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Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach

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ABSTRACT

Several frameworks are introduced to address occupancy-based building performance. However, the performance predictions obtained using these frameworks deviate from real performance. So, this study's aim is to represent a new framework for the automatic assessment of occupants' comfort and building indoor performance using BIM and the SD-ABM platform. Initially, an office space in Hong Kong, consisting of 10 occupants, was considered for the BIM model construction. The occupancy, indoor data and required equations are defined using the SD-ABM model. Essential data from the BIM model can be transferred using the Dynamo-Excel platform. Furthermore, a validation study was conducted using a paper-based survey from the occupants and sensor data for environmental data monitoring while error metrics were also calculated. The framework actively predicts occupant presence, comfort level, temperatures, and CO_2 concentration in the office space. However, a comprehensive usability and feasibility study is required to assess the efficiency of the framework.

1. Introduction

Building Information Modeling (BIM) is an intelligent 3D-based modeling technique that provides Architecture, Engineering, and Construction (AEC) specialists broad understanding and insights to develop more efficient building systems. It is a modern approach to design and management in the construction industry and mostly contains information about a building from all phases of the building life cycle [1]. The models are created using BIM tools (Revit, ArchiCAD), closely approximating the real building. The closer the model is to reality, the greater the chance of creating a high-performing building. This concept itself is described as a modernization that accumulates the rules, technologies, and approaches establishing a technique to manipulate the construction policy. Furthermore, it records and digitally organizes the construction components for creating comprehensive schedules. As stated in the National BIM Report 2016, BIM implementation all the advanced participants have been grown because of its plentiful opportunities provided for construction projects, inclusive of value and time saving, first-rate and performance improvement, decreased human resources, clash detection, greater collaboration and communication, increased profitability, improved accuracy, higher documentation and presentation process, sophisticated plans and design, and also better visualization and advanced data [2,3]. Currently, BIM is supported by several Building Performance Simulation (BPS) tools (i.e., EnergyPlus, eQuest, OpenStudio, etc.) in order to improve the overall construction performance and to represent the minimal effects of the environment through the advanced expertise [4]. It has a considerable impact on the precise estimation of building energy and environmental data [5,6]. Moreover, BPS is a tool for estimating precise building data that can be used to forecast the retrofit energy efficiency by generating existing building models, analyzing, proposing solutions, and the evaluation of building performance. It is also recognized as a technique and approach to enhance the efficiency and suitability of a project from the initial stage to the operation and maintenance stage [7].

There are a few constraints on the use of BPS in building performance study [6,8]. For instance, energy-improved building assessment (e.g., net-zero-energy building) indicates that some of the real performance is not as planned or designed [9]. Also, most

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of the BPS tools account for i) deterministic or fixed settings and rules; ii) homogeneous profiles for schedules, and comfort requirements; iii) hard to use custom features; and iv) represent occupant input differently [10]. To achieve more precise performance, it is necessary to simulate building performance study under realistic conditions, including accurate modeling of human perception [11]. A common and significant source of error in BPS tools under realistic circumstances is inaccurate or misleading input associated with the occupant profile, comfort and building system [12]. Typically, occupants in building simulation tools (i.e., BPS tools) are represented in terms of static schedules as shown in Fig. 1. The common BPS tools place emphasis mainly on the physical design aspects, for example, external weather and building envelope or HVAC (Heating, Ventilation, and Air Conditioning) rather than the interaction between buildings systems and occupants. It is essential to understand the distinction between the actual and optimal building performance by considering occupancy effect [13]. Typically, occupants' movement and comfort are depicted by setting the indoor temperature, CO_2 concentration, and HVAC systems [14,15]. These are highly variable and completely unpredictable for individuals or groups of occupants [16]. These parameters, meanwhile, also have a significant impact on real energy consumption and overall building indoor performance as well [17]. Furthermore, most of the existing building modeling frameworks consider static or fixed schedules based on certified codes, rules (i.e., American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), building codes, etc.) or occupant surveys, which ultimately drive energy wastage and occupant discomfort [11,18,19]. Several developed energy modelling frameworks include modified or customized BPS code which may generate stochastic profiles; however, it requires more advanced capabilities with broad expertise in the field of control engineering.

A more flexible building occupancy model or framework is required to address better building performance. Generally, the outcomes of two especially challenging models, BIM vs. BPS, that ignore the complexity of an occupant's behavior and comfort, add to the assessment of building performance [20–22]. It is very thriving to see that research subjects have been moved from social science and psychological investigation to modeling building occupant behavior and building performance simulation, which proposes a change of research motivation from quantitative study to qualitative study or modeling. In recent years, there have been several approaches and models developed for occupant behavior study. Countless studies relate to BIM-BPS application and implementation for building performance analysis. The implementation of these tools involve an advanced level of incorporation into existing approaches with a strong emphasis and standards aim at meeting the conditions [23]. Recently, the topics related to BIM and BPS have accumulated by the broadly recognized as a "performance gap" [24]. Attempts to fill the gap have been made in regard to the data exchange and synchronization between the BIM and BPS models. Presently, BIM offers a key role in enhancing the reliability of building information related to performance study. Using BIM tools, the process of creating a BPS model can be easily automated while the occupant stochastic profile is ignored. More clearly, the climatic or environmental conditions where a resident/occupant lives will cause adaptive behavior, while proper energy use may be ignored [11]. Thus, improving the knowledge of occupant stochastic profile is essential for assessing its influence on overall building performance [7,25]. Also, occupant behaviors are relevant to building performance throughout the building operation phase. In spite of the fact that occupant behavior is difficult to show because of the stochastic nature and randomness of people, it is important to investigate the common pattern of behavior and incorporate the data with the energy simulation model.

In recent times, researchers have focused their efforts on modeling for occupant stochastic behavior using several approaches. One of the latest approaches is the application of the Agent-Based Modeling (ABM) concept, which can be appropriated for behavior prediction from the occupant individual level to group level [8,11]. ABM is a simulation-based framework that consists of single or multiple autonomous actors, called "agents," which interact with each other and their exterior/interior environmental condition according to definite behavior rules. Mostly, an ABM agent is capable of simulating each occupant by unifying characteristic rules or data items of the indoor/outdoor environment as well as modification of behavior changes in order to accomplish a specific task. In contrast to other modeling techniques, ABM starts and ends with the agent's (occupant's) perception and purpose. Each agent has individual characteristics that include behaviors and responses, and they have the ability to interact with other agents as well as building systems, which are mainly controlled by user-oriented well-defined rules. In ABM we do not define the relations or the global behavior of the system, but the behavior of individual persons or occupants, and then relations emerge. However, System Dynamics (SD) can model the structures such as relationships, programs, and inducements that underlie the behavior of systems and it does not take into account the mood of the decision makers. Basically, system dynamics (SD) is an approach to understand the nonlinear behavior of complex systems over time using stocks, flows, internal feedback loops, table functions, and time delays. The SD approach is related to building or construction simulation programs because it

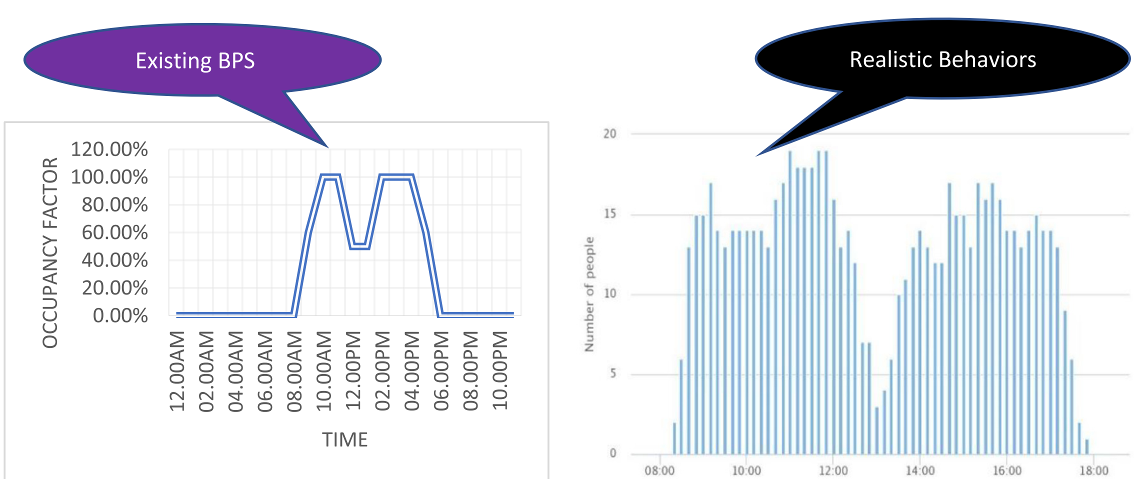

Fig. 1. Occupant behavior pattern in existing BPS tools (Left) and a realistic behavior (Right): Source: http://occupancysimulator.lbl.gov/

has a wider range of capability to model the highly dynamic factors (temperature, CO_2, etc.). It emphasizes the fundamental framework of the system that permits incorporation and combination of soft features which can support the capture of the occupant behavior of the building [26].

Beyond the fact that above approaches described the model developments regarding to building indoor performance/environmental monitoring field, yet related to numerous difficulties and challenges that should be performed effectively. The occupant comfort of a building is extremely dynamic and relies on multiple parameters, for example, indoor environment, climate, number of occupants, and even the design features as well. To break down these components, the integrated methodology may require simulating the impacts of numerous variables arising during the building operation phase. Moreover, existing occupant behavior study solely considers the single behavior model or ABM approach with some static natural/environmental parameters using BPS tools (i.e., EnergyPlus, eQuest). At the end find the accumulated estimations of building performance requirement and determine the conclusion based on that. However, this methodology ignores the loss due to the impacts of dynamic events, for example, the building's indoor performance, occupant perception, and cognitive activity during the operation stage [27]. Therefore, the primary aim of this research was to introduce a new hybrid framework between the Building Information Modeling (BIM), System Dynamics (SD), and Agent-Based Modeling (ABM) in the field of occupant comfort studies in the existing BPS concept and other relevant areas. The framework should cover a combined system approach and support message/data exchange over the BIM, SD, and ABM platform. This arrangement adds another feature to the existing occupant behavior study in order to upgrade the simulation performance. Moreover, the majority of occupant-related studies have been formed based on synthetic data and scenarios. Also, one of the significant problems for the most prominent part of occupant behavior studies is implementation of ABM approach without real data involvement. It has rarely been seen that researchers validate their model data using real-world incorporation [11,19]. So, this investigation also attempts to fill this gap by offering a validation approach using a simple survey for occupant true comfort assessment and sensor data for environmental data monitoring.

The proposed hybrid framework is useable to improve the building performance simulation program. It is appropriate for the circumstances where the building system is very dynamic or highly complex in regard to time and space. Moreover, it focuses on the basic structure of the building performance modeling, allowing automatic integration of BIM data (Using Dynamo- Application Programming Interface) which can help to evaluate the individual human comfort and indoor environmental data of the space.

This article is organized as follows. Section 2 discusses the literature review of the study; Section 3 explains the framework/methodology used in this study; Section 4 describes the results and discussions of case scenarios; Section 5 explains the validation study of the model; Section 6 concludes the study and covers contributions, future works, and limitations.

2. Literature review

Along with the energy-behavior interaction, the latest studies in residential and commercial buildings have established that the building occupants' behavior within an indoor space has a double impact on both the total building energy consumption and occupant satisfaction [28,29]. Subject to this transferring and receiving relationship between the comfort and energy, scholars no longer have to consider building occupancy-related variables as a boundary condition. Alternatively, previous studies considered the default presumptions of an occupant's behavior in building performance simulation [30]. Lee & Malkawi's [31] study developed a framework (i.e., ABM and BPS tool). The main purpose of this study was to identify how occupants balance the dynamic thermal variations in a prototype office space to improve both energy savings and comfort. Occupant comfort is correlated with modeling and energy simulation to consider its effects on building energy and indoor environmental performance [32]. Micolier et al. [33] proposed a BIM-AMB integrated framework that simulates the building occupant behavior and their indoor comfort. It provides the opportunity to evaluate the different setup of design performance for a residential building occupant. Mitterhofer et al. [34] presented a modular simulation methodology for performing whole-building simulation using a co-simulation approach. It offered an integrated simulation concept where BIM and a FMI (Functional Mock-up Interface) standard is used. This study [1] demonstrated an OOPM (Object-Oriented Physical Modeling) approach to incorporate the BIM and building performance simulations. The approach also facilitates the multiple domain simulations from a single BIM model. Naghshbandi's [35] study described the issues related to interoperability and data exchange between the BIM and facilities management for improved building performance. This study also highlighted the potential issues related to BIM implementation for effective construction management.

Haider et al. [36] presented a detailed comparison between the manual and BIM-based cost estimation process. The study revealed that BIM-based (using Revit tool) estimation has displayed better performance over the traditional estimation methods. The study [24] coordinated the geometric data sharing of BIM to BPS while it was performed autonomously by integrating Agent-Based Modeling (ABM), occupant's comfort, and energy consumption. Putra et al. [37] researched the occupant behavior and comfort effect due to the load-shedding problem using the ABM and BPS tool (e.g., EnergyPlus) where the model claim was only verified rather than being validated. Prashant et al. [38] established a simplified framework based on thermal comfort using the Predicted Mean Vote (PMV) index. Thermal comfort simulations were performed using a BPS tool (e.g., Ecotect) for 14 diverse orientations and a type of available room layout based on window configurations at various locations in India. Another study [39] analyzed the predictable information and outcome generation after applying condition-based maintenance (CBM) using Weibull distribution. It was mainly used to model the distribution of equipment failures and the potential improvement of the information relating to hospital indoor environmental conditions for occupants' health. Based on the theoretical framework, this [40] case study described the benchmarking for revitalization projects. The study observed that occupants' tendency to preserve and revitalize their old buildings had increased. So, the study proposed new solutions that can help the revitalization of old constructions in the future and preservation of local construction wealth as well. Sang et al. [41] and Uddin et al. [42] analyzed the building envelope features of high-rise buildings in Hong Kong using a BPS tool (e.g., eQuest) by considering the static occupancy profile. Their research focused on cooling energy consumption that can be reduced significantly, as much as by 46.81%. Jung et al. [43] also used a BPS tool for analyzing an office building's indoor performance in three different climates.

Although a small number of studies have suggested coupling the simulating models (i.e., BIM and BPS) for better building performance using several frameworks or systems, it was carried out in a disintegrated way. Some studies [24,33,44] focus on independent coordination for data exchange between BIM and BPS through occupancy-based ABM or other modeling tools. Moreover, the above domain-specific engines and frameworks cannot guarantee the effective and efficient implementation of building performance studies during the early design phase due to the absence of a proper occupancy and validation approach. Furthermore, there are few above-mentioned studies that explain the importance of considering the building occupant comfort for building indoor modeling and they illustrate a limited research significance in regard to this matter. Although the importance and uncertainties of occupant satisfaction in buildings performance analysis are somewhat difficult to recognize, most of the research has paid no or little consideration to the indoor comfort level in BPS tools. It is also mentioned that the significant difficulty for the most prominent part of the building occupant studies is the absence of real data involvement [11,19]. It has rarely been seen that researchers validate their developed models utilizing real-world data [11,37]. Just a few ABM model validation tests have been seen in the previous literature.

3. Methodology

The flow chart of the research methodology used in this study is shown in Fig. 2. The flow chart represents the data exchange between the BIM-based model (Revit model), system dynamics, and agent-based modeling. The system dynamics and agent-based modeling were executed using AnyLogic modeling tool, an extensively tested simulation environment especially in sociology, business, and engineering fields. Typically, the required data are transferred from the BIM model to system dynamics and ABM model through the Dynamo-Excel platform. The outputs generated from the system are used for studying the individual comfort level and building indoor performance. As a flexible modeling framework, data may be customized within the model, as well as the other parameters/components being adjusted whenever required. In general, getting the required data from the BIM model for building performance study relies on two core systems, i.e., Industry Foundation Class (IFC) and Green Building XML (gbXML). The user of this system has limited control to process and load the required data files. To overcome these issues, Dynamo-API (Application Programming Interface) was used for the BIM-SD spectrum. Dynamo is a visual programming tool that works with BIM. Dynamo extends the power of BIM tools by providing access to the Revit API in a more accessible manner. It allows new users to generate specified programs by developing visual relationships between the several elements within a framework. Some of the previous studies [45,46] demonstrated a graphical visual programming interface, i.e., DynamoAPI, which stimulates the BIM-BPS interoperability. Hitherto, the data extraction contained mainly the building geometric features whereas the dynamic occupant incorporation within the building space had to be presumed as per energy code.

This study opposes the above-mentioned interface and describes a holistic framework for assessing the dynamic and diverse variation of an occupant's comfort using a BIM-based tool (i.e., Revit), SD, and ABM model. The comprehensive discussions on the proposed framework are described as follows.

The **first step** was the development of an architectural BIM model for a selected case study office zone in Hong Kong. The office is located at the northwest of the university campus; Faculty of Construction and Environment (Block Z), Hong Kong Polytechnic University. The essential data such as layout plans, floor, materials, and occupancy data were collected from the Campus Development Office (CDO) and the Facilities Management Office (FMO) of the campus. The **second step** was to develop a Dynamo-Excel platform that automatically generates the input data for the SD-ABM model. Here, the input data includes office wall area, floor characteristics, number of people, metabolic rate, airflow rate, etc. The **third step** involved designing a system dynamics model for generating the dynamic variation of indoor temperature (^{0}C) and CO_2 concentration (ppm). As a verification tool, the model atmospheric data such as outdoor maximum/minimum temperature and CO_2 concentration were obtained from the Hong Kong Observatory (www.hko.gov.hk). Here, the SD model progressed based on two formulas. The first formula (Equation (1)) was established by Givoni [47] for indoor temperature prediction for similar types of thermal mass as follows:

$$\mathrm{Tmax-in} = \mathrm{Tmax-out} - 0.31(\mathrm{Tmax-out} - \mathrm{Tmin-out}) + 1.6 \tag{1}$$

where,

$T_{max\text{-}in}$ = Maximum indoor temperature (^{0}C);
$T_{max\text{-}out}$ = Maximum outdoor temperature (^{0}C); and
$T_{min\text{-}out}$ = Minimum outdoor temperature (^{0}C).

The above formula applies to buildings with a continuous cross-ventilation system, where the maximum indoor temperature (i.e., $T_{max\text{-}in}$) leads to the variation of maximum outdoor temperature (i.e., $T_{max\text{-}out}$).

The second formula (Equation (4)) defines the current technique which is used in the ventilation and Indoor Air Quality (IAQ) study to estimate the amount of CO_2 generated by a building's inhabitants. Currently, the ASHRAE Fundamentals Handbook [48] and ASTM D6245 [49] define the rates of CO_2 generation as follows.

The oxygen consumption rate (L/s) per occupant is specified by Eq. (2),

$$\mathrm{Volume\ of} O_2 = \frac{(0.00276 * AD * M)}{(0.23 * RQ + 0.77)} \tag{2}$$

where,

AD = DuBois surface area (m^2);
M = Rate of metabolic (met); and
RQ = Respiratory quotient (dimensionless).

Usually, DuBois surface area (AD) is estimated from occupant height H (m) and the body mass W(kg) as follows (Equation (3)):

$$AD = 0.202H^{0.725} * W^{0.425} \tag{3}$$

So, the rate of CO_2 generation (L/s) per occupant is given by Equation (4),

$$\mathrm{Volume\ of\ } CO_2 = \mathrm{Volume\ of\ } O_2 * RQ = \frac{0.00276AD * M * RQ}{0.23 * RQ + 0.77} \tag{4}$$

The above-mentioned resulting indoor data (i.e., room temperature) generated by the SD model was further used to run the ABM model. So, the **fourth step** to create the ABM model that contains individual occupant comfort level (PMV value) with the dynamic variation of indoor parameters at different time intervals was followed by **the final step** to comprehensively model data validation approach. The detailed model implementation protocols are presented in Fig. 3 and Fig. 4. Moreover, Appendix A shows the sample code that defines the custom agent rules based on PMV indices (Table A1) and system dynamics variable for indoor performance study (Table A2).

4. Results & discussions

Using the developed hybrid model, multiple simulations were performed. The following figures (Fig. 5, Fig. 6, and Fig. 7) show the simulation outcomes of each category. These include individual comfort level, dynamic indoor/outdoor temperature, and CO_2 variation, as well as the stochastic nature of an occupant's presence in office space. Usually, the simulation outcomes were calculated at a 1-minute interval.

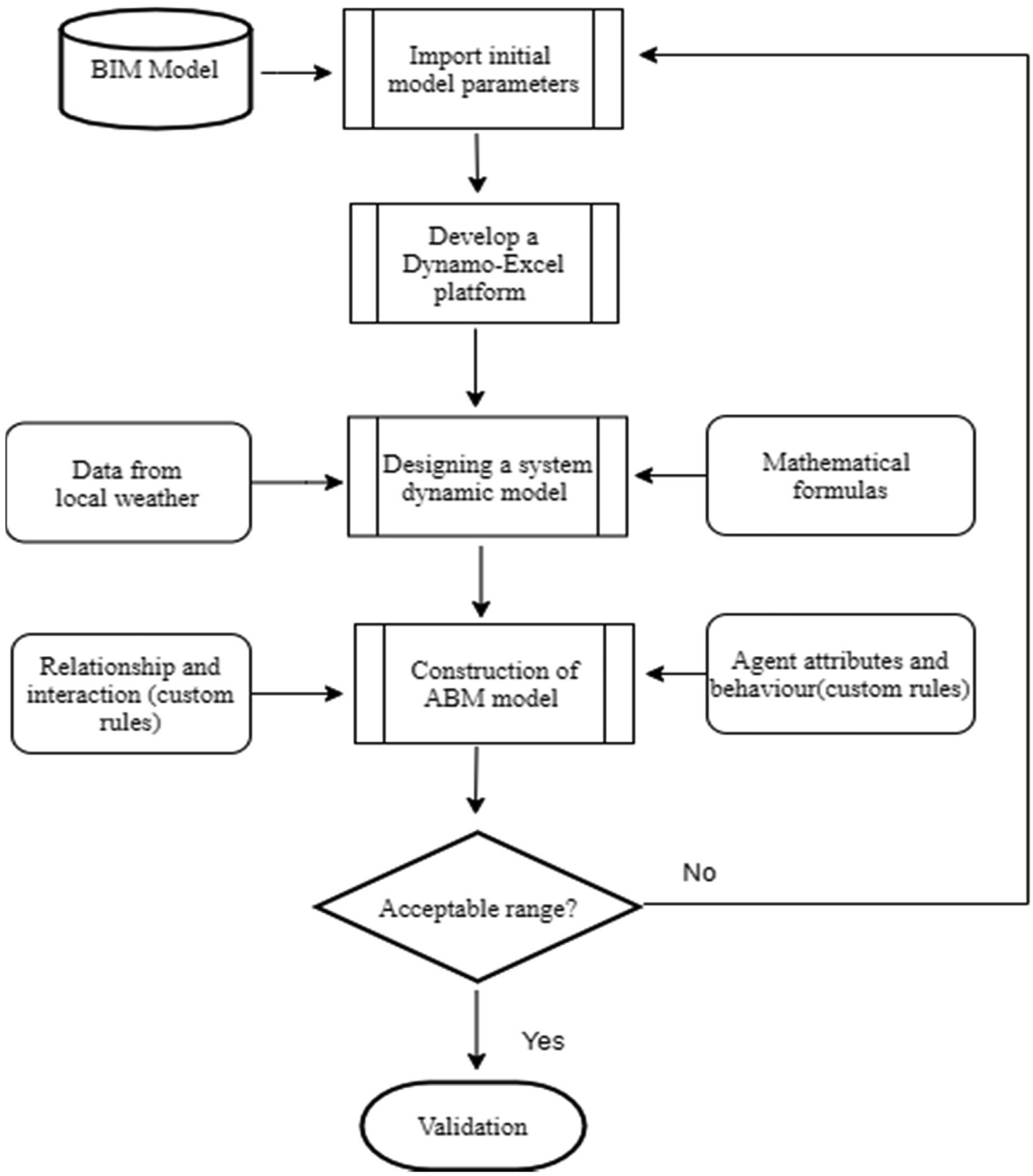

Fig. 2. A flow chart of the research methodology.

In general, indoor data in the office relate to an individual occupant's satisfaction level. The PMV value represents (Fig. 5) that the occupant comfort was not neutral (i.e., PMV = 0) throughout the simulation periods (both summer and winter) whereas it was slightly hot or cool in summer (Fig. 5: Left) and mostly cool during the winter season (Fig. 5: Right). It was also observed that model calculated thermal comfort indices repeatedly fluctuated due to indoor temperature, CO_2 concentration, and occupants' metabolic rate. There is a need to understand the relationship between PMV values, clothing level, indoor temperature, and CO_2 concentrations. In Fig. 5, a wide diversity of thermal conditions among the office occupants is significant. And offices with warmer temperatures during the winter necessarily required a greater number of occupants. For further validation, the actual PMV indices will be obtained for individual comfort level from cold (-3) to hot (+3), and the calculated PMV indices are averaged. This will describe how realistically the PMV indices can capture the actual comfort level under different seasons. Moreover, it also appears that the blunder is higher in the hot climatic region compared with the cold climatic region. It is possible because the occupants' tolerances for thermal conditions of the hot and cold regions are completely dissimilar. Since this model was designed in Hong Kong, which is located in a hot humid climatic region, the occupants who live in this zone may be more responsive to hot environments and have less tolerance of these conditions. Nevertheless, more specifically the indoor temperature and CO_2 concentrations are key factors dominating the occupant comfort level. Fig. 6 and Fig. 7 indicate the 10-day simulation outcomes of temperatures and CO_2 concentration as well. These outcomes reveal the 10-day indoor temperature and indoor CO_2 distribution in the office space which are quite steady.

Typically, a rise in indoor temperature in an office room is dependent on both the occupant number (due to metabolic gains form occupants' bodies) as well as the outdoor temperature intensity. In general, during the daytime, while the outside temperature and solar radiation are high, heat gains from the building envelope (i.e., windows, walls, etc.) raise the interior temperature. The variability of the indoor and outdoor temperature was observed and is shown in Fig. 6. The highest temperatures were found on June 1st, 4th, 5th, and 6th during the daytime with the maximum occupancy. Moreover, during this period, the CO_2 concentration level

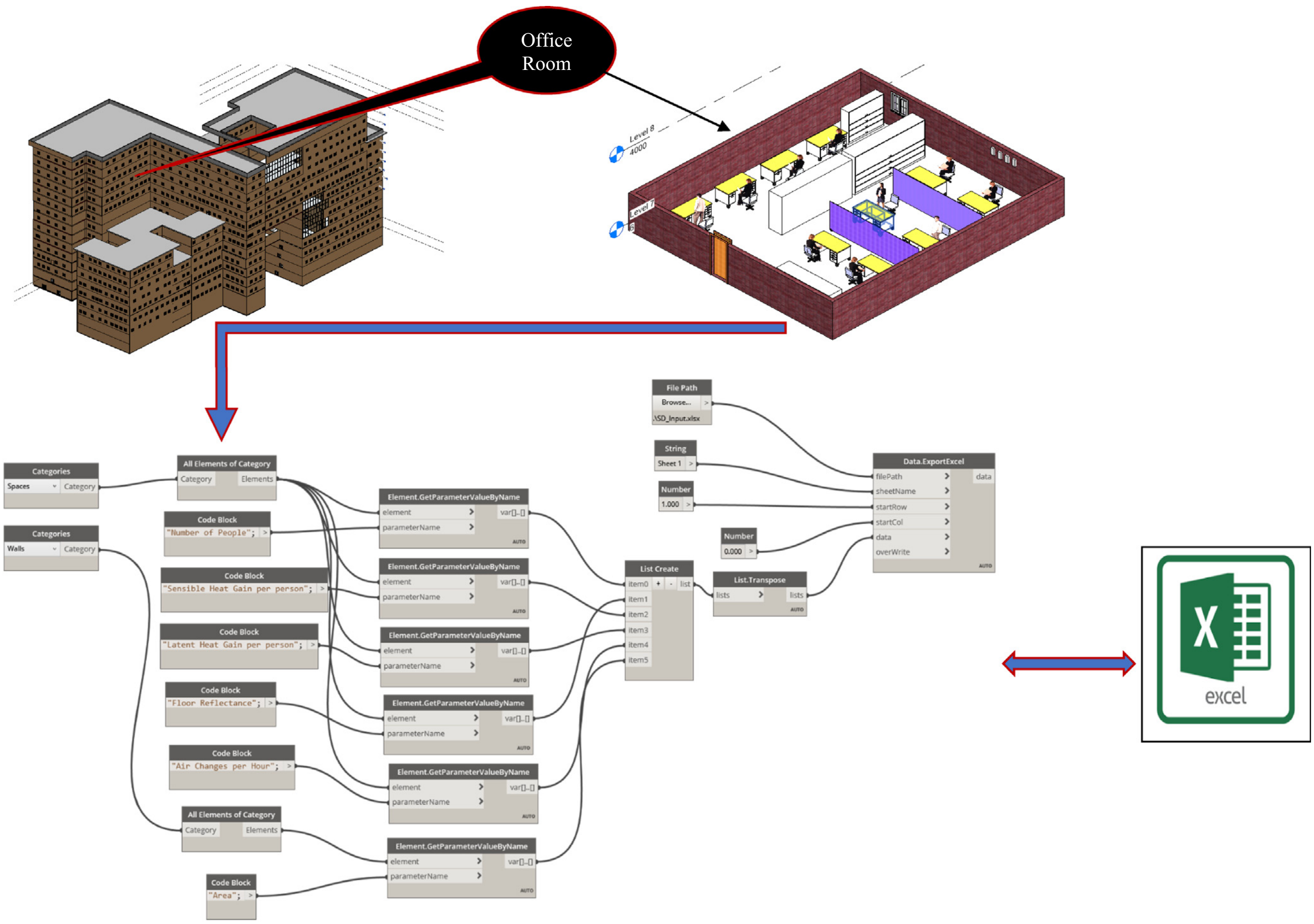

Fig. 3. Data exchange between BIM and Excel through Dynamo API.

and indoor temperature was also higher. Throughout the 10-day simulation period, the indoor temperature (^{0}C) in the office space was measured in the range of 18.31 °C to 20.97 °C where the outdoor temperature was measured in the range of 25.5 °C to 29.87 °C. The high increment of the outdoor temperature of 29.87 °C was recorded on June 1st while the interior temperature was stated to be 20.27 °C due to controlling HVAC and the tight infiltration system.

The consequences of measurements and model computations of indoor carbon dioxide level based on Equation (4) are presented in Fig. 7. For most of the days, the indoor CO_2 levels started at ~275 ppm and rose to a stable value within 10–20 mins. There is no proper correlation visible between the indoor CO_2 levels and number of occupants. But indoor CO_2 levels did not exceed 300 ppm for any of the days, staying below 285 ppm on most of the days. So, it indicated that the office had appropriate ventilation and air quality and were not a cause for occupant concern. Moreover, this value is accepted by the World Health Organization (WHO) as the maximum allowable value for indoor [50] environments. The highest level of outdoor CO_2 concentration observed for 10 days of the simulation period was June 10th (approximately 573.13 ppm). This is also a daytime fact when the office space is mostly occupied. Also, there is a higher fluctuation of natural factors and outdoor CO_2 contamination on consecutive days.

5. Validation and calibration tolerance

Validation and data reliability checking permit the systematic gathering of information about the object of study while taking into consideration the setting of information gathering. For these tasks, it is important that the depth and scope should be taken into consideration. As discussed earlier, the current office building model is a realistic building model located in Hong Kong, and its occupancy-based building performance was calculated using an automated platform of BIM, SD, and ABM approach. In this section, the above-mentioned platform which generated a data evaluation technique has been discussed. The purpose of this task was to verify the data validity/reliability as well as the robustness of the applied framework. Here the data verification study of computational outcomes was performed using the realistic data obtained from the office occupants as well as sensor data. Typically, real data are empirical, often called "true" data, and are considered a powerful validation tool [51]. In order for the results obtained from the automated platform to be reliable, the data from this framework must be within an acceptable limit as well [51]. Here, the validation and reliability checking in this study was mainly performed in two parts:

1. Validation and reliability checking for PMV indices and
2. Validation and reliability checking for environmental data (Temperature, CO_2, etc.)

Here, the data generated using the proposed framework were verified against the occupant survey (for PMV indices) and hourly data (e.g., sensor data for temperature, CO_2) generated from the real office building located in Hong Kong. In this process ASHRAE Guideline 14–2002 [52] and FEMP standards [53] were followed to check the calibration tolerance as well. This involved determining two dimensionless indicators of errors, such as Co-efficient of

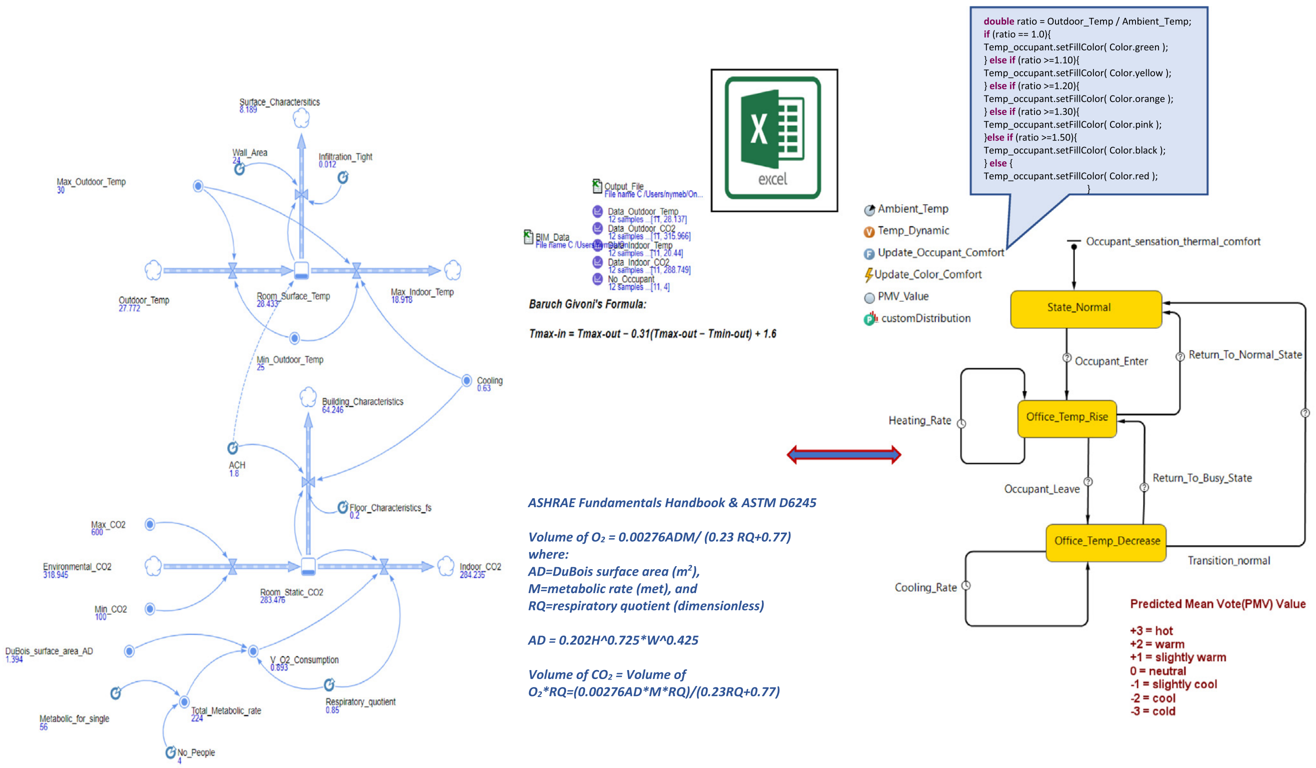

Fig. 4. Data exchange between SD (Left) and ABM (Right).

Variation of Root Mean Square Error CV(RMSE) and Mean Bias Error (MBE). Typically, the acceptable calibration tolerance of MBE and CV(RMSE) are ± 10% and 30% respectively while utilizing system-level calibration with hourly monitored data. The MBE and the co-efficient of variation CV(RMSE) were calculated and verified to be consistent with the ASHRAE and FEMP guideline. Eqs. (5) and (6) represent the formulas employed for RMSE and MBE, where n is the number of observations, Tavg.m. is the average monitored data for n observations, Ts is the simulated data for n observations, and Tm is the monitored data for n observations.

$$RMSE(\%) = \left(\frac{100}{Tavg.m}\right)X[\frac{1}{n}X\sum(Ts - Tm)^2]^{0.5} \quad (5)$$

$$MBE(\%) = \left(\frac{100}{Tm}\right)X\frac{1}{n}\sum(Ts - Tm) \quad (6)$$

5.1. PMV indices

Ten office occupants were enlisted for this validation study. These office occupants worked in a large office space situated in the Hong Kong Polytechnic University. The occupants comprised five males and five females of various nationalities. All the office occupants were within the age range of 23 to 32. The occupants were distributed an information sheet clarifying the study's aims and objectives. Meanwhile, the occupants' consent was obtained using the typical consent form. Afterwards, the occupants were asked to assess their thermal sensation based on ASHRAE seven-point scale from cold (-3) to hot (+3) as presented in Fig. 4 (ABM component). This was to collect the computed thermal sensation of the office occupants (-3 to + 3) known as Real Mean Vote (RMV). The occupants were requested to freely mark anywhere on the scale at every 20-minute interval. These are the values that Fangers' PMV equation tries to forecast. Finally, in order to investigate the model's validity, the model-generated PMV indices were compared to the real PMV data obtained from the office occupants. Fig. 8 indicates the model-calculated PMV indices and occupant-reported RMV indices for 20-minute intervals.

Generally, the prediction success of the earlier PMV model never exceeded 30% [54]. When the PMV fails to predict the occupant thermal sensation perfectly, it usually undervalues it, especially the occupant stochastic nature and air speed inside the space. In this study, the model-predicted PMV findings concur with the other previous studies from different regions as well [54–57]. Also, this study revealed that there is an acceptable calibration tolerance level of MBE and CV(RMSE) for both simulated and experimental comfort indices. The current values of MBE and CV(RMSE) are 0.35% and 2.70% respectively while the acceptable tolerance of MBE and CV(RMSE) are ± 10% and 30% respectively.

5.2. Model- and Sensor-Estimated temperature data

Indoor and outdoor environmental data collected using a customized sensor platform are shown in Fig. 9. The time interval for environmental data collection was approximately 1–2 h and these data were stored on a Micro-SD card. One of the key benefits of the customized sensor is its flexibility, and allows more sensors to be added whenever required.

Temperature computed from the model versus the actual temperature obtained from the sensors is plotted in Fig. 10. The model-predicted maximum and minimum indoor temperatures were 20.97 °C and 18.31 °C respectively whereas the sensor-recorded maximum and minimum indoor temperatures were 22.2 °C and 21.5 °C. The average difference between the maximum and minimum indoor temperatures was roughly 1.13 °C and 3.18 °C. This indicates that the model-predicted indoor temperatures were slightly lower than the actual temperature. Some other occupant comfort studies [58–60] also revealed several reasons for this discrepancy between the model- and sensor-predicted temperatures. The difference between the predicted and actual temperatures was

Fig. 5. The dynamic thermal comfort level for three occupants: Summer season (Left) and Winter season (Right).

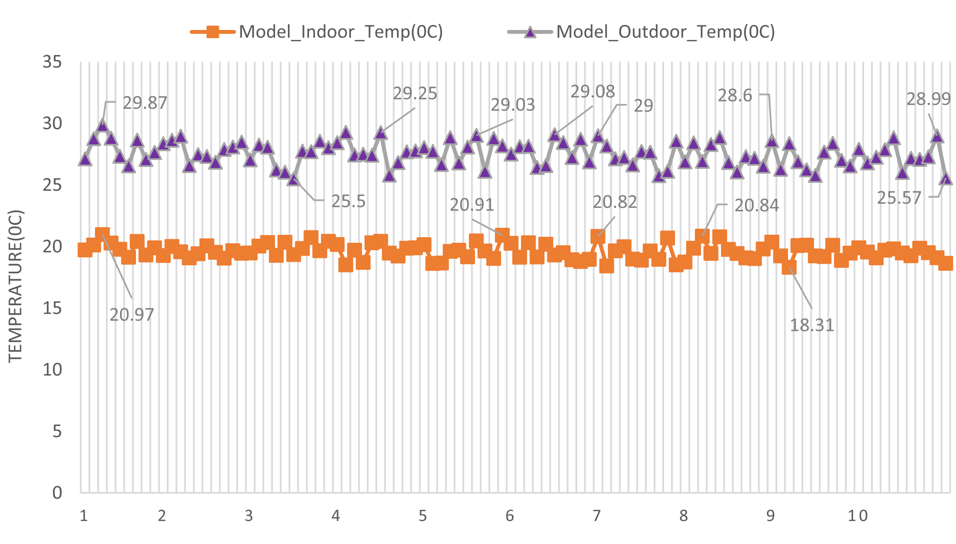

Fig. 6. Indoor and outdoor temperature (^{0}C) variation in office space.

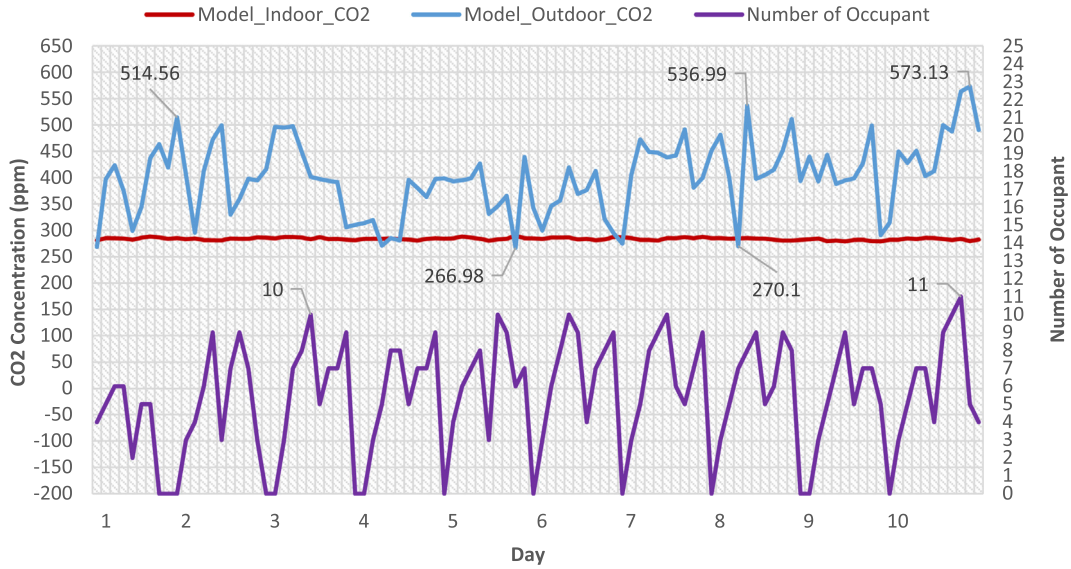

Fig. 7. Stochastic nature of occupants with indoor and outdoor CO_2 concentration (ppm).

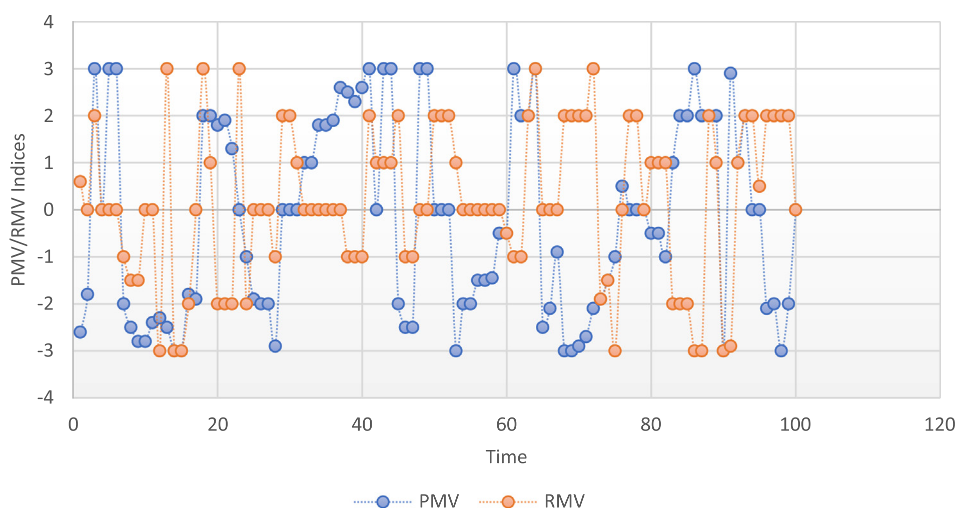

Fig. 8. Model-predicted PMV indices and occupant-reported RMV indices.

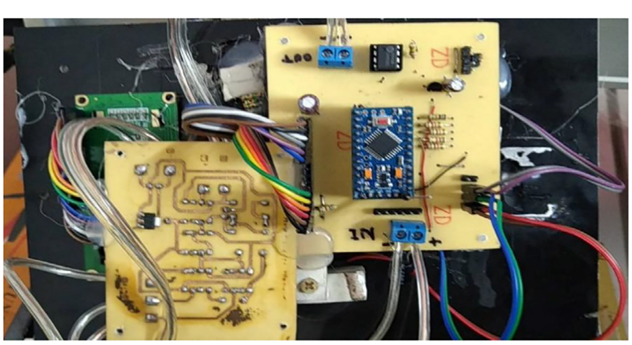

Fig. 9. Customized sensor panel.

also observed from these particular studies [56,61,62] as well. Naramura's [61] study revealed that the influence on the curve of indoor temperature trend is about 0.24 °C/5 min in the predictive model and about 0.28 °C/5 min in the calculated results. Also, in Smith et al. [62], the predictive model error was within ± 2 ○F (±1.11○C) of ground truth.

Some possible reasons for this error or discrepancy include the random door operations, a computer or other electronic device turns on for a longer period of time, and window or blind operation with the constant alternation of opening or closing during the experiment. Also, the model did not consider any heat loss/heat gain or infiltration issues during the simulation process. On the other hand, it has been observed that the proposed model offered an acceptable range of RMSE (2.73%) and MBE (-2.28%) for indoor temperature evaluation as compared with other previous studies [63,64]. Hence, the computational effects of the integrated framework may be regarded as correct as no additional calibration is required. Turning to the assessment of outdoor temperature, there was a very slight difference between the model- and sensor-estimated outdoor temperatures as the model employed atmospheric data from the local weather station. The model-estimated maximum and minimum outdoor temperatures were 29.87 °C and 25.5 °C respectively whereas the sensor-estimated maximum and minimum outdoor temperatures were 28.20 °C and 25 °C correspondingly. It is also noted that the RMSE and MBE values for outdoor temperature were 1.20% and 0.45% respectively which lie within an acceptable limit.

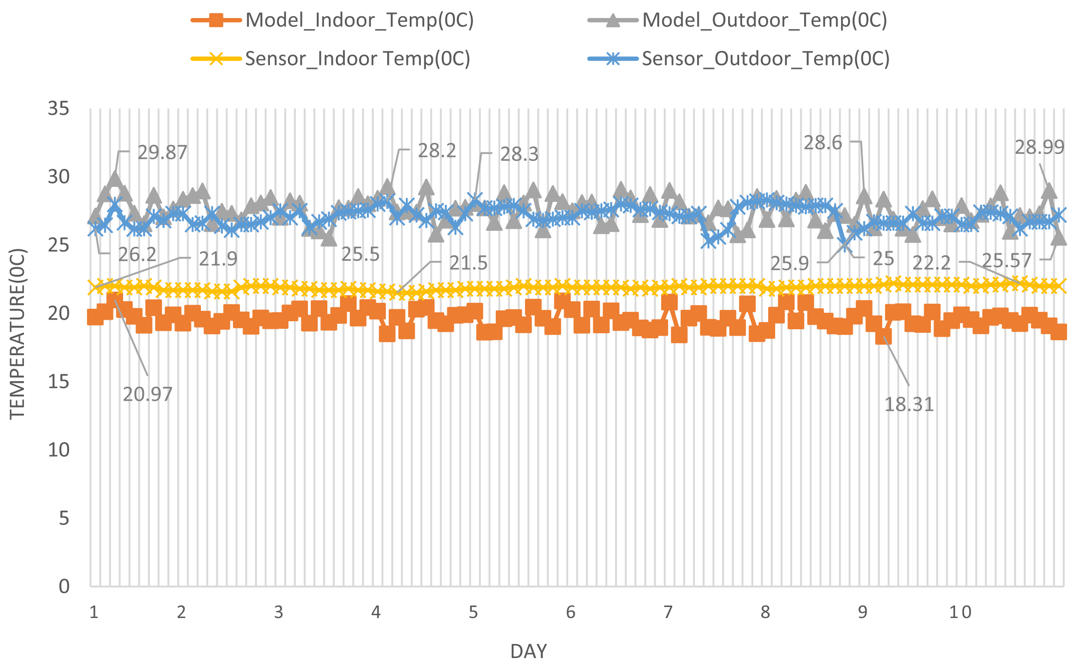

Fig. 10. Model-predicted and sensor-calculated indoor and outdoor temperatures (^{0}C).

5.3. Model- and sensor-estimated CO_2 data

Fig. 11 shows the indoor and outdoor CO_2 variations for the simulated model and the real data obtained from the CO_2 sensor. The results show that the simulated model slightly underestimated both the indoor and outdoor CO_2 level. The maximum and minimum simulated outdoor CO_2 concentrations for this study were 514.56 ppm and 266.98 ppm respectively while sensor-estimated maximum and minimum outdoor CO_2 were 580 ppm and 255 ppm, correspondingly. However, there is a significant gap between the simulated and sensor-estimated indoor CO_2 concentration data. Sensor-estimated indoor CO_2 data provided a higher level of variation (for June3rd, June4th, June 8th, and June9th) than model-estimated indoor CO_2 level. A study [65] also showed a similar discrepancy of hourly CO_2 value for three monitored rooms (i.e., office 1, office 2, and library room) in Singapore. Nesibe et al. [66] also found a similar gap between the measured and predicted CO_2 concentration while ignoring the occupants (i.e., students). However, here the stochastic nature of occupant presence, and indoor and outdoor CO_2 level during the HVAC operation were derived from both the model and experimental records. Turning to RMSE and MBE checking, the outdoor CO_2 level (RMSE: 25.94%, MBE:10.01%) was more significantly deviated than indoor CO_2 level (RMSE: 19.22%, MBE: −9.47%). However, in all cases,

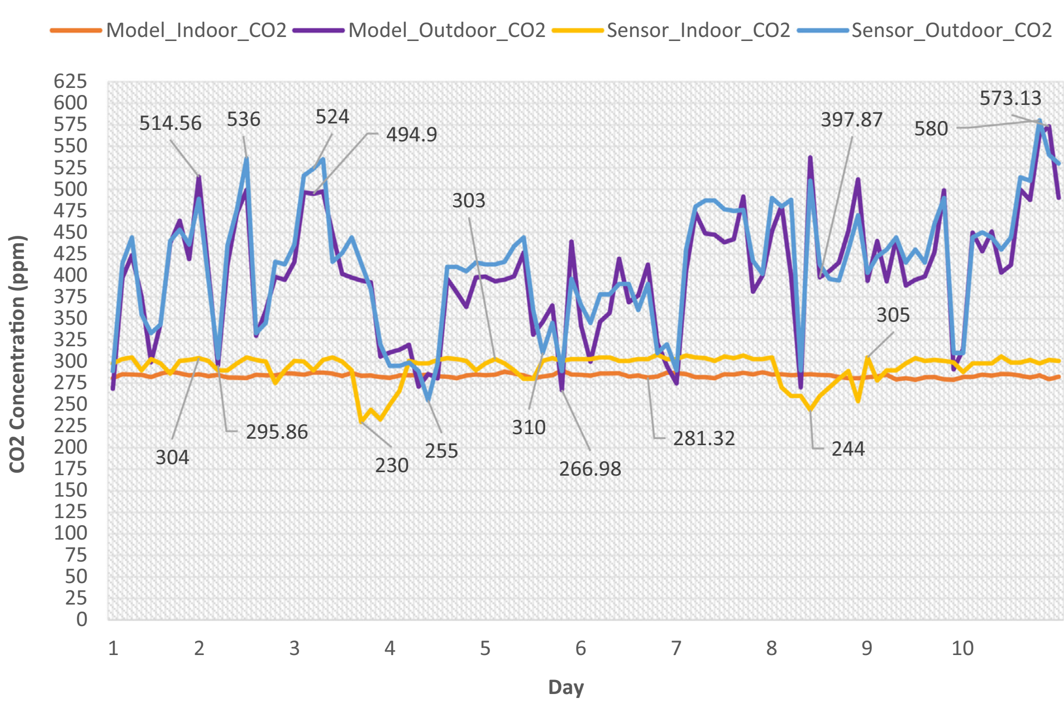

Fig. 11. Model-predicted and sensor-calculated indoor and outdoor CO_2 (ppm).

CV(RMSE) and MBE values lay within the acceptable range. This study [67] also has shown a higher value of CV(RMSE) and MBE for an office building model located in Turkey. Several factors may be involved in this issue, for instance, Hong Kong is a hot-humid climatic zone, and there was a sudden change in the weather conditions during the experiment, i.e., sudden rain, clouds outside of the room, the office occupants may still keep the window open even though the indoor environment is only a little comfortable, or highly stochastic movement of occupants in the office space. Similarly, blinds operation and the control of doors are also influenced by environmental factors. So, further model improvement may require the resolution of these issues.

6. Conclusions and future work

This study proposes a combined framework to integrate building indoor performance and human comfort simulation with the help of emerging BIM and SD-ABM models. The demonstrative example presented a new modeling framework in the field of building occupant study. The case study model along with the validation and reliability test were implemented in a realistic educational office building to represent the applicability and robustness of the framework. The proposed framework allows the estimation of several key parameters, namely occupant presence and comfort level in terms of PMV indices, indoor/outdoor temperature, and CO_2 concentration. Although some major to minor variations occurred between the observed and modeled data, most of the data fell within the calibration tolerance (i.e., RMSE and MBE) limit defined by ASHRAE Guideline 14–2002 and FEMP standards. Thus, the research aim was satisfied by establishing a hybrid framework and evaluating the realistic profile as well as analyzing building performance in depth. The outcomes established that the preferred parameters could be suitably determined and accomplished in other building spaces as well. The study also presents a more precise dynamic building indoor performance and occupant comfort transformation between the BIM and SD-ABM which significantly improved the conventional BPS-based modeling. Furthermore, it enables building geometry development in the simulation framework and helps engineers, researchers, and policymakers to improve building design. However, a limitation of the study was the fact that due to procedural constraints, only hourly environmental data could be obtained. So, it is appropriate to assume that a higher sampling frequency of data will produce more comprehensive output. Moreover, in order to improve the model's accuracy and efficiency, further inclusive and diverse real-world building projects are required. So, future study will expand the framework (additional behavioral rules will be recognized and added to the framework) with test cases to cover other building models, including occupants and their adaptive behavior as well.

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.

Table A1
Agent-Based Modeling (ABM).

@Override
public void executeActionOf(TransitionCondition self) {
if (self == Occupant_Enter) {
exitState(State_Normal, self, true);
enterState(Office_Temp_Rise, true);
return;
}
if (self == Occupant_Leave) {
exitState(Office_Temp_Rise, self, true);
enterState(Office_Temp_Decrease, true);
return;
}
if (self == Return_To_Busy_State) {
exitState(Office_Temp_Decrease, self, true);
enterState(Office_Temp_Rise, true);
return;
}
if (self == Transition_normal) {
exitState(Office_Temp_Decrease, self, true);
{
Outdoor_Temp = Max_Indoor_Temp
;}
enterState(State_Normal, true);
return;
}
if (self == Return_To_Normal_State) {
exitState(Office_Temp_Rise, self, true);
{
Outdoor_Temp = Max_Indoor_Temp
;}
enterState(State_Normal, true);
return;
}
super.executeActionOf(self);
}
	@Override
	public boolean
	testConditionOf(TransitionCondition _t) {
	if (_t == Occupant_Enter) return
	PMV_Value>1
	;
	if (_t == Occupant_Leave) return
	PMV_Value<1
	;
	if (_t == Return_To_Busy_State) return
	PMV_Value>1
	;
	if (_t == Transition_normal) return
	PMV_Value>=0
	;
	if (_t == Return_To_Normal_State) return
	PMV_Value>=0
	;
	return super.testConditionOf(_t);
	}

Table A2
System Dynamics (SD).

Static Variable	Dynamic Variable

@Override
public boolean setParameter(String _name_xjal, Object _value_xjal, boolean _callOnChange_xjal) {
switch (_name_xjal) {
case "Ambient_Temp":
if (_callOnChange_xjal) {
set_Ambient_Temp(((Number) _value_xjal).doubleValue());
} else {
Ambient_Temp = ((Number) _value_xjal).doubleValue();
}
return true;
case "Infiltration_Tight":
if (_callOnChange_xjal) {
set_Infiltration_Tight(((Number) _value_xjal).doubleValue());
} else {
Infiltration_Tight = ((Number) _value_xjal).doubleValue();
}
return true;
case "Respiratory_quotient":
if (_callOnChange_xjal) {
set_Respiratory_quotient(((Number) _value_xjal).doubleValue());
} else {
Respiratory_quotient = ((Number) _value_xjal).doubleValue();
}
return true;
case "Wall_Area":
if (_callOnChange_xjal) {
set_Wall_Area(((Number) _value_xjal).doubleValue());
} else {
Wall_Area = ((Number) _value_xjal).doubleValue();
}
return true;
case "Metabolic_for_single":
if (_callOnChange_xjal) {
set_Metabolic_for_single(((Number) _value_xjal).doubleValue());
} else {
Metabolic_for_single = ((Number) _value_xjal).doubleValue();
}
return true;
case "Floor_Characteristics_fs":
if (_callOnChange_xjal) {
set_Floor_Characteristics_fs(((Number) _value_xjal).doubleValue());
} else {
Floor_Characteristics_fs = ((Number) _value_xjal).doubleValue();
	// Dynamic (Flow/Auxiliary/Stock) Variables
	public double Outdoor_Temp;
	public double Max_Indoor_Temp;
	public double Indoor_CO2;
	public double Environmental_CO2;
	public double Building_Characteristics;
	public double Surface_Charactersitics;
	public double Min_Outdoor_Temp;
	public double Max_Outdoor_Temp;
	public double PMV_Value;
	public double Max_CO2;
	public double Min_CO2;
	public double V_O2_Consumption;
	public double DuBois_surface_area_AD;
	public double Total_Metabolic_rate;
	public double Cooling;
	public double Room_Surface_Temp;
	public double Room_Static_CO2;

}
 return true;
 case "ACH":
 if (_callOnChange_xjal) {
 set_ACH(((Number) _value_xjal).doubleValue());
 } else {
 ACH = ((Number) _value_xjal).doubleValue();
 }
 return true;
 case "No_People":
 if (_callOnChange_xjal) {
 set_No_People(((Number) _value_xjal).doubleValue());
 } else {
 No_People = ((Number) _value_xjal).doubleValue();
 }
 return true;
 default:
 return super.setParameter(_name_xjal, _value_xjal, _callOnChange_xjal);
 }
 }	

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Appendix

(Table A1 and Table A2)

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