupants will have different thermal preferences, a variety of spaces for the same activity needed to be available such that occupants in flexible work arrangements could seek workspaces that maximize their personal thermal comfort. Therefore, different indoor temperature setpoints were assigned to buildings with the same building use types. The temperature assignment for different runs of the model is discussed in Section 3.3.

3.1. Data collection and preprocessing

Campus-scale Wi-Fi logs from the National University of Singapore campus during a typical week during the semester (1 October to 7 October 2018) were collected. Due to data access limitations, one week was selected as the minimum time period required to capture variations in occupancy during a normal workweek and weekend. The period chosen was selected as a typical full-occupancy week during the university semester based on the work of Zhan and Chong [62].

The collected Wi-Fi data include a timestamp, a device identifier (MAC address), and the access point to which it is connected (which indicates the building name and floor number). The dataset contains data from 104 buildings and 192,000 individual MAC addresses. In order to protect the privacy of individual users, each record is anonymized, and generic activity plans for synthetic occupants are created. This step involves synthesizing the data into a number of distributions, which are then used to create generic activity plans for each occupant in the district using a Bayesian network approach in the agent-based model.

The data needed to be preprocessed, as shown in Fig. 2, in order to generate feasible daily activity profiles. Since the intention was to track occupant movements at the campus scale, we were only interested in portable electronic devices such as smartphones. We first filtered Wi-Fi records by their organizationally unique identifiers (OUI) [67], which correspond to the first six characters in a device's MAC address. Records that did not correspond to one of the top 70 mobile vendors by market share [68] were dropped from the dataset. However, manufacturers can produce other Wi-Fi-connected devices apart from mobile devices, which need to be filtered as well. A number of devices that only appeared in one location were assumed to be stationary devices, such as printers, IoT sensors, etc., and were therefore dropped from the dataset.

After this initial cleanup, each record was assigned an activity type based on the location on campus and the duration of stay within a building. Occasionally, Wi-Fi-connected devices would frequently change access points, as a device might be connected to an access point

Table 2
Occupant-related internal gains and electricity demands by building use type as defined in the CEA database [66] and associated activity type defined for this study.

Building use type	Activity	Occupant density m^2	Sensible gains W/p	Latent gains g/h/p	Electricity for appliances W/m^2	Electricity for appliances W/p	Ventilation rate l/p/h
Residential	"home"	35	70	80	2	70	10
Office	"work: office"	10	70	80	11	110	10
Lab	"work: lab"	20	70	80	30	600	31
School	"class"	4	70	80	16	64	8
University	"class"	19	70	80	16	304	10
Library	"homework"	9	70	80	2	18	10
Restaurant	"meal"	2.7	73	85	31.7	85.59	25.2
Hospital	"patient"	19	70	80	8	152	10
Gym	"leisure"	9	110	255	2	18	10
Museum	"leisure"	10	70	80	7	70	10

on a different floor of the same building or even to an access point within a different building. Assigning activities based on all records would lead to occupants changing activities and locations impossibly frequently. Therefore, in the first step shown in Fig. 2, in order for a Wi-Fi record to be considered an activity, at least two consecutive records in the same building were required, otherwise the record would be dropped from the dataset. Similarly, in order to avoid implausibly short activities, Wi-Fi records that would imply a stay of less than 5 min in a given location were also dropped from the dataset. All records that met those two conditions were assumed to correspond to an occupant carrying out an activity, which then needed to be assigned.

The following activities were assigned to each record: "home", "class", "work: office" and "work: lab" (primary activities); and "homework", "meal", "leisure", and "patient" (secondary activities). These were assigned based on the building use types available in each building and the duration of the stay. For buildings with a single use type, any records located in that building were assumed to correspond to the activity associated with that main use type, as shown in Table 2. For mixed-use buildings, simple rules were defined in order to differentiate a primary activity (such as "class", "work: office" or "work: lab") from a secondary activity (e.g., "meal" or "leisure"). For example, if an office building included a food court, continuous records of less than 2 h were assumed to correspond to a "meal", while longer records were assumed to correspond to "work: office". By the end of this step, every remaining record had an assigned activity and duration.

A number of records remaining in the dataset had incomplete daily profiles, either due to their short duration (four hours or shorter) or due to long gaps in the records (more than two hours with no access to the Wi-Fi network). Given the information available, it was impossible to differentiate a short record caused by a short-term visitor on campus from a short record occurring due to a rarely used device being operated for a short period of time. Likewise, it was impossible to know whether long gaps occurred due to occupants leaving the campus for a secondary activity or due to devices being turned off or running out of battery for an extended period of time. These records were assumed not to be representative of a typical occupant's daily activities and were also dropped. Our model therefore focuses primarily on occupants who spend most of their workday on campus, who would be in any case the occupant types most affected by flexible work arrangements.

The final dataset contained 10,300 individual anonymized MAC addresses. High shares of discarded records are not uncommon when dealing with telecommunications data (e.g., [52,69]) in spite of the fact that users typically only carry one network-connected device and devices generally stay connected as long as they remain within the mobile network. This is, however, not the case when dealing with Wi-Fi data for a number of reasons. Unlike mobile phones, users typically have multiple Wi-Fi-connected devices that they may use at different times of the day. Laptops, for example, may be used at different times of the day and in different locations on campus, but will typically have large gaps in their daily usage, and would therefore be discarded from the dataset. Additionally, a large number of stationary devices, such as printers, IoT sensors, etc., are known to be placed within the campus, and therefore, their records are not relevant to occupant modeling. Therefore, a high discard rate is actually desirable, as the number of Wi-Fi-connected devices present in the Wi-Fi logs would not be representative of occupants' location and activity patterns. Given that the goal of this paper is not to track the individual occupants of the case study area, but to generate typical aggregated activity and location patterns in order to generate a synthetic population of agents, the number of individual MAC addresses in the final dataset was deemed sufficient.

This dataset was then used to generate a number of distributions: the probability of an occupant choosing an activity as a function of the time of day $P_i(t)$; the probability of an activity being chosen as an occupant's next as a function of the current activity and time of day $P_{i,j}(t)$; the duration of each activity as a function of the current activity and time of day $D_i(t)$; and the distance an occupant is willing to travel to go from the current activity to the next activity $X_{i,j}(t)$. The distribution for the current activity as a function of the time of day $P_i(t)$ is given by the share of all devices with an assigned activity i at time t. The distribution for activity duration $D_i(t)$ is given by the duration of each new instance of activity i at time t for all devices at each time step. The distribution for the next activity $P_{i,j}(t)$ is obtained from the share of all devices whose assigned activity at time $t-1$ was i and j at time t. The distribution for the distance traveled $X_{i,j}(t)$ is similarly generated by calculating the distance between the location where activities i and j were carried out at times $t-1$ and t, respectively. Since there are some buildings in the case study area for which no data were available, the activity distributions were then normalized by floor area in order to estimate the distributions for a case study with a slightly different functional mix.

In addition to occupant activity and location choices, public thermal comfort datasets were used to model occupants' comfort indoors. The smartwatch application Cozie [70] was used to collect micro-survey data in the form of "right-here-right-now" responses from 20 people over a 6-month period [23] and 17 people over a 4-week period [24] in Singapore. Alongside the self-reported thermal comfort labels, air temperature and location (e.g., indoor/outdoor) were also collected via environmental sensors and self-report labels, respectively. Following the methodology in Quintana et al. [71] and Jung and Jazizadeh [72], thermal preference profiles of occupants were generated based on the empirical density distributions of all combined occupants' "right-here-right-now" responses. A total of 13 511 unique thermal preference responses across different air temperatures in indoor environments comprise three distributions for each thermal preference class: "Cooler", "No change", and "Warmer". In order to account for the diversity of actual occupants' thermal comfort preferences, four occupant comfort profiles were defined based on their *tolerance* [71]: *low* tolerance (occupants with 0 to 50% "no change" votes), *medium* tolerance (50% to 75%), *high* tolerance (75% to 100%), and *neutral* tolerance (all occupants considered). Each tolerance profile's empirical density distribution is shown in Fig. 3.

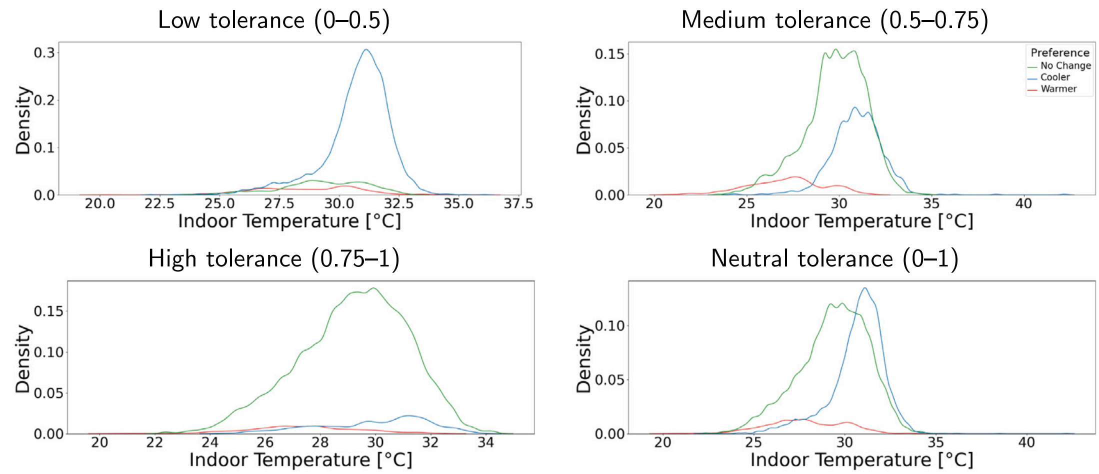

Fig. 3. Empirical density distribution for each of the tolerance profiles defined for the occupants in the district.

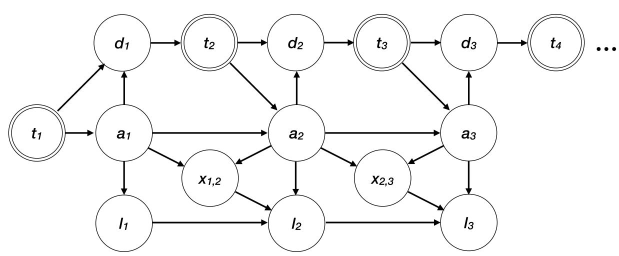

Fig. 4. Graphic representation of the Bayesian network for the assignment of activities, durations, and locations for all occupants.

3.2. Agent-based modeling of occupants' activity and location choices

The distributions obtained by processing the Wi-Fi data were used to model occupant activities, duration, and location choices using a Bayesian network approach similar to Anda et al.'s [51], shown graphically in Fig. 4. The complete workflow for each run of the agent-based model for all location choice scenarios is presented in Fig. 5.

3.2.1. Activity choice and duration

Before each run of the simulation, each occupant was assigned a single "home" location. For each occupant o, at an initial time t, an activity a_t and duration d_t are drawn from the corresponding distributions. A location for the initial activity a_t is assigned by randomly selecting a suitable location on campus unless the activity is "home", in which case the current occupant's home location is assigned. Subsequently, at $t = t + d_t$, a new activity a_t and duration d_t are drawn, and a distance the occupant is willing to travel to go from activity a_{t-1} to activity a_t, x_{a_{t-1},a_t}, is randomly selected from the corresponding distribution. Given that there are not enough records to generate a distribution for every possible transition probability from activity i to activity j at every time of day t, on occasion, an occupant might arrive at an activity and time of day combination for which there is no distribution for the next activity at the current time. In such cases, a new activity would be drawn from the complete distribution for all activities at that time of day $P_i(t)$.

In order to make the resulting schedules feasible, some simple sampling rules were also implemented. As a simplifying assumption, whenever an occupant needed to be assigned a new activity between 0:00 and 6:00, the activity was immediately assumed to be "home". This does not mean that all occupants were home between these times, just that no new activities were started at this time. This restriction was implemented in order to ensure occupants would eventually return home after their daily activity plan.

Certain other building use types' opening hours were also used to restrict the availability of their corresponding activities. Therefore, the activities associated with classrooms, gyms, and the university health center (shown in Table 2) were only available during their corresponding opening hours. Finally, since "class" activities are recurring activities with a fixed time and weekday, any time a student encountered a "class" activity, this activity was assigned for all future instances of that weekday and time of day.

3.2.2. Location choice

Each time an occupant selects an activity, an adequate location needs to be selected as well. The building use types available for each activity are shown in Table 2. For all buildings, the maximum capacity for each activity was defined by dividing the floor area per use type by the assumed occupant density for each use type. If a given building is at full capacity at the time an occupant is looking for a new location, it will not be considered a suitable location for the occupant's next activity.

In the *fixed* location assignment case, the first time an employee or graduate student encounters a "work" activity, this location is permanently recorded as their assigned workspace and will subsequently always be assigned as their workspace for all future "work" activities. Likewise, any time a student encountered a "class" activity, the assigned location was fixed as the future location for that student on that weekday at that time of day. For secondary activities, a location L_{n+1} for the current activity a_{n+1} is selected within a distance of $x_{a_n,a_{n+1}}$ of the current location.

In the *distance*-driven case, every time an occupant needs to find a new location, the same procedure as for secondary activities in the *fixed* case is followed. That is, a maximum distance that the occupant is willing to travel to their next activity $x_{a_n,a_{n+1}}$ is drawn from the corresponding dataset, and subsequently a new location L_{n+1} within this distance, if available, is selected. If no suitable location within $x_{a_n,a_{n+1}}$ is found, the occupant will need to expand the distance they are willing to travel to the next activity. Thus, the closest available location for activity a_{n+1} is selected.

In the *comfort*-driven case, each time an occupant finishes an activity, they assess their comfort in their current location and keep track of their assessment for future location choices. In subsequent time steps, when a new location needs to be selected, a maximum distance they are willing to travel $x_{a_n,a_{n+1}}$ is again selected. If a location that they have previously assessed as comfortable is available within this distance, they will select it. Conversely, if an uncomfortable location is available, they will avoid it. If no known comfortable location within $x_{a_n,a_{n+1}}$ is available, but an unknown location suitable for activity a_{n+1} is, this location will be selected. If no locations suitable for this activity

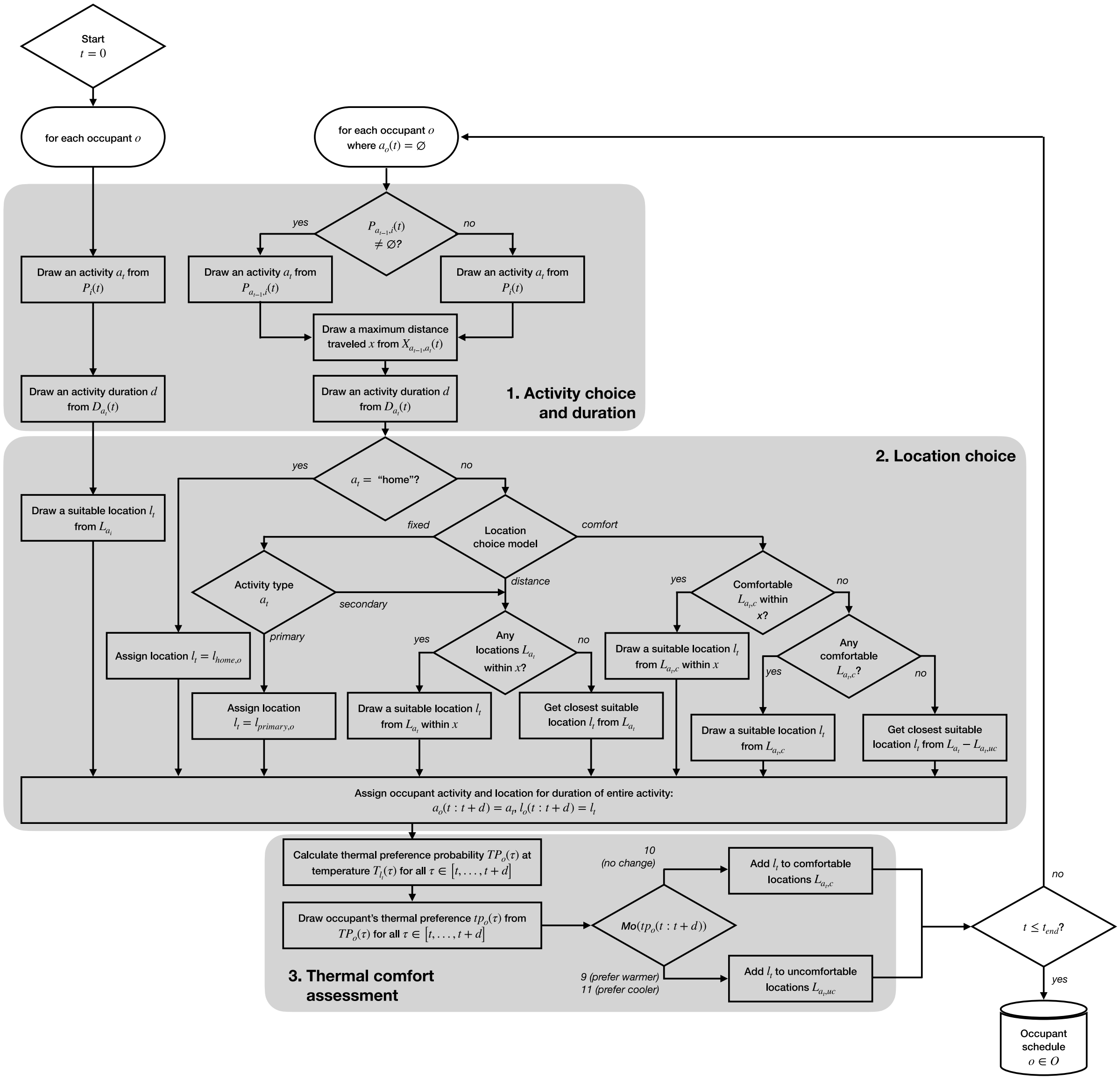

Fig. 5. Workflow used to generate schedules based on distributions.

are available, or all available locations have previously been assessed to be uncomfortable, the occupant will again seek locations beyond their preferred maximum distance. Thus, they will select the closest location suitable for activity a_{n+1} that has not been previously assessed as uncomfortable.

3.2.3. Thermal comfort assessment

At the end of each activity, occupants assess their thermal comfort in their current locations. For each timestep within the current activity, the current location's indoor air temperature is assumed to be equal to the building's scheduled setpoint/setback temperature. If the current building's cooling systems are scheduled to be off at the current timestep, the indoor air temperature is assumed to be equal to the outdoor air temperature. The probability of each thermal comfort label ("prefer cooler", "prefer no change", or "prefer warmer") at each temperature is then extracted from the empirical distribution based on the current occupant's tolerance profile (Fig. 3). The occupant's thermal preference at each timestep is then assigned randomly based on the probability for each thermal comfort label. Thus, each occupant has an assigned thermal preference label at each timestep in the simulation, regardless of whether they changed location or not, meaning that an occupant's thermal preference in a given location might change over time. The exceedance cumulative index is then used to quantitatively assess discomfort [73]. This metric counts all the occurrences when the occupant's thermal preference is either "prefer cooler" or "prefer warmer". This value is then normalized by the cumulative timesteps that the occupant utilizes the space, resulting in a value ranging from 0 to 1, where the ideal value for occupant comfort should be close to 0.

For the *fixed* and *distance*-driven cases, occupants' thermal comfort assessments of each location are used to calculate occupants' overall satisfaction with their environments. This is done by calculating each occupant's exceedance throughout the simulation, which gives an indication of each occupant's comfort throughout the simulated time period. In a real-world application, occupants' thermal comfort feedback could also be aggregated into a building's average occupant rating. Such scores could then be used to select which buildings are more suited for intervention to improve occupants' comfort.

In the *comfort*-driven case, each occupant decides at the end of the activity whether they were mostly satisfied with the current location. This is done by taking the mode of the occupant's thermal preference labels throughout the duration of the previous activity. If the occupant

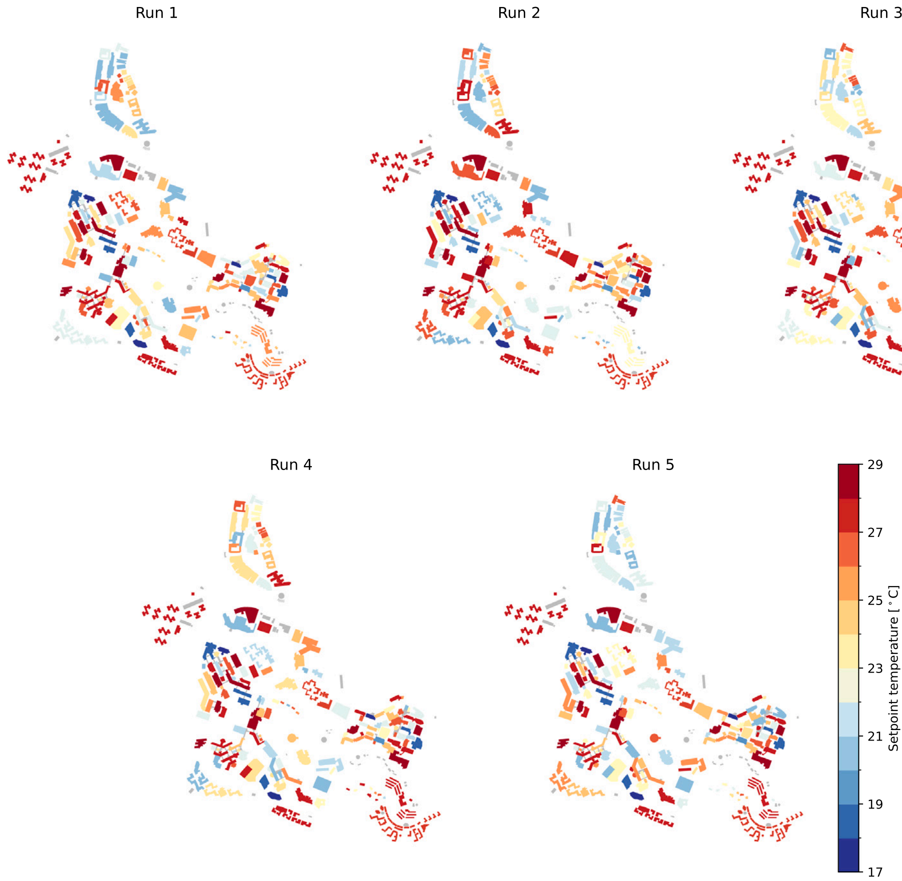

Fig. 6. Distribution of setpoint temperatures in the case study district for each of the runs of the model.

mostly rated their thermal preference during the previous activity as “prefer no change”, the building will be assumed to be stored in a list of occupant-specific preferred locations. Likewise, if the occupant’s thermal preference labels were mostly “prefer cooler” or mostly “prefer warmer”, the building will be stored in a list of locations to be avoided. In subsequent timesteps, occupants will choose comfortable locations when available and avoid choosing uncomfortable ones even if it implies a longer walk to their next location. Since occupants’ thermal comfort assessments of any given location can change through time, a building that was previously rated as comfortable may be removed from the preferred list if the occupant assesses it as too cold or too warm at the end of a subsequent activity, and vice versa.

The activity and location choice and thermal comfort assessment process is repeated for each occupant for the entire period until a set of occupant schedules O is created. Each schedule contains an activity, a location for each of the location choice cases selected, and a thermal preference label for each location at each time step in the simulation. These individual occupant schedules can then be translated into occupancy profiles for individual buildings, including the activity being carried out by each occupant in a building. These building-level schedules are then used as an input in the building energy simulation.

3.3. Building energy modeling

Building energy simulation is carried out using a campus-scale building energy demand model for the National University of Singapore campus built on City Energy Analyst (CEA) [11]. During model construction, no information was available on the construction properties of the buildings or the operating parameters of the building systems. Therefore, the building envelope properties and cooling system set points were calibrated based on hourly electricity and cooling demand data. However, this information was only available for 50 buildings on campus, so standard-based assumptions were used for the remaining buildings.

Since standard-based assumptions were used for more than half of the buildings on campus, building setpoints in our model ended up being very consistent, as the CEA database assumes a 24 °C setpoint for non-residential buildings and 28° for residential buildings. Therefore, the building stock ended up having very consistent operating parameters, leading to minimal opportunities for occupants to improve their personal comfort [74]. In order to add diversity to the building stock’s operating parameters, before each simulation each building with a standard-based setpoint temperature was assigned a number between −4 and 4, and their setpoint temperature was adjusted by that number. Thus, different buildings with the same use type were assigned different setpoint temperatures. This process was repeated five times to generate five different setpoint combinations for the university’s building stock (Fig. 6). Each campus-scale model was then used for one run of the workflow in Fig. 1.

The building-aggregated activity schedules generated by the agent-based model were used as input into the building energy simulation. The sensible and latent gains per occupant for individual activities were obtained from the CEA database [66], which is largely based on ASHRAE [75] and SIA [76] standards. However, the power density for appliances in the CEA database is defined per m^2 (as typically done in building standards) and had to be converted to electrical loads per occupant. As a simplifying assumption, the electrical loads per occupant were obtained by multiplying the values per m^2 from the CEA databases by the occupant density (m^2/p) to obtain a power density per occupant (W/p) for each activity and building use type. The occupant-driven internal loads and electricity demands are shown in Table 2.

In addition to the five different setpoint temperature combinations and the three location choice models considered, three building system

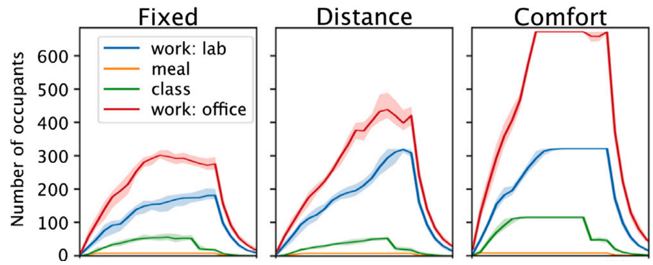

Fig. 7. Sample activity profiles for one day for one building (mean profiles and range of values for all runs on that day).

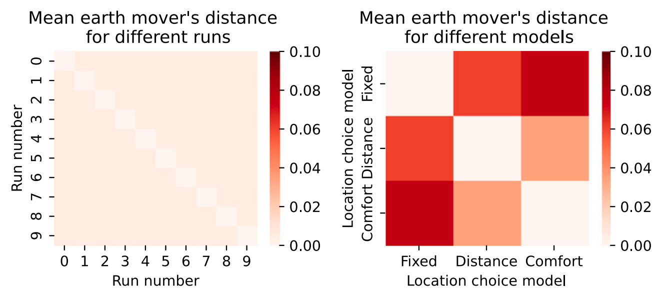

Fig. 8. Comparison of the difference between schedules produced by different runs of the model compared to the difference between schedules produced by different models.

operation strategies were simulated. The selected building system operation strategies are meant to compare status quo building operation strategies with the implementation of occupant-driven building system controls to better support the needs of occupants in flexible work arrangements. In the *centralized* building system operation strategy, buildings have a set operation schedule, such that the ventilation rate and setpoint temperature follow a predefined hourly schedule. This represents a typical status quo building system operation strategy for large academic buildings, as presented in this case study. In the occupant-driven *ventilation* case, buildings are assumed to have demand-driven controls such that the ventilation rate is proportional to the number of occupants in the building per the minimum ventilation rate per occupant specified in Table 2. In the occupant-driven *temperature* control case, in addition to demand-driven ventilation controls, buildings' operating temperatures are also assumed to be controlled by the number of occupants in the building. Thus, when occupants are present, buildings are maintained at their setpoint temperature, while whenever buildings are unoccupied, they are automatically set to their setback temperature. The resulting space cooling demands for each of these strategies under each location choice scenario can then be compared.

3.4. Stochastic behavior and number of model runs

Due to the stochastic nature of the model presented in this paper, each run of the simulation will give different activity plans for each occupant and, thus, different thermal comfort and energy demand results. In a preliminary version of this study [74], we ran the simulation ten times in order to account for the deviations in the results for each run of the model. However, as shown for an example building in Fig. 7, the deviation in the results for individual runs of the model is small compared to the deviation between the results of different location choice models. This is due to the fact that while individual occupants' schedules might diverge widely, at building scale, they will tend to aggregate to a fairly consistent profile.

The deviation between building schedules was explored further using the Earth Mover's Distance (EMD) as a comparison metric. The EMD quantifies the difference between any two schedules, *i.e.*, their general similarity or dissimilarity [53]. Fig. 8 shows the comparison of

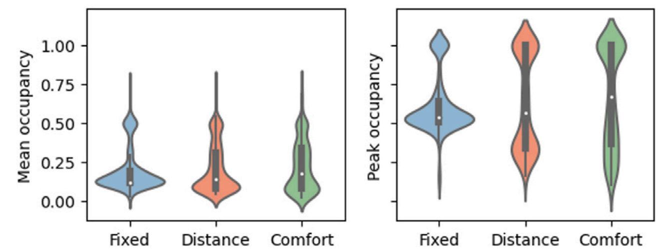

Fig. 9. Distribution of the mean and maximum occupancy for each building for all runs of the model for each of the location choice models.

the mean EMD between schedules generated by different runs of the model for all buildings and the mean EMD between the schedules for all buildings for different location choice models. For the comparison of different runs of the model, the EMD between the schedule generated for each building in each run and the schedule generated in the first run was calculated for each model. For the comparison of the schedules generated by different models, the EMD between each location choice model and the *fixed* case was calculated for one run of the model. The results show that the biggest deviation in schedules occurs between the *comfort*-driven and the *fixed* location choice models, with a smaller deviation between the *distance*- and *comfort*-driven cases.

The deviation between each run of the same model is comparatively very small, meaning that the deviation caused by the choice of location choice model is small compared to the effects of the stochastic nature of the model. Therefore, in this paper, each version of the campus-scale model was run only once, and the results presented correspond to a single run of each of the five different setpoint combinations.

4. Results

As discussed in Sections 3.3 and 3.4, five different temperature scenarios were defined, and the simulations were run once for each scenario. In the following sections, in order to avoid overrepresenting any single randomly assigned setpoint combination, the results presented correspond to all five simulations combined.

4.1. Building occupancy

As a result of the different location choice strategies considered, building occupancy varies from one scenario to another. Fig. 9 shows the distributions for the mean and peak occupancy for all buildings in the case study area for each location choice model for all setpoint temperature scenarios. The buildings in the case study area all have very low occupancy on average regardless of location choice model, though the *distance*- and *comfort*-driven scenarios show an increase in the number of buildings with an average occupancy of 25% or higher.

These results point to certain buildings being preferable to others either because of their proximity to other amenities or due to their desirable indoor environment. This difference is even clearer when observing the distribution of the peak occupancy for all buildings in the case study area. In the *fixed* location choice scenario, since workspaces are assigned at random and maintained throughout the whole simulation, peak occupancy is fairly consistent for all buildings at around 50%. When occupants are allowed to choose workspaces that minimize the *distance* traveled between activities, two clear clusters form, with some buildings achieving maximum occupancy and others consistently below 50% peak occupancy. This shows that when occupants are allowed to choose their workspaces and minimize the distance between their activities, some buildings will be strongly preferred over others. When accounting for *comfort* in the decision-making process, on the other hand, the low occupancy cluster is much more spread out. This would appear to indicate that buildings that are further away

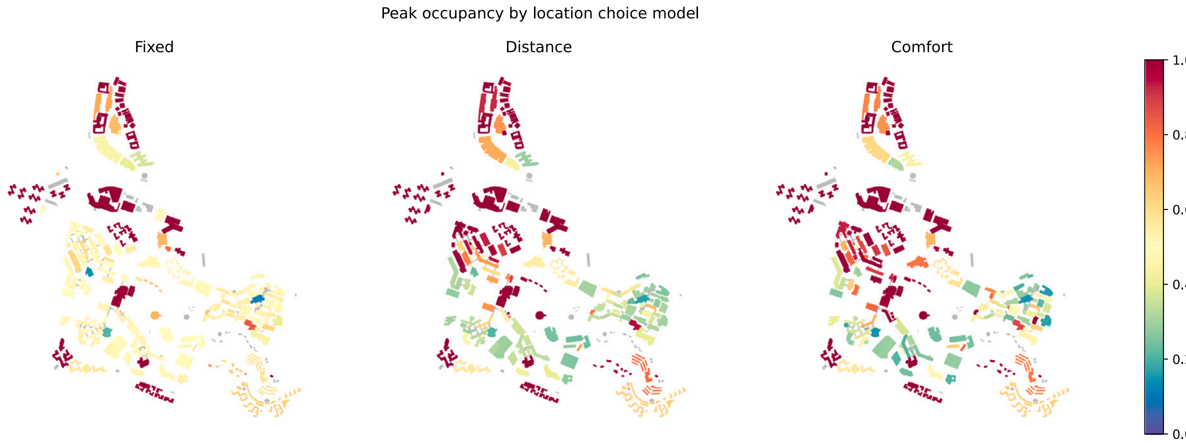

Fig. 10. Average peak occupancy for each building for all runs of the model for each of the location choice models.

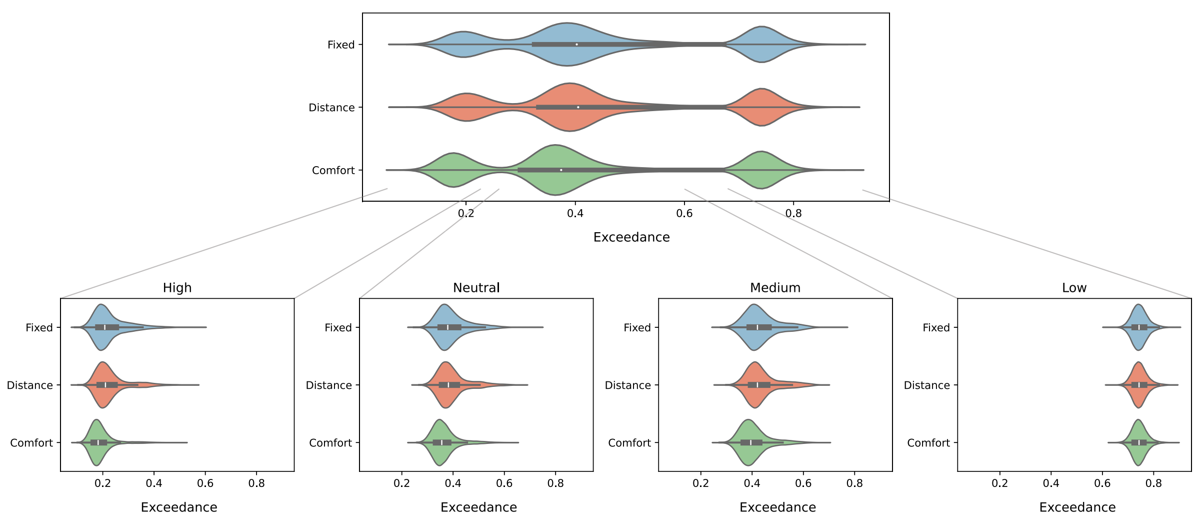

Fig. 11. Distribution of the exceedance for each occupant (the lower, the better) for all runs of the model for each of the location choice models by occupant tolerance profile.

from occupants' activities may still be preferred due to their indoor environment.

The spatial distribution of occupants in each of the scenarios is shown in Fig. 10. In the *fixed* case, only a few buildings achieve peak occupancy, and they mainly correspond to residential buildings. As seen in the violin plot, most buildings' peak occupancy remains low at about 50%. In the *distance* case, a strong preference for buildings in the middle of the campus is preferred, as these minimize the distance traveled between activities. This same trend is observed for the *comfort* case, although, as discussed, some buildings that are further away from the center are observed to have increased occupancy, likely as a result of their desirable indoor environment. Furthermore, some buildings with even lower peak occupancy are also observed, again likely due to their less comfortable indoor environment.

4.2. Thermal comfort

In order to assess whether this elastic space allocation of workspaces improves occupants' thermal comfort, the exceedance was calculated for all occupants for each of the location choice models and setpoint combinations. The distribution of the results is shown in Fig. 11.

The violin plot for the exceedance for all occupants shows three distinct clusters, roughly corresponding to the thermal comfort tolerance profiles assigned to each occupant at the beginning of the simulation. As a result, low tolerance occupants consistently report very high exceedance values (0.74–0.75 for all location choice models), meaning they spent most of their time in uncomfortable environments regardless of the location choice model used. This is consistent with the empirical density distribution function shown in Fig. 3, as study participants in this group generally reported preferring cooler environments regardless of the indoor temperature to which they were exposed. Therefore, even when they are allowed to seek more comfortable indoor environments, occupants in this group only decrease the number of uncomfortable hours spent by less than 0.2%.

Occupants with high tolerance, on the other hand, generally have low exceedance scores regardless of the location choice model used. Again, this is consistent with the empirical density distribution function obtained from the smartwatch data, where occupants in this category generally indicated a preference for "no change" in their surrounding environment. Nevertheless, by allowing occupants to maximize their thermal comfort on campus, the average exceedance score for occupants in this category improves from 0.23 to 0.19.

The remaining two occupant tolerance profiles, medium and neutral, strongly overlap. This is due to the "neutral" tolerance profile being a combination of all other three profiles, leading to a somewhat average thermal preference distribution. In both cases, a middle exceedance value is observed for the fixed case (0.43 for the medium tolerance profile and 0.39 for the neutral tolerance profile), with an improvement of roughly three percentage points for the comfort-driven case. Likewise, the average exceedance for all occupants improves from 0.4 in the fixed case to 0.37 in the comfort-driven case.

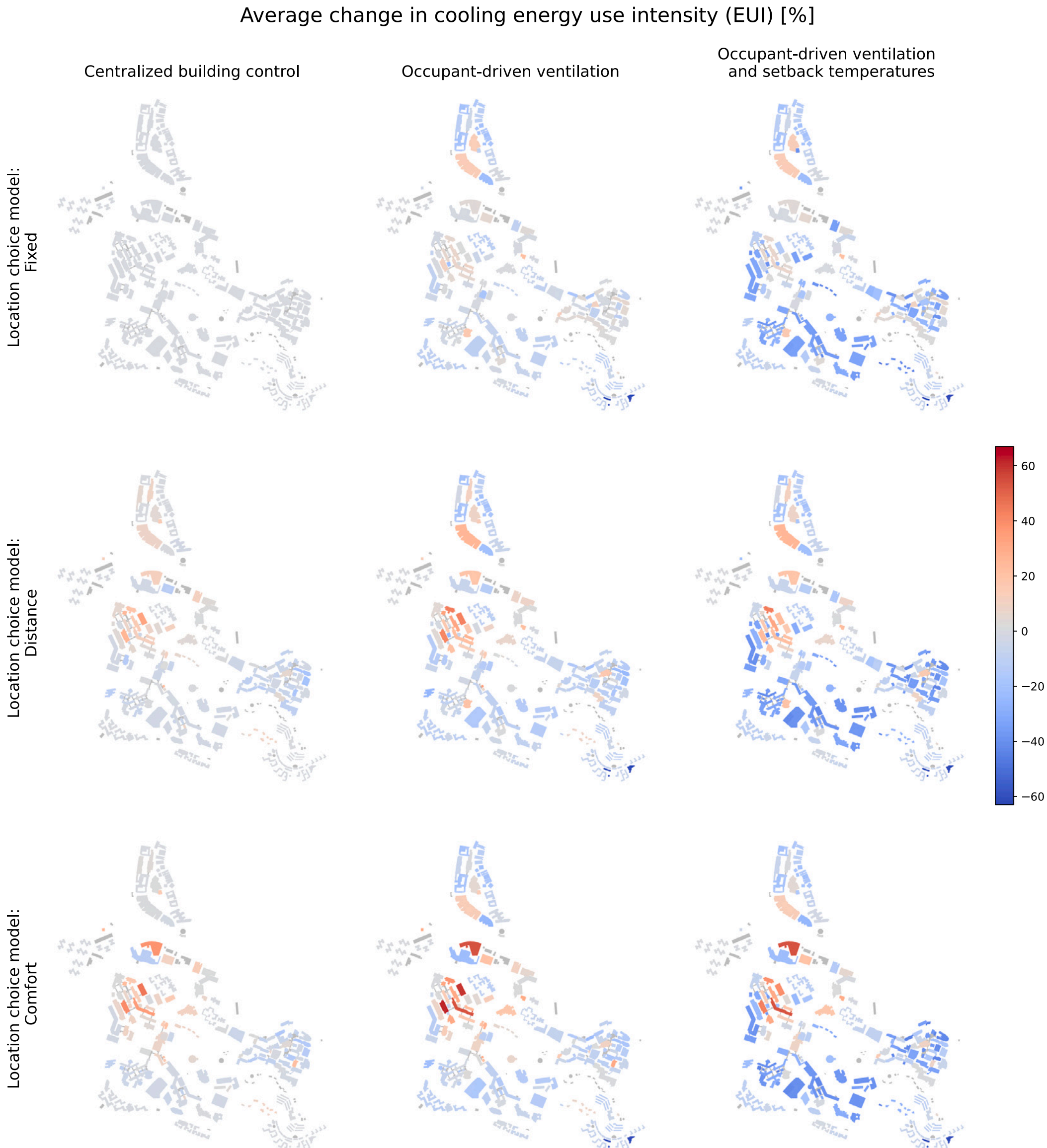

Fig. 12. Change in cooling energy use intensity over one week by building for each location choice model and building system control strategy.

4.3. Space cooling demand

Changes in the distribution of building occupants in the area consequently lead to changes in each building's space cooling demand. Fig. 12 shows the average change in space cooling energy use intensity (EUI) for each building compared to the status quo scenario (centralized building operation and fixed space allocation). The changes in the space cooling demand tend to correlate strongly with the changes in occupant distribution seen in Fig. 10.

For the centralized operation case, as occupants are increasingly concentrated in the buildings in the middle of the campus for the *distance*- and *comfort*-driven space allocation scenarios, the space cooling demand for those buildings increases, while the demand in buildings further away decreases. Fig. 13 shows the space cooling demand per m^2 for each building for each of the location assignment cases and system operation scenarios. The results shown correspond to all runs of the model. There is a slight net increase in space cooling demand when spaces are allocated flexibly, with a 0.4% increase in space cooling demand for the *comfort*-driven scenario with centralized system operation compared to the *fixed* case baseline. This is due to the increased internal gains caused by higher occupancy in buildings that would have otherwise operated at relatively low occupancy (as seen in Fig. 9). Allowing occupants to choose the location of their activities can therefore pose a challenge to system operation at building scale. However, it also illustrates the opportunity presented by occupant-driven building system operation to make buildings more responsive to occupant choices while reducing space cooling demand.

Implementing occupant-driven ventilation controls leads to a decrease in space cooling demand for most buildings, although for buildings with very high occupancy, the space cooling demand actually increases when ventilation is controlled to match building occupancy. This would indicate the standard-based ventilation rates for the baseline case might have been insufficient for buildings with very high occupancy. This effect is mitigated when occupant-driven temperature controls are implemented. At the same time, the space cooling demand for buildings with low occupancy decreases significantly for all cases. This is especially notable for the *distance*- and *comfort*-driven cases, in which occupancy is much lower for a number of buildings in the area. For all space allocation strategies, there is an average 6.1%–6.5% decrease in space cooling demand when implementing demand-driven ventilation controls. Likewise, the use of occupant-driven temperature

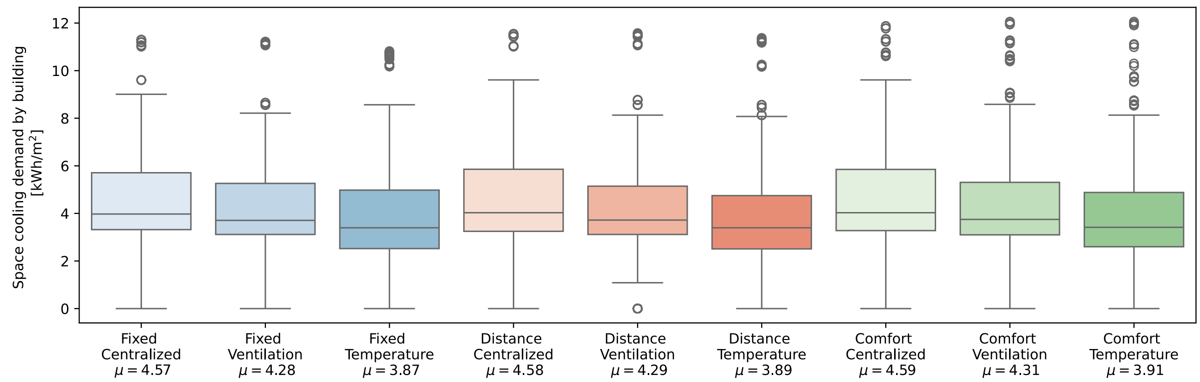

Fig. 13. Distribution of the space cooling demand per m^2 for each building over one week for all runs of the model. Each scenario corresponds to a combination of one location choice model (*fixed* location assignment, *distance*-driven and *comfort*-driven location choice) and one building system operation strategy (*centralized* building system operation, demand-driven *ventilation*, and demand-driven ventilation and *temperature* controls). For each scenario, the mean space cooling demand per m^2 (μ) is also shown.

and ventilation controls leads to an average decrease in space cooling demand of 15% for all location choice models. Therefore, the implementation of such demand-driven controls appears to be a promising strategy regardless of whether a fixed or elastic space allocation approach is assumed.

5. Discussion

The results of this implementation outline an alternative structure for the planning and operation of non-residential spaces in an age of increasing occupant flexibility. Dynamic space allocation and utilization are becoming more common compared to the conventional Monday to Friday, 9 am to 5 pm office worker schedule. This paradigm shift has an impact on the design of both building form and orientation, as well as the space use planning, interior design, and amenity distributions. There is also an impact on both the building system controls for lighting and climate control as well as desk and space utilization policies.

5.1. Impacts on system operation policies and building design

The methods presented here provide a foundation for space use policies that allow occupants to use a diversity of space types throughout their work week. By providing different spaces with different operational characteristics, buildings might be able to better match different building occupants' comfort preferences as well as their specific needs when carrying out different activities. By providing a simulated test bed for different space allocation policies, planners can assess how their interventions might affect the decisions of occupants and consequently energy performance in a district.

However, one limitation of the work in this paper is that our agents' assessment of the built environment focused solely on thermal comfort, which is only one of the many factors that affect indoor environmental quality. This is also the trend in building-scale agent-based modeling, where several studies focus on occupants' behavioral adaptations to achieve thermal comfort, but only a smaller number of ABM studies concern occupants' requirements regarding visual comfort, acoustic comfort, and air quality [45]. Again, incorporating each of these aspects was out of scope for our intended purposes and scale and would have added enormous complexity to the model. Furthermore, the simplified nature of the CEA building energy demand model makes it impossible to assess aspects of visual and acoustic comfort within the case study buildings.

A limitation of this approach is that real occupants make their location choices based not only on their personal comfort but on any number of other aspects, such as the need for interactions with colleagues and socialization [77]. A survey of co-working spaces in the Netherlands [78] found that while some of the most important characteristics relate directly to the focus of our paper (accessibility, indoor environment), other characteristics such as interior design and access to an inspiring work environment were equally important to occupants. Likewise, activity-based working (ABW) arrangements such as hot desking were found to present numerous challenges and shortcomings due to lack of control over the work environment and lack of opportunity to modify the workspace [79].

As a simplifying assumption, we assumed any workspace to be equivalent to any other workspace in our case study area, which is, of course, not the case in a real-world application. However, methods such as the ones presented here could be expanded to incorporate further occupant preferences. Thus, architects and urban planners could test different space allocations and floor plan arrangements through scenarios that optimize energy and space utilization.

5.2. Occupant adaptation

This work aimed to demonstrate a methodology to build a data-driven, district-scale agent-based model of building occupants with personalized activity plans and thermal comfort preferences. The range of thermal comfort adaptations considered in this work was limited, however, as agents were only allowed to change their location to improve their thermal comfort. While large academic buildings with centralized controls somewhat restrict occupants' abilities to change their indoor environment (*e.g.*, no availability of operable windows, no temperature controls, etc.), in a real case study, occupants may still undertake minor adjustments to improve their thermal comfort (*e.g.*, changing their clothing level). Given the lack of information on these adaptations in our dataset, however, we decided to restrict the available options to the one most relevant to the scope of our study, which was specifically focused on flexible work arrangements.

Despite these limitations, our model provides insight into the macroscale behaviors that might emerge when occupants in flexible work arrangements are allowed to choose their workspaces. The methodology we presented furthermore helps to assess, in a simulated way, how district operation strategies might affect thermal comfort and building energy performance. Based on these findings, facilities management professionals can assess occupants' satisfaction with the thermal environment in different buildings on campus and the potential for different system operation strategies to improve energy performance and occupant satisfaction.

6. Conclusions

This work presents a methodology to develop a data-driven agent-based model of occupants' thermal comfort-related decisions in the context of flexible work arrangements. By using campus-scale Wi-Fi logs, we were able to develop feasible activity plans for synthetic campus occupants and assign them realistic thermal preference profiles based on comfort feedback data collected through field studies on campus. We then used a Bayesian network approach to model occupants' activity and location choices at the campus scale and test the comfort and energy performance of buildings on campus under different space allocation and system operation scenarios.

Our results show that by providing a diversity of building operation conditions, with different buildings having different set point temperatures, occupants' thermal comfort hours could be improved by an average of about 10%. This improvement in overall thermal comfort came at an energy penalty of less than 0.5%. Thus, a campus operation strategy aimed at providing a diversity of indoor spaces to match occupants' different and changing comfort preferences might be worth pursuing. This is especially important in the context of the increasing reliance on flexible work arrangements, where building occupants may be able to choose activity-based workspaces rather than having a constantly-assigned desk.

Different energy system operation strategies were also considered, focusing on the implementation of demand-driven ventilation and temperature controls. The results showed that flexible campus operation had little effect on the performance of different demand-driven operation strategies. A 6%–15% average decrease in space cooling energy use intensity at the campus scale was observed when implementing these occupant-driven controls, regardless of the location choice scenario used. Therefore, our results point to the advantages of implementing a diversity of indoor environments to maximize occupant comfort and occupant building system controls to maximize energy performance.

Our model provides insight into the macroscale behaviors that might emerge when occupants in flexible work arrangements are allowed to choose their workspaces. The methodology presented here could be further implemented by facilities management professionals to assess different space allocation strategies and building setpoints to support this transition to flexible work arrangements. Our study's results point to the potential implications of flexible space allocation strategies for district energy and comfort performance. With relatively minor interventions (implementing buildings with different indoor characteristics and installing demand-driven system controls), occupants' thermal comfort and building energy performance could be improved. In a real-world case, occupants' feedback information (collected here via a smartwatch application and simulated by our model in the thermal preference calculation) could also be incorporated into the decision-making process to assess different buildings' performance and correspondingly take proactive measures to improve occupants' perception of the building. Future work on this approach could incorporate other occupant behaviors, such as thermal comfort adaptations and social relationships, in order to further refine the model's ability to mimic real occupants' location choice decisions.

CRediT authorship contribution statement

Martín Mosteiro-Romero: Writing – original draft, Visualization, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Matias Quintana:** Writing – review & editing, Software, Project administration, Formal analysis, Data curation, Conceptualization. **Rudi Stouffs:** Writing – review & editing, Supervision, Funding acquisition. **Clayton Miller:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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