AMERICAN UNIVERSITY OF BEIRUT

AN AGENT-BASED FRAMEWORK FOR STUDYING OCCUPANT MULTI-COMFORT LEVEL IN ACADEMIC BUILDINGS

by
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AN ABSTRACT OF THE THESIS OF

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With the trend towards low energy or energy efficient buildings that diminish fossil fuel usage and carbon emissions, getting occupants actively involved during the design and operation phases of buildings is vital in achieving high energy performance without jeopardizing occupant satisfaction or comfort level. However, recent tools did not examine simultaneously, while considering different occupant behavior types, visual, thermal and acoustic comfort levels. This paper presents work targeted at efficiently studying occupant multi-comfort level using agent-based modeling with the ultimate aim of reducing energy consumption within academic buildings. The proposed model was capable of testing different parameters and variables affecting occupant behavior. Several scenarios were examined and statistical results demonstrated that (1) the presence of different occupant behavior types is deemed necessary for a more realistic overall model , (2) the absence of windows results in an acoustic satisfaction with an increase in HVAC off and medium level uses, and high lighting usage, and (3) the overall light usage decreases when two light switches instead of one are introduced.

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ABBREVIATIONS

BIM	:	Building Information Modeling
ABM	:	Agent Based Modeling
LEED	:	Leadership in Energy and Environmental Design

CHAPTER 1

INTRODUCTION

1. Background

With the expected increase in global population by 39% in 2035 [1], relying on new renewable resources of energy such as solar energy, wind energy, wave energy among many others has become imperative. Besides opting for alternative energy resources, current use of energy should be optimized [2]. Recently, attention has been placed on energy efficient buildings. Although several types of buildings exist, targeting the commercial type, in particular academic buildings, is of paramount importance, as the occupants seldom have the incentive to reduce their energy consumption [3-7].

For this purpose, several building energy optimization tools were created and are categorized into two main groups: (1) tools that assessed the relative energy performance of design alternatives [8-13], and (2) tools that evaluated the impact of occupant behavior in improving energy consumption estimates of design alternatives and optimizing energy use at the building operation phase [4-6, 14-21].

However, these tools did not examine simultaneously, while considering different occupant behavior types, visual, thermal and acoustic comfort levels.

2. Objectives and Scope of Work

The overaching objective of the present study is to design and implement a comprehensive framework aiming at studying occupant multi-comfort level in academic buildings using agent-based modeling. Four specific interim objectives are identified in the proposed initiative:

- Understand the effect of environmental space conditions on occupant behavior through varying conditions separately
- Study how dependent relationship among all comfort levels (thermal, visual and acoustic) would impact energy consumption
- Understand why different occupant behavior types (green, neutral, non-green) should be considered
- Understand the emergent effect of occupants interaction within the space

3. Thesis structure

Besides this introductory chapter, the thesis consists of two appendices which include the detailed results, discussions and conclusions.

- Appendix A is a review article. It is a detailed critical review of the literature on tools developed to optimize energy in commercial buildings.
- Appendix B is a research article. It presents the proposed framework and the ABM model developed in addition to the statistically analyzed results.

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APPENDIX A A Review of Building Energy Optimization Tools

ABSTRACT

This paper presents a review of published research articles that focused on energy consumption within commercial buildings. The presented papers are categorized into two main groups that include (1) tools that assessed the relative energy performance of design alternatives, and (2) tools that evaluated the impact of occupant behavior in improving energy consumption estimates of design alternatives and optimizing energy use at the building operation phase. The objective of this study is to shed light on what have been developed in the field of commercial buildings and energy optimization and provide future researchers with access to relevant and diverse body of prior research efforts. The review revealed that there is substantial room for improvement and adoption of new tools to further optimize energy consumption within commercial buildings, in particular academic buildings.

KEYWORDS

Energy Consumption, Energy Optimization, Buildings, Occupant Behavior, Comfort Level

A.1. INTRODUCTION

This paper aims at summarizing published work on the topic of energy optimization in commercial buildings. The review is divided into two main sections covering (1) tools that assessed the relative energy performance of alternative designs, and (2) tools that evaluated the impact of occupant behavior in improving energy consumption estimates of design alternatives and optimizing energy use at the building operation phase. In each main section, the available tools and a summary of the methodologies, were discussed. The main objectives of this paper are thereby to (1) gather, in one resource, published articles from the field of building energy optimization to provide future researchers with rapid access to information, (2) present recent tools and methodologies developed to optimize energy use in commercial buildings, and (3) provide a summary of the major findings from this set of papers and highlight the needs for future research.

A.2. LITERATURE REVIEW

The rapid increase in energy consumption and the limited resources of non-renewable energy triggered researchers to look for new resources in order to fulfill the needs of future generations. With the expected increase of the population by 39% in 2035 [1], people had to search for new renewable resources of energy such as solar energy, wind energy, wave energy among many others. Besides finding new energy resources, current use of energy should be optimized. According to Yang et al. [2], reductions in energy expenses and decrease in the environmental pollution may be achieved by reducing consumption of building's energy. For clarification, people spend more than 90% of their time indoors [3]. Consequently, 40% of the global energy is consumed by buildings [4-7]. Therefore, energy consumption should be optimized to limit the current and future use of energy in buildings which will increase by 19% [8].

Although there are several types of buildings, targeting commercial ones is most important. Occupants of commercial buildings do not have any incentive to save energy. They focus more on completing their jobs rather than on saving energy [9]. Consequently, it was stated that energy consumed during nonworking hours is typically more than half of the total energy consumed by commercial buildings [7, 10]. This is mainly due to behavior of occupants such as keeping electrical devices, HVAC, appliances and lights on when leaving. Specifically, university and office buildings consume the highest energy among commercial buildings [7]. Thus, there is a huge room to optimize energy consumption through conserving energy during the operation phase and improving the design of buildings as well to be more energy friendly.

There are several possible ways to reduce energy consumption of buildings such as coming up with better designs that would consume less energy. In order to estimate the amount of energy that would be consumed, several energy simulation tools were developed. These tools aided engineers at the design phase to assess their designs from the perspective of energy consumptions. Some of these tools are Green Building Studio, eQuest, EnergyPlus, and many others. In general, these simulation tools take the building geometry and materials to estimate how much energy would be consumed. However, when more than one design alternative is present, it would not be efficient to do multiple models and evaluate each one separately. Therefore, researchers investigated several approaches to find tools that would inspect all available alternatives and choose the most suitable one.

A.2.1 Tools that assessed energy performance of design alternatives

Traditionally, architects and civil engineers are the main parties involved at early stages of the design phase. After developing the full design of the project, both parties forward the project to mechanical engineers. However, when mechanical engineers intervene at a late stage in the design phase to apply energy analysis, any proposed solution would incur a relatively huge cost with a minor influence. On the other hand, the new arising technology of BIM allows all parties in the project to share the same model and to get involved in the design of the project from the very beginning [11]. Therefore, mechanical engineers were capable of testing several energy saving alternatives at early stages. As a result, applying any of these alternatives would be highly effective with a considerable construction cost [12]. These alternatives were explored using energy simulation tools such as Blast, EnergyPlus, Trace, eQuest among many others [11]. In order to improve the coupling between BIM tools and energy simulation tools, gbXML was created to exchange energy information. The availability of this combined technology facilitated the advancement in the field of energy and buildings. When considering different alternatives, engineers usually target the option that optimizes energy most. However, this option might greatly increase construction costs. Therefore, Chen and Gao [13] stated that a tool should be developed in order to choose the alternative that optimizes both energy consumption and construction costs. Thus, a multi-objective generic algorithm was used since it minimizes several variables at the same time. In order to do so, a group of possible solutions should be proposed. The algorithm forms possible combinations and tests each one. The one with minimum output cost and highest energy savings is chosen. This approach was developed using Autodesk Revit, Integrated Energy Solutions (IES) and Matlab optimization tool [13]. The BIM model of the project under question was created using Autodesk Revit. A gbXML format of the BIM model was then exported and imported into IES. Within IES, the total energy consumption per year was obtained. From the obtained results, Chen and Gao [13] created empirical formulas that were used to estimate the energy performance of all possible design combinations. In addition to energy consumptions, construction costs had to be estimated. Hence, it was obtained from RSMeans online database [13]. As an application of this approach, Chen and Gao [13] considered building orientation with respect to the true north and windows to walls ratio as design variables. Using the proposed methodology, the best combination of both variables was obtained.

Similar to what have been discussed before, Nour et al. [14] developed a tool that is capable of finding the most feasible building design based on the selection of building materials. With the huge variety of materials available to be used in buildings, researchers studied the use of energy efficient ones to optimize energy consumed [14, 15]. In the study done, different types of windows, walls, insulating materials and roof segments were considered. As a start, quantity takeoff for all elements used was done using Autodesk Revit. Then, random combinations of all options available were created. In order to assess all combinations, a while loop using Java engine was generated. Within this loop, energy consumption and life cycle cost (LCC) were estimated using EnergyPlus and LCC databases respectively. Thus, the ultimate combination of all materials was chosen and transferred back to the BIM model for update [14].

When applying any similar tool to what had been discussed earlier for energy simulation and optimization, the user was obliged to leave the BIM platform and open another energy simulation tool. Hence, a simulation tool capable of combining both platforms was created within Autodesk Revit [16]. To achieve this, information from the BIM model should be read by the energy simulation plugin. However, some information in the BIM model might not be important to be delivered to the energy model and vice versa. For illustration, a room in the BIM model does not always resemble a thermal zone [16]. On the contrary, the information about the thermal zone limits, that is required by the energy simulation tool, is not present in the BIM model. Consequently, a certain level of information translation was required in order to have a fully developed building energy model that can be tested using the energy simulation plugin within Revit. For this reason, Revit2Modilca library was used to fulfill the above mentioned objective. Upon using the modified model information, energy simulation was done using Dymola that is an Integrated Development Environment for Modelica [16]. Finally, results and plots of the simulation were reported within Autodesk Revit user interface. Using this plugin would facilitate engineers’ work and increase interoperability between modeling tools and energy simulation tools to get more reliable results.

In addition to design improvements and energy optimization, some parties aimed further to have LEED (Leadership in Energy and Environmental Design) certified projects. To be eligible to obtain this certification, the project should have a sustainable design achieving a number of LEED points. According to points collected, the project can be classified as a LEED certified, LEED-silver, LEED-gold or LEED-platinum. Consequently, there will be lots of requirements regarding building materials and many others. If referring to these requirements would take place at a late stage of the design phase, then it would be very difficult to fulfill it as discussed earlier. Therefore, two tools that carry out energy optimization and attain LEED points at an early stage in the design phase were generated [12, 17]. As an illustration, Jalaei and Jrade [12] states that analyzing consumption of energy at the conceptual design phase allows engineers to make better decisions regarding the selection of the most applicable sustainable design. For this purpose, an external database for material families was created to be used in Autodesk Revit. Using these materials, a BIM model was drawn using Autodesk Revit. Moreover, a plugin was developed to export a gbXML and IFC files and to import it to the ECOTECT energy simulation tool that is called automatically as well. Finally, cost and LEED points were calculated directly through getting bill of quantities and detailed information about every component from the BIM model. In like manner, Bank et al. [17] developed another tool that created a link between Anylogic and Revit to transfer data and to implement the optimized alternative. This link was created between a system dynamics decision making software and a BIM software. The transferred data was used to make decisions regarding design alternatives. These decisions were optimized to offer the most suitable sustainable building design. Using proper sustainability indicators, decisions were made and transferred back to the BIM model in order to apply components modifications.

A.2.2 Tools that used Occupant Behavior for Estimating and Optimizing Energy Consumption

Although the aforementioned developed tools were capable of assessing design alternatives, estimated figures of energy consumption obtained from these tools deviate from the actual energy consumed by 30% to 40% [18]. This is due to the fact that current building energy modeling tools do not consider the effects of occupant behaviors on energy. Instead, it considers fixed occupancy schedules and fixed environmental conditions. Therefore, these estimations may underestimate or overestimate what energy would actually be consumed during the operation phase of the building lifecycle. On the other hand, studies showed that occupant behavior has considerable effect on energy consumption [9, 19]. If these behaviors are properly oriented, it can reduce energy consumption significantly up to 40% of the total energy consumed [5, 18].

Occupant behavior is defined as the actions taken to increase the level of satisfaction which will affect the level of energy consumed. In commercial buildings, the use of energy would be direct through using personal electrical appliances. However, the use of HVAC system, lights, water system and other services are considered to be indirect use of energy. Studies showed that a change in occupant behavior may result in higher energy savings than implementing new technological solutions [10]. Therefore, several parties focused on studying the impact of the occupants' behavior on energy use. This was done using agent based modeling.

Agent based modeling is one of the most powerful simulation techniques that has been developed lately [20]. This technique allows researchers and users to simulate real life systems by looking to its constituent units. These units are called agents whereby every agent, a member of a group of decision making individuals, within this environment will have its own properties that will trigger it to act in a similar way to what it would have done in real life [21]. This heterogeneity in agents' abilities and features illustrates the differences in their behavior towards dealing with a certain situation [5]. Beside their features, agents' behavior is influenced by the factors present in the surrounding environment. Although agents' behavior can be modeled using other techniques, agent based modeling is the best among others due to its emergent property, naturality and flexibility [21]. First of all, ABM offers the emergent property. It is not only important to know the behavior of the single agent. On the contrary, applying any idea on a group of agents and looking on their behavior as independent agents gives a wrong vision of what would actually happen if this idea were to be implemented. People decisions in real life are not only affected by their individual properties and the surrounding factors but also by their interaction with other agents. In other words, a personal network of an agent affects its behavior [5]. Therefore, when looking for the behavior of any agent, it is highly important to place all agents within one environment and allow them to interact in order to know the emergent behavior of the system as a whole. When doing so, it becomes possible to get a more reliable simulation of what would actually happen when implementing any idea [22]. Moreover, naturality and flexibility of ABM is another powerful property. Instead of transforming a behavior to mathematical equations which is quite cumbersome, it is more natural to represent it as a behavior of an agent. By this, it becomes more flexible to visualize all agents while adding parameters and variables to the system rather than coming up with textual information such as complex equations. There are several platforms that adopt agent based modeling. However, the programs that were mostly used by researchers are Anylogic, NetLogo and Matlab.

Therefore, when testing what-if scenarios, it is highly important to study the impact of each case on both building and occupants. Consequently, Andrews et al. [9] came up with a modeling framework that was capable of assessing alternatives at the operation phase. First of all, the building geometry was modeled using Google SketchUp. Then, the building model and building systems (HVAC, lighting, etc.) were entered into OpenStudio. Using these information, the energy model of the building was created using EnergyPlus. In order to reduce deviations from actual energy consumptions, the energy model was calibrated using utility bills and other objective data. Additionally, occupant behavior was modeled using NetLogo based on survey data. The EnergyPlus and NetLogo models were integrated and recalibrated since applying any alternative would have an effect on building energy consumption and on occupant behavior. Finally, all sub-models were linked together using a connective tissue of Java code to form a dynamic simulation system [9]. Eventually, what-if scenarios were considered and the output was analyzed to choose the best alternative. Although applying new technologies or testing different design alternatives might reduce energy consumption, changing occupant behavior is another way to save energy [5].

In general, the behavior of a person is highly affected by his/her social network. Therefore, Jain et al. [6] indicated that social influence motivates energy savings. More precisely, users were encouraged to adopt a green friendly energy behavior. Therefore, it is important to show the change in occupant behavior with time in energy simulation tools rather than taking it to be static [6, 18, 23].

Energy consumption campaign and peer to peer effect are two factors that influence energy consumption behavior of occupants positively [18]. An energy simulation model was established by Azar and Menassa [18] to study the impact of the above mentioned factors. Occupants within this model had three different energy consumption behaviors: high energy consumers, medium energy consumers and low energy consumers. Each behavior had a unique energy consumption rate and an initial level of influence that were imported into the agent based model. With every iteration of the model, the level of influence of energy behaviors will be updated according to the interaction of occupants with the environment and with other agent in the space. Consequently, the number of occupants in each category will be updated. Finally, using the rates imported, energy consumption of each category is calculated. The model keeps iterating until total simulation time is reached. Upon adding the two influencing factors, electrical consumption dropped by 25.2% and gas consumption dropped by 4.7% [18]. Thus, it is highly important to model occupants with different energy behaviors that change over time.

For further minimization of the deviations of building energy simulation outputs, Menassa et al. [24] developed the model created by Azar and Menassa [18] further and coupled it with energy simulation tool. Azar and Menassa [18] recognized that the agent based model can account for different energy behaviors but it cannot get actual energy consumption rates. On the other side, DOE2, an energy simulation federate, lacked the ability to account for different energy behaviors but it is capable of estimating actual energy consumption rates. Therefore, Menassa et al. [24] developed a model whereby it coupled the DOE2 federate with the agent based model federate to overcome the deficiencies present in each tool. The coupling was achieved using CERTI implementation of high-level architecture. In order to facilitate the flow of information between DOE2 federate and agent based model federate, two parameters, energyConsumption and behaviorLevel, were defined in CERTI. The model worked as follows. First of all, the building model was imported into the DOE2 federate. This federate performed energy simulation and exported energy consumption rates. The ratio of the obtained rates to the actual energy consumption rates was saved as the energyConsumption parameter in CERTI federate. Within the agent based model, green and non-green occupants were considered. The energyConsumption parameter was then imported to the agent based model as the level of influence of green occupants. However, the level of influence of non-green occupants was assumed to be between 0 and level of influence of green occupants. Based on the obtained actual figures, the Anylogic federate, the federate of the agent based model, ran the simulation to update number of occupants in each category based on the previously mentioned interactions. The obtained number of green and non-green occupants was then exported to the CERTI federate to be saved as behaviorLevel parameter. Then, this parameter was imported to the DOE2 federate where every category had its own energy use characteristics. Based on the number of both categories, the total energy consumption was estimated again and the ratio of estimated consumption rates to the actual rates were then saved as energyConsumption parameter. Similarly, the model kept on recapitulating until the energy consumption estimated reach the actual one.

In addition to external factors, achieving great comfort levels is one of the most important factors that affects the behavior of occupants. An occupant in a building might be disssatisfied due to the conditions of the system he is in. For example, if the temperature in the room was high enough, the occupant will feel hot. As a result, he might either turn the HVAC or open the window. Consequently, the action made to increase the thermal satisfaction of the occupant affects the consumption of energy in buildings [25]. Therefore, [26] simulated multiple models of occupant behaviors. Occupants in the model aimed to increase their thermal comfort. At the start of the simulation, the occupant present in the space observed the surrounding conditions to get information about number of agent, clothing level and the activity level that he will do in the space. Based on these information and climate data, PMV, thermal satisfaction factor, is calculated using EnergyPlus. If the PMV was not according to standards, the occupant checked possible behaviors to increase thermal satisfaction. For each behavior, a cost was calculated to check the probability of doing a behavior. This probability was calculated using a cost function that takes behavioral beliefs, control beliefs and normative beliefs into considerations [26]. Behavioral belief represented the expected outcome of the behavior whether it would have a positive or a negative consequence. Control belief represented beliefs about the factors in the surrounding environment that would assist or hinder the attempt to make a certain behavior. Normative belief expressed beliefs about important people in the space that might accept or reject the behavior that would be carried out. According to this function, the agent ranked all behaviors to choose the one having the highest cost. Based on the chosen behavior, the system conditions were updated and the new PMV is calculated. Finally, the behavior was interpreted to check if comfort was achieved, if energy was saved and if it affected others within the same space. The coefficients used in the cost functions were updated based on behavior interpretations. Consequently, this model simulated actual occupant behavior that would be carried out to achieve thermal comfort.

In order to further understand the influence of occupants' behavior on energy consumption in commercial buildings, Kavulya and Becerik-Gercer [27] observed occupants' activities for 5 weeks. To simplify the problem statement, energy consumption of desktop computers, laptops and printers were only monitored. A load monitoring apparatus was used to measure consumption. Besides, Arduino sketch upload was used to calculate other electrical figures such as real power, apparent power, power factor, root mean square current and root mean square voltage. Using these apparatuses, appliances power consumption was logged every second. In order to know the behavior behind such consumption, visual observations were done. Interpretation of the effect of occupant behavior on energy consumptions showed that 38% of the consumed energy was wasted during standby modes [27]. Consequently, energy consumption would simply be optimized if occupants turn off the appliances they do not want to work on. Thus, if occupants were aware of the energy they waste and were asked to turn what they do not need off, around 40% of the energy would be saved without any effort.

In addition to optimize standby wasted energy, focusing on reducing non-wasted energy consumption is essential to reach long-term savings [28]. In order to study the direct influence of occupant behavior on energy consumption, Azar and Menassa [28] considered three typical building sizes, small, medium and large, that were assumed to consume energy during operating hours only. Moreover, five main weather conditions were taken into consideration that were subdivided into dry type and moist type each. Combinations of two factors resulted in 30 different building models that were developed in eQuest. When developing the models, standards were used to define building and energy properties. Furthermore, occupancy schedules were assumed to be that of the US national average schedule of office buildings. Upon running the models, total energy consumption of buildings were estimated. For the purpose of knowing the effect behavior of occupants on energy use, nine variables were varied individually. These variables were: 1) after-hours equipment use, 2) after-hours lighting use, 3) occupied hours cooling temperature set points, 4) occupied hours heating temperature set, 5) unoccupied hours cooling temperature set points, 6) unoccupied hours heating temperature set, 7) after-hours active HVAC system, 8) hot water consumption and 9) building schedule [28]. As a result, influence coefficient or each parameter was calculated. The influence coefficient showed the ratio of change in output to that of the input with respect to the base case. For illustration, results showed that hot water consumption had an influence coefficient value of +1.2 [28]. Accordingly, if the consumption of hot water increased by 1%, the total building energy used will increase by 1.2%. Similarly, a -1.4 influence coefficient for unoccupied hours heating temperature set points parameter means that an increase of 1% in that parameter will cause a decrease of 1.4% in total energy consumption [28].

If users were able to know the energy consumption and the influence of their behaviors on it, it might be possible to save up to 80% of energy consumed [29, 30]. Thus, several commercial parties designed energy dashboards to allow users visualize their energy consumption. Although these dashboards were appealing, it did not always show what a user needs to see [30, 31]. Consequently, [30] proposed a framework to show components that should be included in energy dashboards. The platform of this dashboard was developed based on the software/hardware it would have been installed in. Within these dashboards, dynamic data and static data were utilized. Dynamic data and static data demonstrate real-time sensor data obtained from sensors placed in buildings intentioned and information about buildings that does not change often respectively [30]. For clarification, figures of energy consumptions, such as electricity, gas and water consumption, are considered to be dynamic data. On the other hand, buildings temperature, humidity and CO_2 emissions for example are considered to be static data. Occupants will not only be able to check their energy consumption, but also they will be able to take wiser decisions regarding their behavior that will decrease energy consumption [30].

Although energy use in buildings is relatively high, 35% of the occupants are not satisfied with indoor thermal conditions [32-34]. For this reason, Klein et al. [35] created a multi-agent comfort and energy system (MACES). When building management systems are designed, full occupancy of buildings is considered to set building indoor conditions. However, monitoring actual occupancy levels, even at peak times, indicated that occupancy in office buildings is at most one third the full occupancy assumed [35]. Therefore, four control strategies, manual, reactive, proactive and proactive – MDP, were tested to improve energy consumption and comfort levels. To find the best strategy, MACES was developed. First of all, the system received information about building occupants and the physical buildings to figure out occupancy schedules, rooms and thermal zones. Then, a virtual building model was developed whereby agents were proxy agents. These proxy agents resembled a real occupant through his/her mobile application. Information from agents and real-word sensors will form the model inputs [35]. The first system tested was the manual system. Within this baseline system, temperatures were set according to previously defined setpoints. Moreover, lights were considered always on when occupants enter a space and stochastically turned off when leaving. Besides, appliances were considered to be always on. On the other hand, the reactive system reacted according to actual occupancy and occupancy preferences in each zone. As for proactive system, lighting and temperature were adjusted according to actual occupancy and occupancy preferences in each zone based on scheduled occupancy. Finally, the proactive – MDP system is similar to the proactive system, but agents had the option to reallocate their meetings. Upon testing the four systems in MACES, it was proved that the three systems were better than the baseline one. The energy simulation of reactive, proactive and proactive – MDP showed a reduction in energy consumption by 4.46%, 6.86% and 12.17% respectively. As a result, applying proactive – MDP energy system will yield the highest energy saving rate with an acceptable occupancy comfort levels. Spending an additional effort on developing the proactive – MDP system, [36] worked on developing the idea of schedule flexibility. Transformative energy saving schedule leveraging agent (TESLA) was developed in order to save energy through changing occupant schedules. TESLA took inputs, information regarding occupants' schedules such as location, preferred meeting time, number of attendees, etc., form occupants and their proxy agents. Upon receiving these information, it aimed to form energy efficient schedules. The schedules considered flexibility in meetings time, location, and user preferences according to energy satisfaction [36]. At first, an algorithm was used to arrange all meetings and to come up with the schedule meeting including all requests that have flexibility. Then, another algorithm arranged meetings within the flexible range to find the most energy efficient schedule. When assuming the full amount of flexibility, TESLA was able to reach a 48.08% of energy savings. Thus, applying such tool to manage meeting schedules will reduce consumed energy significantly.

Furthermore, Jazizadeh et al. [34] developed a mobile application that captured occupants comfort profile and adjusted indoor qualities accordingly in order to increase satisfaction levels of the majority. Using the mobile application, occupants were able to express their satisfaction toward temperature, light intensity and airflow. In addition, GPS was used to shortlist buildings options. However, the user had to enter his exact location manually. This data was then inputted to the building system that adjusted the indoor conditions accordingly to reach a minimum of 20% of dissatisfaction [34]. In order to capture data regarding building indoor quality, [34] designed a sensor box that hosted: 1) temperature sensor, 2) CO_2 sensor, 3) relative humidity sensor, 4) sound sensor, 5) light intensity sensor, 6) passive infrared sensor, 7) motion sensor and 8) door sensor. The data was logged every minute [34]. As a result of increasing satisfaction percentages, productivity and health of occupants were improved [32, 34, 37].

A.3. SUMMARY OF MAIN FINDINGS

Optimization of current building energy use triggered several researchers to develop tools aiming at reducing energy consumption in commercial buildings. These tools can be divided into two main categories. The first category includes tools that assessed the relative energy performance of design alternatives. Others developed tools to optimize both energy consumption and cost of implementation. Moreover, low interoperability triggered some researchers to develop Autodesk Revit plugins and simultaneously visualize graphical building information together with energy consumption data. However, researchers observed that occupant behavior has a great influence on energy consumption. Therefore, the second category of developed tools incorporate occupant behavior to improve energy estimates at the design phase and optimize energy comsumption at the operation phase. To understand the effect of occupant behavior on energy consumption, researchers stated that 54% of the energy is wasted during non-working hours and 38% of the energy during working hours is wasted by appliances placed on standby mode. Thus, orienting the occupant behavior in a good way can highly affect energy consumption. For more detailed information, other researchers worked on calculating the influence factor of each behavior. Even with all this waste, 35% of the occupants are still not satisfied with the indoor qualities. Therefore, researchers worked on improving indoor qualities through capturing occupants comfort levels. Other researchers tried to save energy through arranging meetings within flexibilities to create an efficient meeting schedules. Moreover, prior research efforts created a tool to assess the effect of social influence on occupant behavior. Finally, researchers created a framework whereby occupants changed their behaviors to increase thermal satisfaction/comfort levels.

A.4. NEED FOR FUTURE RESEARCH

The summary of main findings presented in the previous section shows that there is a need for a tool that would mimic actual world environment where occupants within the same space should interact to increase their satisfaction levels. For this reason, this tool should be able to overcome the limitations of previously developed tools. Consequently, potential areas for future research in this field are summarized below:

1. Consideration of acoustic comfort is needed to model a real world environment where occupants would behave to achieve ultimate satisfaction. For example, when the occupant closes the window to achieve acoustical comfort, he might feel hot and turn the HVAC system on. Thus, the energy consumed by the HVAC system is mainly due to acoustic dissatisfaction.
2. Consideration of occupant multi-comfort levels is needed to have a reliable model. This is due to the fact that the behavior of the occupant might affect more than one comfort level simultaneously. As mentioned in the previous example, the state of the window affected both acoustic and thermal comfort. Moreover, when the occupant is visually unsatisfied, he might open the shades.

However, the occupant might be unsatisfied thermally due to the sun effect. Therefore, the state of the shades affected both thermal and visual comfort. For this reason, considering simultaneously all comfort levels is of paramount importance.

3. Different occupant behavior types should be considered when testing for multi-comfort levels. As previously mentioned, occupants within the same space might have different behaviors. For illustration, occupants behavior may be classified into three categories, green, non-green and neutral.
4. Different categories of occupants within the same space should be considered. Wihtin the same space, occupants with different statuses may meet and interact. For illustration, professors may meet with students in offices. However, the professors might have a higher decision power than students to control the state of variables within the system. Therefore, occupants with different decision powers should be modeled.
5. Leaving behavior of occupants should be taken into consideration to have a full insight about the occupant behavior. As previously mentioned, more than half of the energy is wasted during non-working hours. For illustration, the occupant might leave lights, HVAC system and electrical appliances on when leaving. Therefore, the leaving behavior of occupants should be modeled.
6. Consideration of the position of occupants within the space is needed. Occupants within the same space might be unsatisfied on a different level. For example, occupants in proximity to the HVAC supply units will be more satisfied that others in the space and vice versa. Moreover, occupants near the window might be more satisfied/unsatisfied visually than others due the sun

light effect. Therefore, the position of occupant should be considered when modeling multi-comfort levels.

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APPENDIX B STUDYING OCCUPANT MULTI-COMFORT LEVEL IN ACADEMIC BUILDINGS USING AGENT BASED MODELING

ABSTRACT

With the trend towards low energy or energy efficient buildings that diminish fossil fuel usage and carbon emissions, getting occupants actively involved during the design and operation phases of buildings is vital in achieving high energy performance without jeopardizing occupant satisfaction or comfort level. However, recent tools did not examine simultaneously, while considering different occupant behavior types, visual, thermal and acoustic comfort levels. This paper presents work targeted at efficiently studying occupant multi-comfort level using agent-based modeling with the ultimate aim of reducing energy consumption within academic buildings. The proposed model was capable of testing different parameters and variables affecting occupant behavior. Several scenarios were examined and statistical results demonstrated that (1) the presence of different occupant behavior types is deemed necessary for a more realistic overall model , (2) the absence of windows results in an acoustic satisfaction with an increase in HVAC off and medium level uses, and high lighting usage, and (3) the overall light usage decreases when two light switches instead of one are introduced.

KEYWORDS

Academic Buildings, Occupant Behavior, Occupant Multi-Comfort Level, Occupant Interaction, ABM, Energy Optimization

B.1. INTRODUCTION

With the expected increase in global population by 39% in 2035 [1], relying on new renewable resources of energy such as solar energy, wind energy, wave energy among many others has become imperative. Besides opting for alternative energy resources, current use of energy should be optimized. Recently, attention has been placed on energy efficient buildings [2]. As a matter of fact, increasing energy use efficiency is one of the key approaches for energy consumption and carbon emissions reduction as part of the climate change mitigating efforts. According to Yang et al. [2], reductions in energy expenses and decrease in the environmental pollution may be achieved by reducing the consumption of energy in buildings. People spend more than 90% of their time indoors [3], and as such around 40% of the global energy is consumed by buildings [4-7]. Therefore, efficient energy use should be adopted especially that it is anticipated that the energy consumption in buildings is expected to increase by 19% in the upcoming years [8].

Although several types of buildings exist, targeting the commercial type, in particular academic buildings, is of paramount importance, as the occupants seldom have the incentive to reduce their energy consumption [7]. They usually focus on completing their job tasks rather than saving on energy [9]. Additionally, it was stated that the energy consumed in commercial buildings during non-working hours is typically more than half of the total energy consumed [7, 10] as typical occupant behavior includes keeping the HVAC, electronic devices, appliances and lights on even when not needed or upon exiting the space.

Therefore, getting occupants actively involved during the design and operation phases of buildings is vital in achieving high energy performance without jeopardizing occupant satisfaction or comfort level. However, recent tools did not examine simultaneously, while considering different occupant behavior types, visual, thermal and acoustic comfort levels. The overarching goal of the paper is to design and implement a comprehensive framework aiming at studying occupant multi-comfort level in academic buildings using agent-based modeling. The proposed model was capable of testing different parameters and variables affecting occupant behavior. Several scenarios were examined and statistical results demonstrated that (1) the presence of different occupant behavior types is deemed necessary for a more realistic overall model , (2) the absence of windows results in an acoustic satisfaction with an increase in HVAC low and medium level uses, and high lighting usage, and (3) the overall light usage decreases when two light switches instead of one are introduced.

The remainder of the paper is organized as follows. Section B.2 shed light on prior research efforts on energy optimization and occupant behavior, while Section B.3 presents the limitations of existing approaches and the proposed study's contributions. Section B.4 describes both the design and implementation of the agent-based proposed framework. Results and statistical analysis are detailed in Section B.5. Section B.6 discusses our findings, concludes the paper and states envisioned future steps to further enhance the overall model.

B.2. LITERATURE REVIEW

Recent energy optimization needs in commercial buildings necessitated the development of several tools. These tools can be divided into two main categories: (1) tools that assessed the relative energy performance of design alternatives, and (2) tools that evaluated the impact of occupant behavior in improving energy consumption estimates of design alternatives and optimizing energy use at the building operation phase.

B.2.1 Building Energy Simulation Tools

To estimate the level of energy consumption at the building design phase and assess different design alternatives, several tools were developed that include but are not limited to Green Building Studio, eQuest, EnergyPlus, etc [11]. These energy simulation tools rely mainly on the building geometry and materials [11] or LEED requirements [11, 12] to estimate the amount of energy consumed and decide upon the best alternative [13]. However, the implementation cost of the most energy efficient alternative is often high. Consequently, other researchers developed multi-generic tools that optimized both energy consumption and implementation cost [14]. On the other hand, Autodesk Revit plugins have been developed [15] to avoid manually coupling energy simulation and design BIM tools. These plugins allowed rapid assessment of design alternatives through generation of energy consumption estimates and graphical output all within the same Revit interface.

B.2.2 Building Energy Simulation Tools and Occupant Behavior

Measured energy consumption in buildings has demonstrated large discrepancies with the original estimates. Among various factors contributing to the discrepancies, occupant behavior is a driving factor [16, 17]. As such, several new developed models used occupant behavior to improve upon the original energy estimates and optimize energy consumption at the operation phase, often using agent-based modeling [18]. This simulation paradigm is a powerful technique mimicing real life systems by looking into its constituent units and testing what-if scenarios [9]. These units are called agents whereby every agent, a member of a group of decision making individuals within this environment, has its own properties that trigger replicating certain real-life acts [19]. As such and unlike traditional tools, ABM allows evaluating the impact of each scenario on both the buildings and occupants, thereby identifying the most energy efficient design alternative [16, 17].

Focusing on building operation, energy efficiency measures can be effective in addressing the problem of high building energy consumption. As a matter of fact, researchers have observed that occupant behavior has a great influence on energy consumption at the operation phase [9, 20]. Studies found that 54% of the energy in a building is wasted during non-working hours and 38% during working hours due to appliances being typically placed on standby mode [7, 10, 21]. Accordingly, with occupants adopting energy conscious behaviors, energy consumption can be greatly reduced [5, 16]. For that purpose, some tools used ABM and looked at the effect of occupant behavior on energy consumption by computing the weight of each behavior's influence factors [17]. It was concluded, for example, that an increase of hot water consumption by 1% leads to an increase of total building energy consumption by 1.2% [17]. On the other hand, previous work [22] found that occupants consumed more energy when occupying large size rooms due to a higher HVAC and light power usage [22]. In this case, energy efficient efforts were channeled toward creating efficient meeting schedules and reallocating occupants in the right rooms [22].

It is worth mentioning that typical occupant behavior includes how an occupant sets comfort criteria. Although the percentages of waste energy are relatively high, approximately 35% of the occupants are still not satisfied with the indoor qualities [23]. Therefore, researchers worked on improving indoor qualities through capturing occupants comfort levels using mobile cellphone applications [23]. As an illustration, occupants within the area studied were asked to specify their satisfaction level toward the room temperature, air flow and light intensity. Based on this input data, the buildings' indoor conditions were adjusted to increase the comfort levels of the majority of occupants. Moreover, researchers studied the impact of occupant behavior on energy consumption based on decisions taken to increase satisfactory levels. For illustration, if the occupant chooses to open a window, it can affect the HVAC system [24]. Therefore, Lee and Malkawi [25] created a tool whereby occupants changed their behaviors to increase thermal satisfaction levels. Occupants interacted with others in the same space and whenever comfort was not achieved, they would adjust the system variables to increase their comfort level.

B.3. LIMITATIONS OF EXISTING APPROACHES AND RESEARCH CONTRIBUTIONS

Although the field of energy and buildings is evolving rapidly, existing approaches in the literature have several limitations that should be overcome in order to achieve a reliable model capable of better mimicing real-life situations. First of all, acoustic comfort of occupants was not considered. Only thermal and visual satisfaction were taken into consideration. However, the behavior of occupant attempting at increasing acoustic satisfaction might affect the energy consumption in buildings. For illustration, the occupant might close the window to avoid the outside noise. Consequently, he might feel hot and turn the HVAC system on. Thus, the energy consumed by the HVAC system resulted was due to acoustic dissatisfaction. Thus, achieving acoustic comfort might impact energy consumption within buildings. Therefore, acoustic comfort was considered in the model when simulating the behavior of occupants.

Moreover, when previous approaches considered thermal and visual comfort only, the interaction of both comfort levels was ignored. In other words, it was assumed that the behavior adopted to increase thermal satisfaction was completely independent from the behavior implemented to increase visual satisfaction. On the contrary, the state of certain variables in the system might affect more than one comfort level. For example, if the occupant was unsatisfied visually, he might open the shades to have sun light. However, he might feel hot because of the sun effect. As a result, the occupant might increase the level of the HVAC system to increase his thermal satisfaction. Consequently, the state of the shades affected both, thermal and visual comfort and both were simultaneously considered in the model.

In addition, different occupant behaviors were not considered when testing multi-comfort levels. Occupants might either have green, neutral or non-green behavior. For illustration, green occupants when feeling hot would rather open the window than turn the HVAC system on. On the contrary, non-green occupants would on average decide to turn the HVAC system on rather than open the window. Thus, considering different behaviors might have a great impact on occupant comfort and energy consumption. For this reason, different occupant behaviors were incorporated in the model.

Similarly, different categories of occupants were not considered. Occupants with different statuses might meet and interact within the same space. For example, a senior engineer might be in meeting with a junior engineer. However, the senior engineer would have a higher decision power to alter system conditions and achieve ultimate satisfaction. Therefore, the decision power of different occupant categories might not be equal which could affect their behavior in increasing their comfort. Thus, this issue was addressed within the simulation model.

Furthermore, the leaving behavior of occupants was not taken into consideration when modeling occupant behavior. Tools used to simulate occupant comfort assumed that energy is consumed during working hours only. However, it was mentioned previously that energy wasted during non-working hours might exceed half the total amount consumed. For illustration, occupants have several options to do when leaving. For example, the occupant might leave everything on, or he might turn some/all systems and appliances off. For this reason, the leaving behavior of the occupant should be modeled to have a full insight about the impact of occupant behavior on energy consumption in buildings.

Finally, the position of occupants within the space studied was not considered. When the size of the space studied is large enough, then identical occupants within the same space might be unsatisfied differently. For illustration, consider the case where an occupant would be adjacent to the window (occupant A) and the other one would be relatively away from it (occupant B). For example, occupant A would be more satisfied visually than occupant B when shades are open only. On the other hand, occupant B would be more satisfied thermally than occupant A because occupant B would not be affected by sun radiations unlike occupant A. For this reason, the position of the occupant should be considered when taking the size of the space tested into consideration. Therefore, the position of occupants need to be taken into consideration.

All of the aforementioned limitations show that there is a great need for a new flexible tool capable of imitating actual world environments where occupants of different behaviors and categories interact within the same space to increase their satisfaction levels. This necessitated the development of an agent-based framework targeted at studying occupant multi-comfort level in buildings with the ultimate goal of optimizing energy use in academic buildings in particular.

B.4. METHODOLOGY

The methodology adopted in this study is divided into two main tasks: (1) Design of a comprehensive agent-based framework or taxonomy for studying occupant multi-comfort level in academic buildings, and (2) Development of an agent-based model addressing several framework key components.

B.4.1 Proposed Framework Taxonomy

Prior to presenting the proposed agent-based framework, a set of parameters and variables should be defined. Parameters are the set of conditions that are defined at the start of the simulation and kept fixed through out the simulation process. On the other hand, variables are the set of conditions that are defined at the start of the simulation and that change during the process according to rules and definitons [26]. Figure B-1 depicts different parameters and variables deemed necessary for modeling occupant multi-comfort levels.

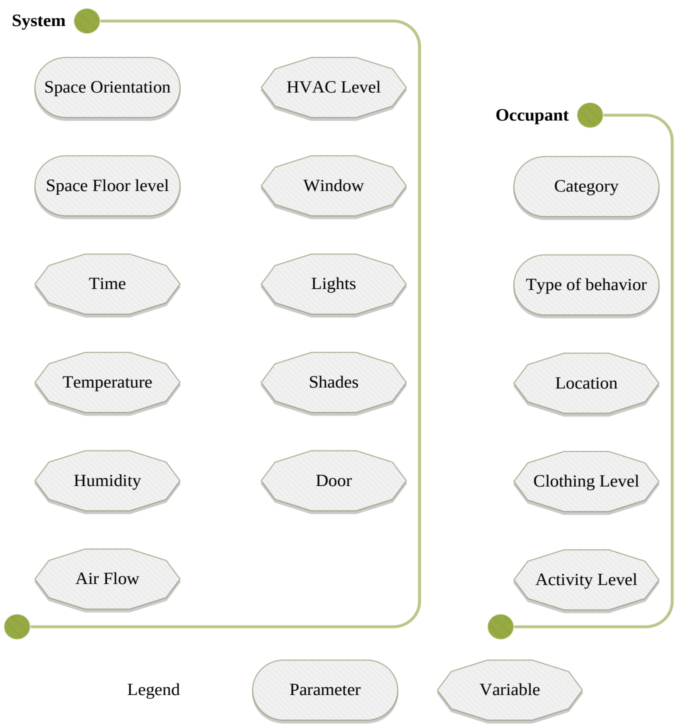

Figure B-1: Model Parameters and Variables

As shown in Figure B-1, the occupant's adaptive comfort behavior is influenced by conditions related to both the system and the occupants themselves. For instance, the floor level and the orientation of the space in question are considered to be system parameters, while the occupant behavior type (e.g. green, neutral, and non-green) as well as the occupant category (e.g. department heads, faculty members, students, etc.) are considered to be occupant parameters. At the start of the simulation model, all parameters are set according to a pool of available options. Based on these parameters, the occupants behave to increase their comfort and satisfaction levels. On the other hand, the HVAC level, door, window, lights and shades statuses are considered to be direct system variables. However, occupants within the system are capable of adjusting these variables to increase their comfort. Furthermore, time (i.e. time of the day or season), temperature, humidity and airflow are considered to be indirect system variables and are adjusted according to the direct ones. Moreover, the time deliberated within the simulation model is considered to be a system variable that can be attuned automatically. Besides, occupants are given the choice to adjust their cloth and activity levels to enhance their comfort, thereby rendering these conditions as occupant variables.

Based on the aforementioned parameters and variables, Figure B-2 presents the agent-based framework designed to address existing limitations and study occupant multi-comfort level in academic buildings. The proposed framework consists of eight key components explained in the following subsections.

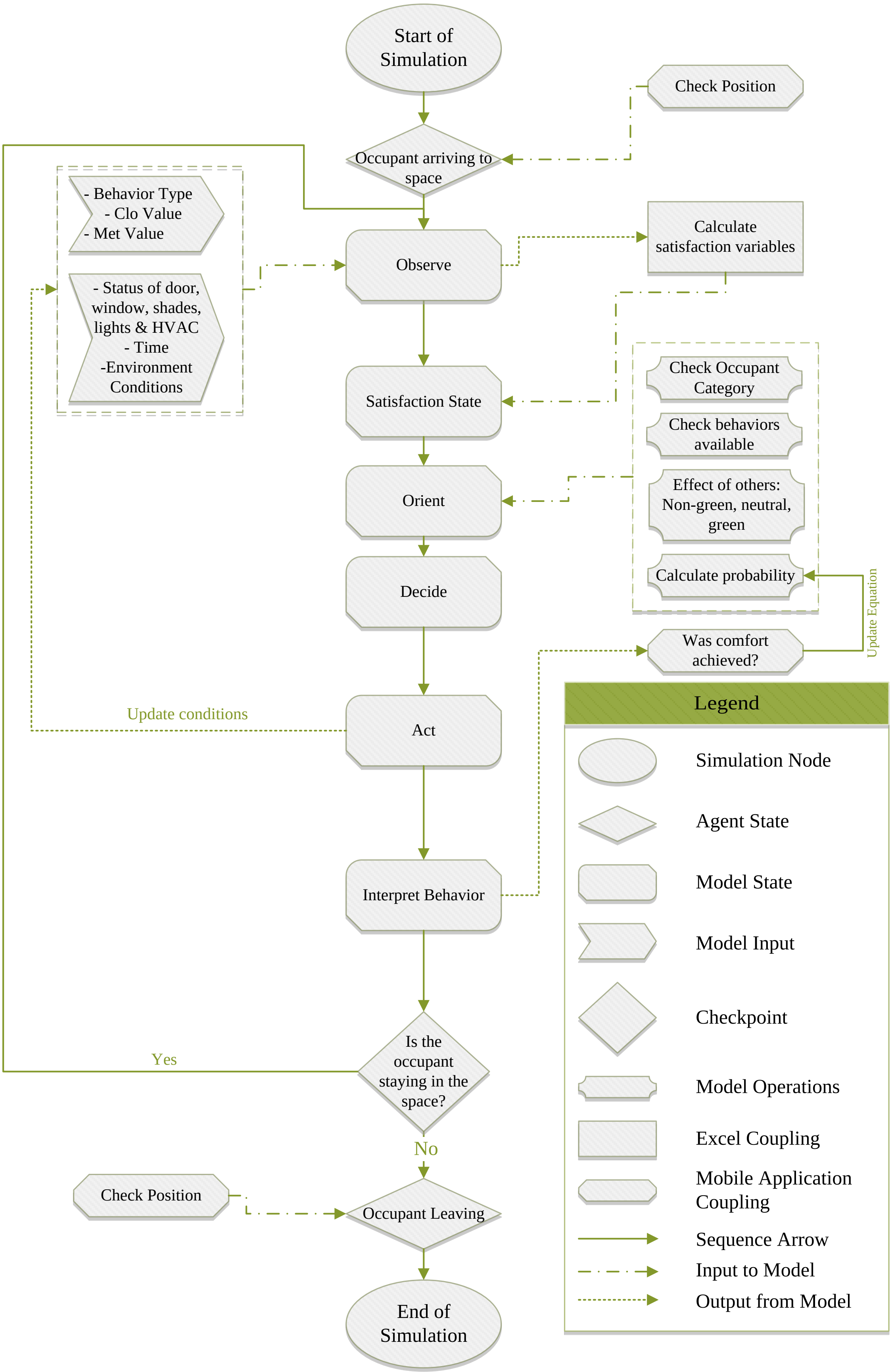

Figure B-2: Proposed Framework

B.4.1.1 Tracking and Localizing Occupants

The first component (Figure B-3) consists of tracking occupants as they enter the studied space and frequently updating their location.

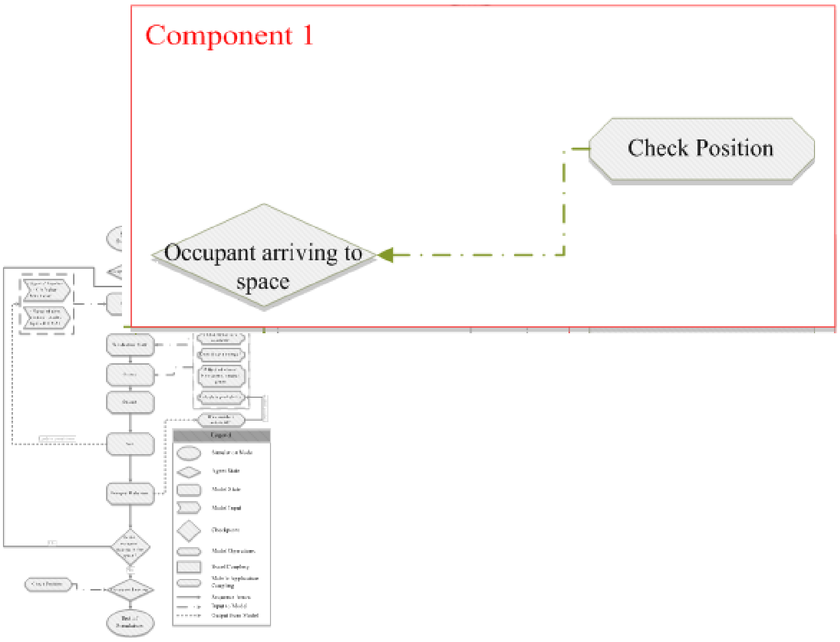

Figure B-3: First Framework Component

This part of the framework makes use of indoor position tracking technologies, such as Wireless Local Area Networks (WLAN), Radio Frequency Identification (RFID), Ultra-Wideband (UWB) [27, 28], etc., whereby sensors (e.g. wristbands, tags, badges, etc.) are mounted on occupants and followed over the network Given the nature of the environment in question (i.e. academic buildings), it was decided to adopt WLAN as a potential tracking solution and make use of the on-campus Wi-Fi network. Several commercial available tools were researched and the authors’ choice landed on a WLAN-based Real-Time Location System (RTLS) called Ekahau because it is widely used in the healthcare sector for people and equipment tracking, temperature and humidity monitoring, and workflow process improvement [29]. Using this technology, the model can detect the presence of occupants in space and start its first iteration from the “occupant arriving to space” state. Moreover, it can acquire the occupant’s exact location, visualize it on a BIM-based floor plan and determine his/her proximity to HVAC diffusers, windows, etc., thereby studying the satisfaction levels vis-à-vis position within space . Once the occupant is located in the space, the system parameters, space floor level and space orientation, are automatically identified.

B.4.1.2 Setting Conditions for Other System and Occupant Variables and Parameters

As shown in Figure B-4, the second component of the proposed framework sets conditions for all variables and parameters within the space that affect occupants’ satisfaction or multi-comfort level.

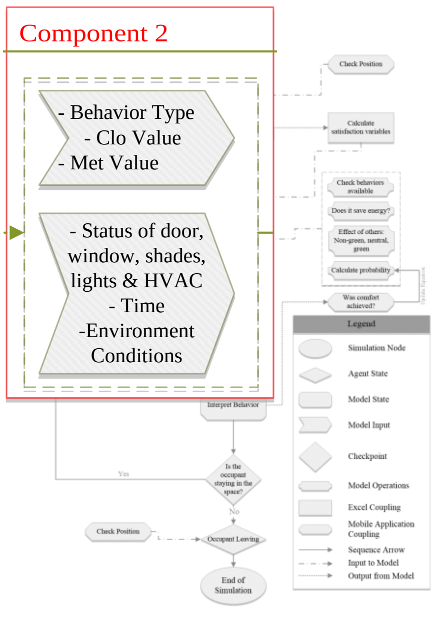

Figure B-4: Second Framework Component

More specifically, occupant variables considered as internal factors, include Clothing (Clo) and Metabolic equivalent value (Met) values [30, 31].

Clo values should be taken into consideration because the occupant typically changes his clothing level to reach thermal satisfaction. Examples of Clo values attributed to some of the clothing options are shown in Table B-1.

Table B-1: Occupant Clo Value (Source: [30])

Clothing		**Insulation**
		Clo
Shirts	Tube top	0.06
	Short sleeve	0.09
	Light blouse with long sleeves	0.15
	Light shirt with long sleeves	0.2
	Normal with long sleeves	0.25
	Flannel shirt with long sleeves	0.3
	Long sleeves with turtleneck blouse	0.34
Trousers	Shorts	0.06
	Walking shorts	0.11
	Light trousers	0.2
	Normal trousers	0.25
	Flannel trousers	0.28
	Overalls	0.28
Sweaters	Sleeveless vest	0.12
	Thin sweater	0.2
	Long thin sleeves with turtleneck	0.26
	Thick sweater	0.35
	Long thick sleeves with turtleneck	0.37

For example, if the occupant is wearing light trousers and a thin sweater, then his Clo value would be be 0.4.

Similarly, the Met value is important and considered as well since it affects the occupant’s thermal comfort. Table B-2 shows the Met values of the activities that can be performed by occupants within a space. A Met value is a physiological measure expressing the energy cost of physical activities [31]. For example, if an occupant is working on the computer, then the Met value is 1.9.

Table B-2: Met Value of the Occupant (Source: [31])

Activity	**MET value**	**Activity**	**MET value**
Taking classes	1.82	Work: Architecture and Engineering	1.64
Taking classes: personal interest	2.4	Work: Life, Physical, and Social Science	2
Research work	1.8	Work: Community and Social Services	2.08
Eating and drinking	1.5	Work: Legal	1.5
Socializing and communicating with others	1.5	Work: Education, Training, and Library	2.5
Teaching	1.6	Work: Arts, Design, Entertainment, Sports, Media	2.13
Standing at Rest	1	Work: Healthcare Practitioner and Technical	2.22
Seated relaxed	1	Work: Healthcare Support	2.83
Relaxing, thinking	1.21	Work: Protective Service	2.56
Listening to/playing music (not radio)	1.38	Work: Food Preparation and Serving Related	2.58
Computer use	1.9	Work: Bldg & Grounds Cleaning, Maintenance	3.58
Reading for personal interest	1.6	Work: Personal Care and Service	2.53
Writing for personal interest	1.8	Work: Sales and Related Occupations	2
Telephone calls	1.5	Work: Office and Administrative Support	1.83
Work: Management	1.73	Work: Construction and Extraction	4.29
Work: Business and Financial	1.67	Work: Installation, Maintenance, and Repair	3.19
Work: Computer and Mathematical	1.58	Work: Production	2.69

In addition to Clo and Met values, thermal, visual and acoustic preferences of occupants are specified according to pre-defined ranges for different behavior types.

On the other hand, conditions should be set for the system variables considered as external factors. This includes regulating door, window, shades, and lights statuses. In general, these variables are considered as binary with open/closed or on/off options. Additionally, conditions are set for the HVAC level and range from off, low, medium to high. Moreover, time variable conditions are set based on the whole day timeframe and seasonal division of the year. Finally, temperature, humidity and air flow values are determined and acquired from respective sensors located in the ambient environment.

B.4.1.3 Calculating Satisfaction Variables

Based on the internal and external factors defined in the previous components, this part of the framework, shown in Figure B-5, reaches the "observe" state, and analyzes the situation by calculating the satisfaction variables.

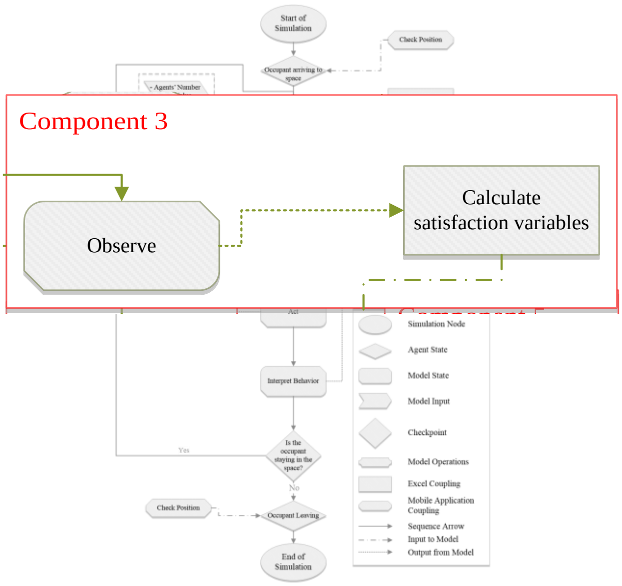

Figure B-5: Third Framework Component

Table B-3: Impact of Internal and External Factors on Comfort Levels

Factors		**Thermal Comfort**	**Visual Comfort**	**Acoustic Comfort**
Internal	Thermal Preference	√	---	---
	Visual Preference	---	√	---
	Acoustic Preference	---	---	√
	Clo Value	√	---	---
	Met Value	√	√	√
External	Space floor Level	---	---	√
	Space Orientation	√	---	√
	Temperature	√	---	---
	Humidity	√	---	---
	Air Flow	√	---	---
	Time	√	√	√
	HVAC System	√	---	√
	Door	√	---	√
	Window	√	√	√
	Shades	√	√	---
	Lights	---	√	---

The table mainly displays the direct effect of each factor on the different comfort levels. To begin with, the Clo value affects thermal satisfaction only. On the other hand, the Met value affects all comfort levels. For example, an occupant dealing with a stressful task might lead to thermal dissatisfaction while an occupant wanting to concentrate on a certain activity yield to light and noise levels adjusted to be within his desired ranges.

Moving to external factors, the floor level of the studied space is considered to affect acoustic comfort. As the floor level increases, the effect of outdoor crowd/equipment noise decreases. Besides, the orientation of a space located on the same floor level affects both thermal and acoustic comfort. For instance, spaces/offices located on the south side of the building and not directly affected by the sun's heat create a better thermal comfort level and a different acoustic comfort level when compared to north side spaces. On the other hand, temperature, humidity and air flow only affect occupant's thermal comfort. However, the time factor is considered to impact all satisfaction/comfort levels. For clarification, during summer time, the occupants typically feel more hot at noon than in the morning. Besides, occupants consume more light at night than during the day. Additionally, outside noise is remarkably high during peak day times. On the other side, the HVAC system level and type affect thermal and acoustic comfort. For example, a room temperature not set at the occupant desired level, leads to thermal dissatisfaction, while the noise generated by the system might affect the acoustic comfort of occupants. Therefore, the level of HVAC affect both thermal and acoustic comfort. Similarly, the door's state has an impact on thermal and acoustic satisfaction. When the door is open, the occupant might increase the level of the HVAC system to compensate for air loss. Moreover, noise coming from others on the same floor level might affect the occupant's acoustic comfort. In the case of windows, any comfort level might be affected. As an illustration, the occupant might open the window when he feels hot. However, other occupants of different behavior type might open the window as well as increase the level of the HVAC system. Needless to say, an open window might lead to acoustic dissatisfaction due to outdoor noise. Furthermore, the type of window glass used greatly impacts all comfort levels. For example, when tinted glass is used, sunlight's effect decreases which in turn affects visual satisfaction. When tempered glass is used, the heat due to sun effect decreases. As a result, the occupant would be thermally satisfied when opening the shades. On the other hand, the status of shades affects occupant thermal and visual comfort levels. When the shades are closed, the occupant is unsatisfied visually because of insufficient light while he is thermally satisfied because the sun's heat is blocked. Finally, the state of lights only affects visual comfort.

B.4.1.4 Identifying Occupant Satisfaction State

Based on the computed satisfaction variables, the fourth component of the proposed framework (Figure B-6) updates the occupant satisfaction state. As an illustration, the occupant might be unsatisfied thermally, visually, or acoustically.

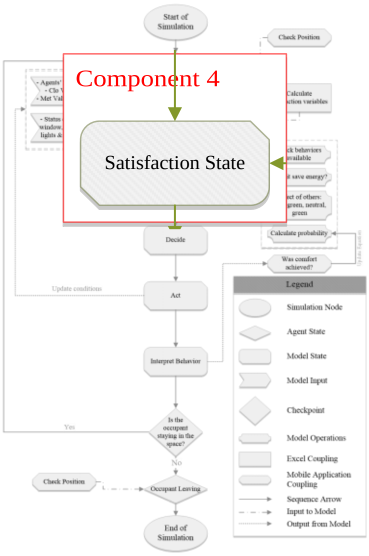

Figure B-6: Fourth Framework Component

B.4.1.5 Enhancing Occupant Satisfaction State

According to the last recorded unsatisfied state, the fifth component, presented in Figure B-7, offers the occupant a set of possible behaviors that can enhance his/her satisfaction level.

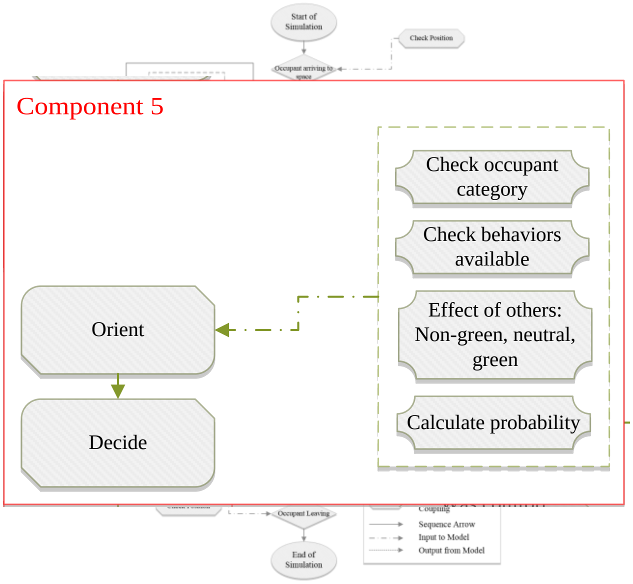

Figure B-7: Fifth Framework Component

As discussed earlier, the probability of reaching any satisfaction state is affected by both the occupant behavior type and occupant category existing in the space. For example, occupants labeled as green adopt energy-efficient behaviors and positively impact others. On the other hand, one category of occupants such as students meeting with another category such as professors, might lead the unsatisfied thermally students to change his Clo level before asking the professor to adjust the HVAC level. Given the agent-based modeling inherent nature, occupants interact with each other and decide upon certain behaviors, thereby updating the probability of certain satisfaction/comfort levels being reached within the studied space.

B.4.1.6 Acting and Updating System Factors' Conditions

Figure B-8 represents the "act" state in the proposed framework. Upon acting, the system factors' conditions get updated. For instance, the HVAC level might increase or decrease, lights might be turned on, shades might be closed, etc.

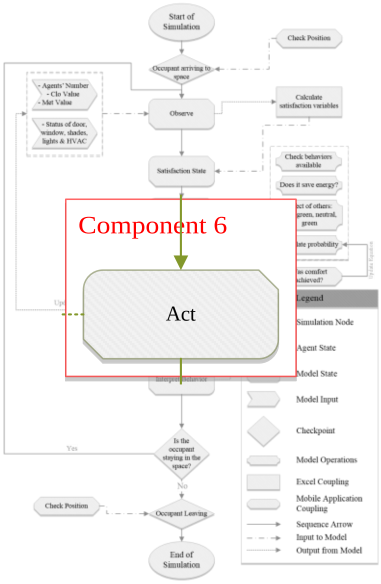

Figure B-8: Sixth Framework Component

B.4.1.7 Examining Occupant Updated Comfort Levels

The seventh component of the proposed framework, presented in Figure B-9, evaluates and interprets the behavior adopted and check whether occupant satisfaction or comfort was achieved. At this stage, it is important to assess the effect of the adopted behavior on comfort levels to ensure desirable results. For example, an occupant feeling hot in an office with a closed window decides to open it with the hope of increasing his/her thermal satisfaction. However, if the outside temperature is higher, then the previous opening act does not incur a positive impact on the satisfaction level and the probability afore-computed in the fifth component needs to be rectified and updated.

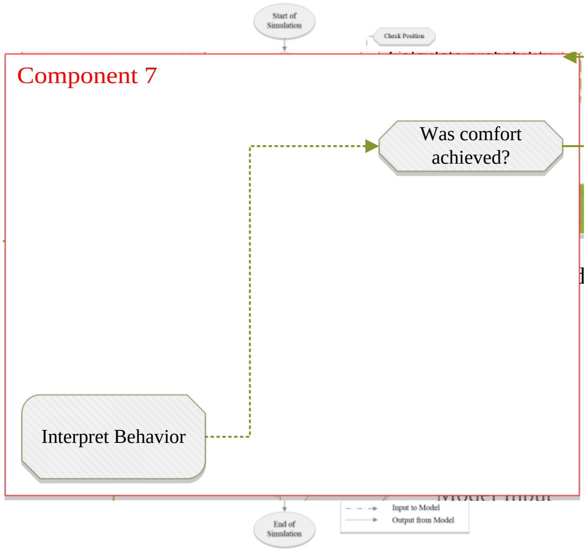

Figure B-9: Seventh Framework Component

B.4.1.8 Inspecting Occupant's Location and Behavior Prior to Exiting Space

Figure B-10 depicts the last framework component. It inspects the position of the occupant and checks whether he/she is staying in the space.

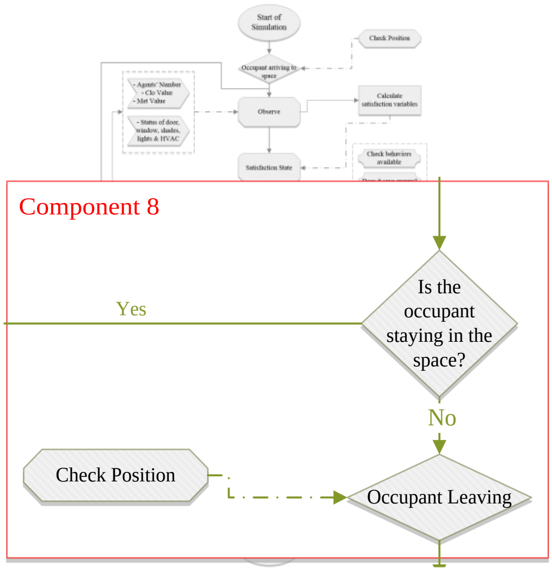

Figure B-10: Eigth Framework Component

In this case, if ultimate satisfaction has not yet been reached, then the occupant goes into the loop again until desired satisfaction/comfort is achieved or he/she no longer wants to remain in the space. As shown in Figure B-11, the occupant has two options upon leaving, either change system variables and update model conditions or keep everything as is. The choice depends largely on the occupant behavior type. For instance, in the case of green occupants , there is a high probability of turning off the HVAC system, lights and appliances than leaving without adjusting the system variables as is the case of non-green occupants. As for neutral occupants, equal probabilities exist toward both options. The above allows the occupant leaving behavior to be captured and assessed and gives an insight on the actual impact of this behavior on energy consumption.

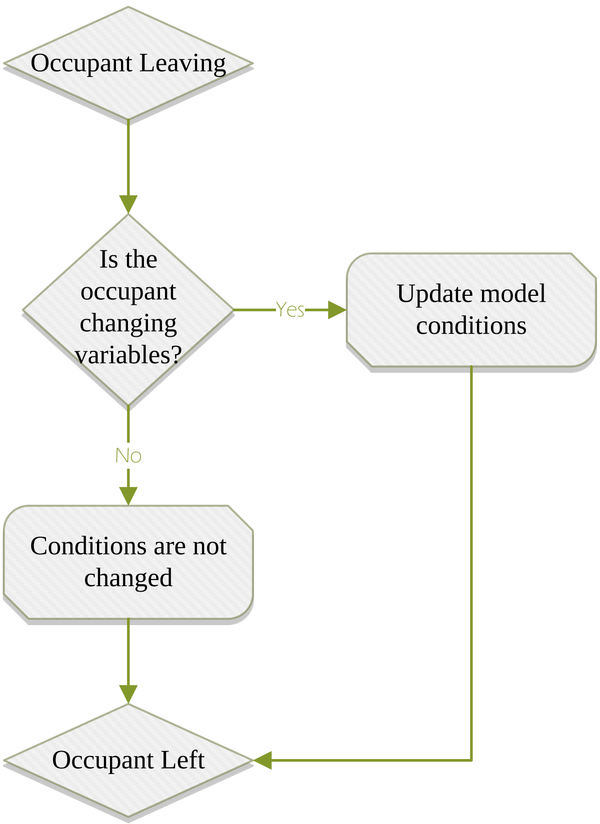

Figure B-11: Leaving Behavior Model

B.4.2 Agent-Based Model Development

In this section, an agent-based model, targeting several of the framework components (i.e. 2-6) and some associated parameters and variables, was developed using the multi-paradigm modeling tool, Anylogic [26]. Within Anylogic, all agents and common variables are usually defined in the Main window as shown in Figure B-12.

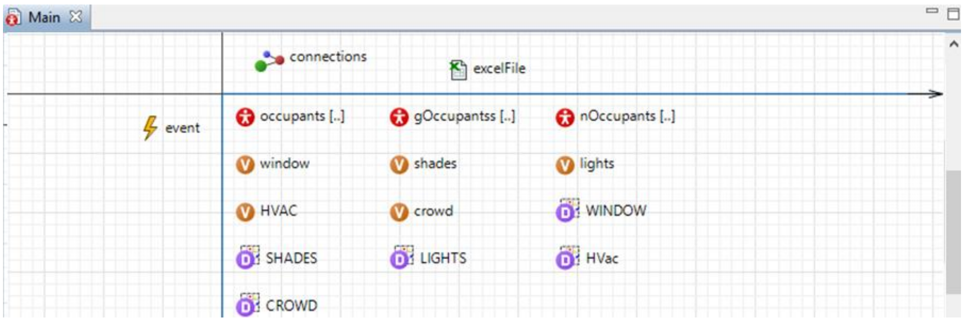

Figure B-12: ABM Model Agents and Variables

In this case, occupants were the only agents considered in this model. However, three different occupant groups, i.e. green (gOccupant), neutral (occupant) and non-green (nOccupant), were created to cater for different behaviors. The three pools of agents shared the same space and variables (i.e. window, shades, lights, HVAC and crowd). As aforementioned, the first three variables were considered binary. On the other hand, the HVAC had four different levels, namely off, low, medium and high. Similarly, the crowd or outside noise, had three different levels; low, medium and high. Variables specific to each agent were added on the Agent window. Figure B-12 displays as well a number of datasets created to store variables'data at each iteration. These were then exported to MS Excel for further analysis. Most importantly, connections shown on the Main window above have the purpose of linking agents together to allow their interaction within the same environment. A last item is an event that was added to stop the simulation model after completing a pre-specified number of iterations.

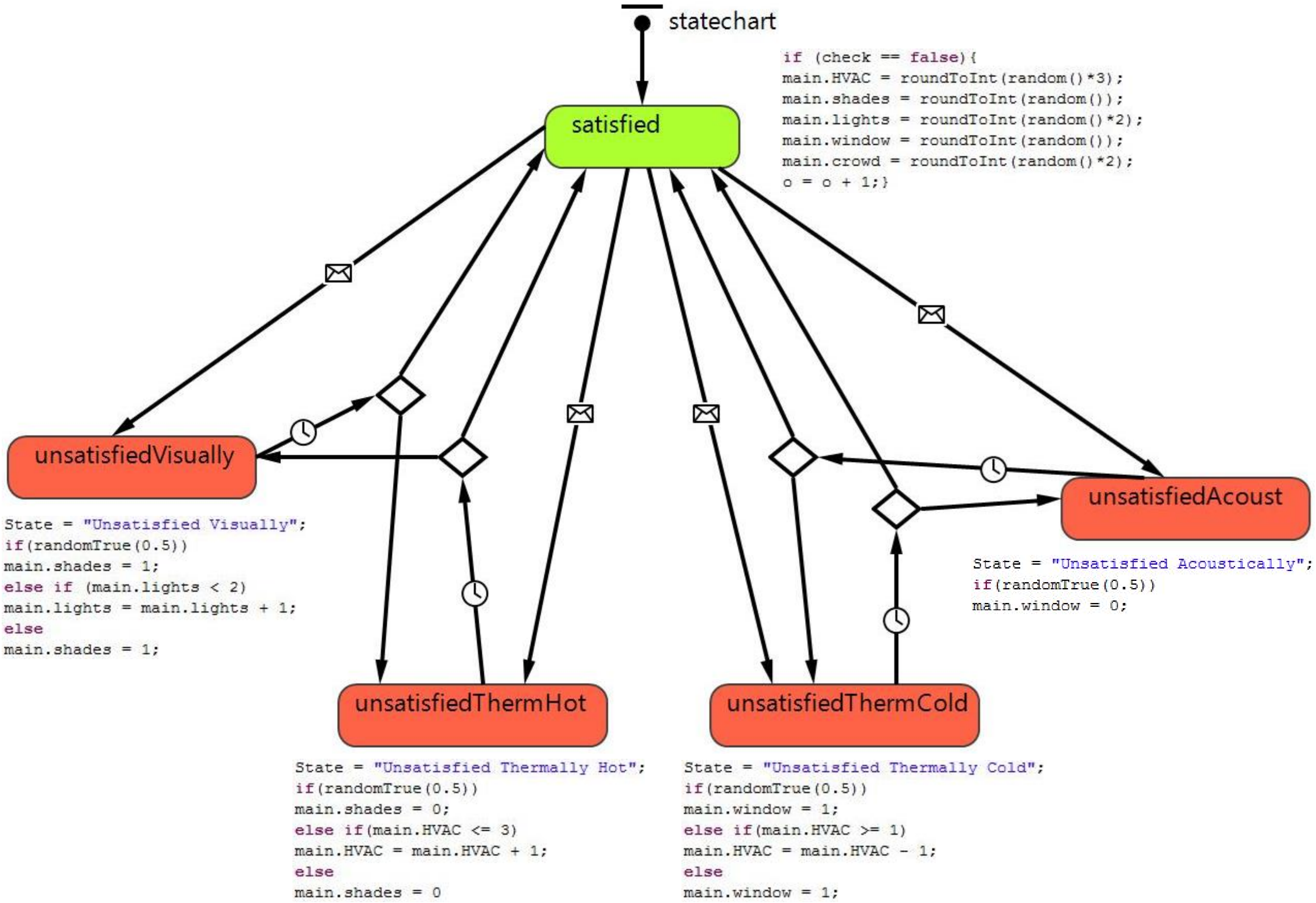

Figure B-13: Multi-Comfort Agent Statechart

Figure B-13 illustrates a multi-comfort agent statechart that is applicable to other agents as well but with different behavioral properties. In this case, a satisfied state and four unsatisfied states were defined. More specifically, at the unsatisfied side of the statechart, many options exist. The occupant was considered to be unsatisfied visually, acoustically, and/or thermally. Moreover, the unsatisfied thermally state was subdivided into unsatisfied thermally hot and unsatisfied thermally cold. In addition, two variables, thermal and acoustic preferences, were added at the agent layer to specify desired levels for occupants in the space, and an event, "Evaluate", was added to evaluate the occupant dissatisfaction. It is worth mentioning, that the model studies and examines an office space and occupant multi-comfort levels during day time hours and in the summer season.

Initially, as shown in Figure B-13, conditions of common variables and agent specific variables were randomly generated (e.g. *if (randomtrue…)*). Based on these conditions, the "Evaluate" event specifies the unsatisfied state of the occupant. Consequently, the occupant had to opt for one of the available behaviors to increase his/her comfort level. Each behavior was assigned a certain probability that varied according to the occupant type (i.e green, neutral, and non-green). Table B-4 illustrates the probabilities associated with each behavior. For instance, when lights were off and shades were closed, the event "Evaluate" triggered a message to inform the model that the occupant was unsatisfied visually. As a result, the occupant moved from the satisfied state to the unsatisfied visually state. Accordingly, the occupant had two options to enhance his/her visual satisfaction state; (1) turn the lights on, or (2) open the shades (Table B-4).

Table B-4: Probabilities of Behavior

State	Behavior	Probability of behavior		
		Green Occupant	**Neutral Occupant**	**Non-green Occupant**
Unsatisfied Visually	Turning lights on	0.25	0.5	0.75
	Opening shades	0.75	0.5	0.25
Unsatisfied Thermally Hot	Increasing HVAC Level	0.25	0.5	0.75
	Closing the shades	0.75	0.5	0.25
Unsatisfied Thermally Cold	Decreasing HVAC Level	0.75	0.5	0.25
	Opening window	0.25	0.5	0.75
Unsatisfied Acoustically	Closing the window	0.5	0.5	0.5
	Bear the outside noise	0.5	0.5	0.5

As shown in Table B-4, if the occupant is a green occupant,there is a 75% chance of opening the shades and 25% chance of turning the lights on. On the other side, when the HVAC level of the space was less than the HVAC preference of the occupant, the “Evaluate” event sent a message to the system that allowed the occupant to move to the unsatisfied thermally hot state, thereby left with either increasing the HVAC level or closing the shades if open. On the contrary, when the HVAC level of the space was greater than the desired one of the occupant, the “Evaluate” event sent a message to the system allowing the occupant to move to the unsatisfied thermally cold state. Hence, for a non-green occupant, for example, there is a 25% chance of decreasing the HVAC system level and a 75% chance of opening the window if closed. Besides visual and thermal comfort levels, the acoustic one was examined as well. When the outside noise level was higher than the preference level of the occupant, an unsatisfied acoustically state was reached, and for all occupant types, there was an equal chance of closing the window or bearing the outside noise.

B.5. RESULTS AND STATISTICAL ANALYSIS

Upon running the simulation model for 10,000 iterations, the graphs shown in Figure B-14 were generated. With a log of 10,000 iterations, a relatively high power of statistical tests can be possibly reached. The charts plotted the state of each variable in the model versus time. For illustration, at a certain time in space, the charts depict that when shades are closed, lights are on. Besides, when the HVAC level is high, the window is closed.

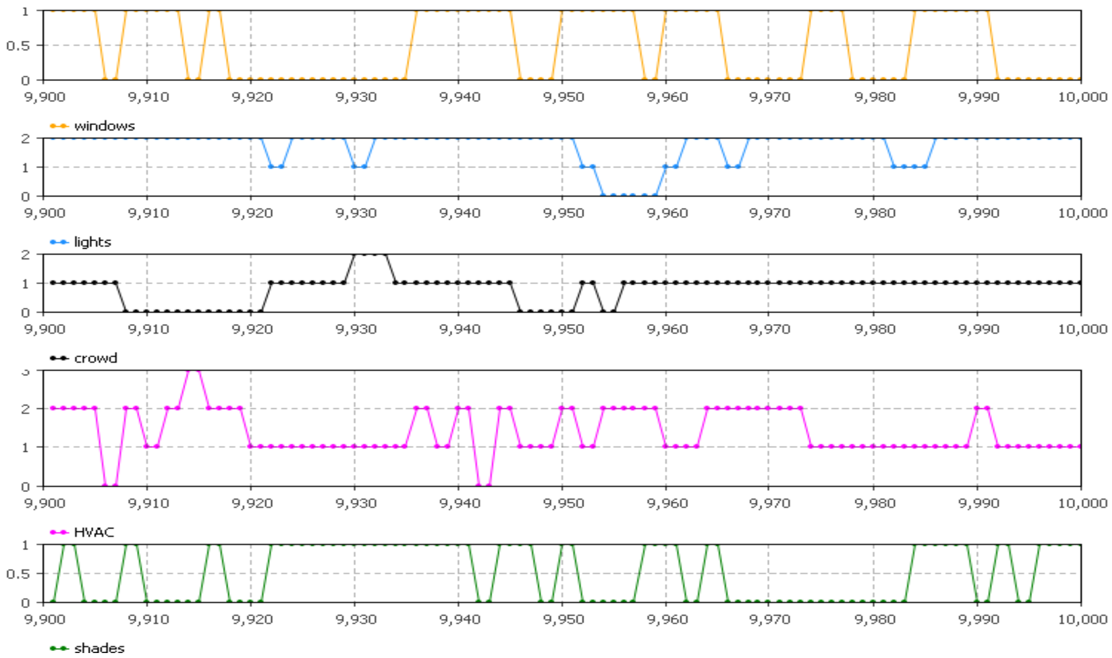

Figure B-14: System Variables Output Graphs

To analyze the results statistically, RStudio was used [32]. It is a software programming language and environment for statistical computing and graphics. Within RStudio, the data exported to the excel sheets were stored as a 10,000 length vector. The code shown in Figure B-15 was then used to divide the original vector of data into 100 vectors having 100 results each.

```
hvac=read.csv("C:/HVAC.csv", header=F)
hvac=hvac[,2]
off_Single=rep(NA,100)
low_Single=rep(NA,100)
med_Single=rep(NA,100)
high_Single=rep(NA,100)
for (i in 1:100){
  off_Single[i]=sum(hvac[((i-1)*100+1):((i-1)*100+100)] == 0)
  low_Single[i]=sum(hvac[((i-1)*100+1):((i-1)*100+100)] == 1)
  med_Single[i]=sum(hvac[((i-1)*100+1):((i-1)*100+100)] == 2)
  high_Single[i]=sum(hvac[((i-1)*100+1):((i-1)*100+100)] == 3)
}
```

Figure B-15: Data Vector Creation Code

The next step involved computing the probability of occurrence of each state and storing it in a new vector. In the case of HVAC for example, the probability of having an off level was calculated by counting the number of zero digits presented in each vector. In order to check whether the trend of the data follows a normal distribution, two approaches were adopted: (1) plotting probability histograms for different levels (Figure B-16) and visually drawing a conclusion about data normality, or (2) carrying out a statistical test, in particular the Shapiro-Wilk test [33] as shown in Figure B-17.

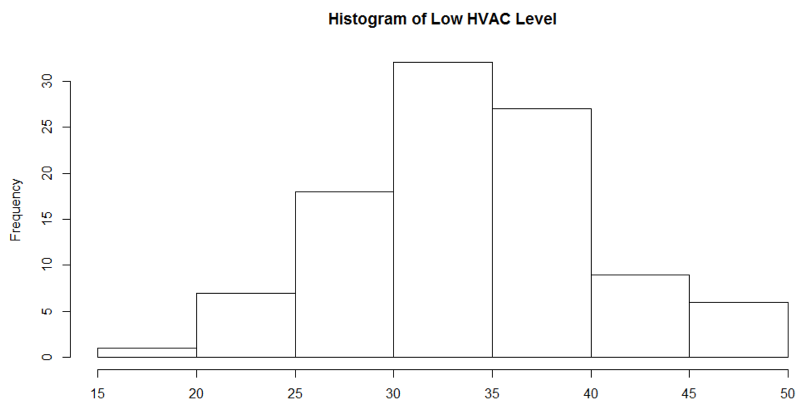

Figure B-16: Sample Histogram of Low HVAC Level

```
shapiro.test(off_Single)
shapiro.test(off_Multi)
var.test(high_Single,high_Multi)
#H0: high_Single = high_Multi
#Ha: high_Single =! high_Multi
t.test(high_Single, high_Multi, alternative="two.sided",
var.equal=T)
power.t.test(n=100,delta=mu,sd=SD,sig.level=0.05,type="two.sample",
alternative="two.sided")
```

Figure B-17: Statistical Analysis Code

The null-hypothesis of this statistical test is that the data is normally distributed. Thus, if the p-value is less than the chosen confidence level (e.g. 0.05), then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed set. On the contrary, if the p-value is greater than the chosen confidence level, then the null hypothesis that the data came from a normally distributed set cannot berejected. After failing to reject normality, F-test is used to check whether two datasets compared against each other have equal variances [34]. This test is shown in Figure B-17 as *var.test*. The hypothesis of data having equal variance is tested. Similarly, if the p-value generated is greater than the confidence level used (0.05), then the test fails to reject the null hypothesis. Both normality and equal variances tests should be checked when applying the T-test since this latter can only be applied to normal sets of data and it should be indicated whether the data has equal variance or not. The T-test (Figure B-17) was used to test the hypothesis under question [35]. Similar to other tests, the p-value generated is compared to the assumed confidence level. One last step include calculating the power of the T-test applied. This power is a good representation of the capability of the test applied in rejecting the null hypothesis when it is false [36].

In the following subsections, the aformentioned statistical analysis is applied on three different scenarios: (1) Single Behavior vs. Multiple Occupant Behavior, (2) Control Model vs. No Window Model, and (3) Control Model vs. Different Light Level Models to check different comfort levels. Information used in these scenarios are summarized in Table B-5.

Table B-5: Model, Parameters and Variables

Definitions		Model			
		Multiple Behavior	**Single Behavior**	**No Window**	**Different Light Levels**
Occupant Behavior	Green	2	NA	2	2
	Neutral	2	6	2	2
	Non-Green	2	NA	2	2
Levels of Factors	HVAC	1) Off Level 2) Low Level 3) Medium Level 4) High Level	1) Off Level 2) Low Level 3) Medium Level 4) High Level	1) Off Level 2) Low Level 3) Medium Level 4) High Level	1) Off Level 2) Low Level 3) Medium Level 4) High Level
	Window	1) Open 2) Closed	1) Open 2) Closed	NA	1) Open 2) Closed
	Shades	1) Open 2) Closed	1) Open 2) Closed	NA	1) Open 2) Closed
	Lights	1) On 2) Off	1) On 2) Off	1) On 2) Off	1) Fully on 2) Half on 2) Off

B.5.1 Scenario I: Single Behavior vs. Multiple Behavior

In order to check the effect of having different types of occupant behavior within the same space, a single behavior model was tested against a multiple behavior model. In the first model, six neutral occupants were considered. On the other hand, two occupants from each type were considered in the second model. The statistical results are displayed both in Table B-6 and Figure B-18.

Table B-6: Scenario I Statistical Details

Scenario	Multiple Behavior Model vs. Single Behavior Model									
Factor Tested	Lights		HVAC							
Level of Factor	Off Level		Off Level		Low Level		Medium Level		High Level	
Dataset	Off_Multi	Off_Single	Off_Multi	Off_Single	Low_Multi	Low_Single	Med_Multi	Med_Single	High_Multi	High_Single
Shapiro Test	0.31	0.53	0.94	0.12	0.2	0.42	0.052	0.78	0.025	0.08
Variance Test	0.63		0.98		0.67		0.31		0.11	
H0	Off_Multi = Off_Single		Off_Multi = Off_Single		Low_Multi = Low_Single		Med_Multi = Med_Single		High_Multi = High_Single	
Ha	Off_Multi != Off_Single		Off_Multi != Off_Single		Low_Multi != Low_Single		Med_Multi != Med_Single		High_Multi != High_Single	
T-test	0.0058		0.00011		0.015		6.35E-06		0.0093	
Power	0.8		0.98		0.7		0.99		0.75	
Result	Reject H0		Reject H0		Reject H0		Reject H0		Reject H0	

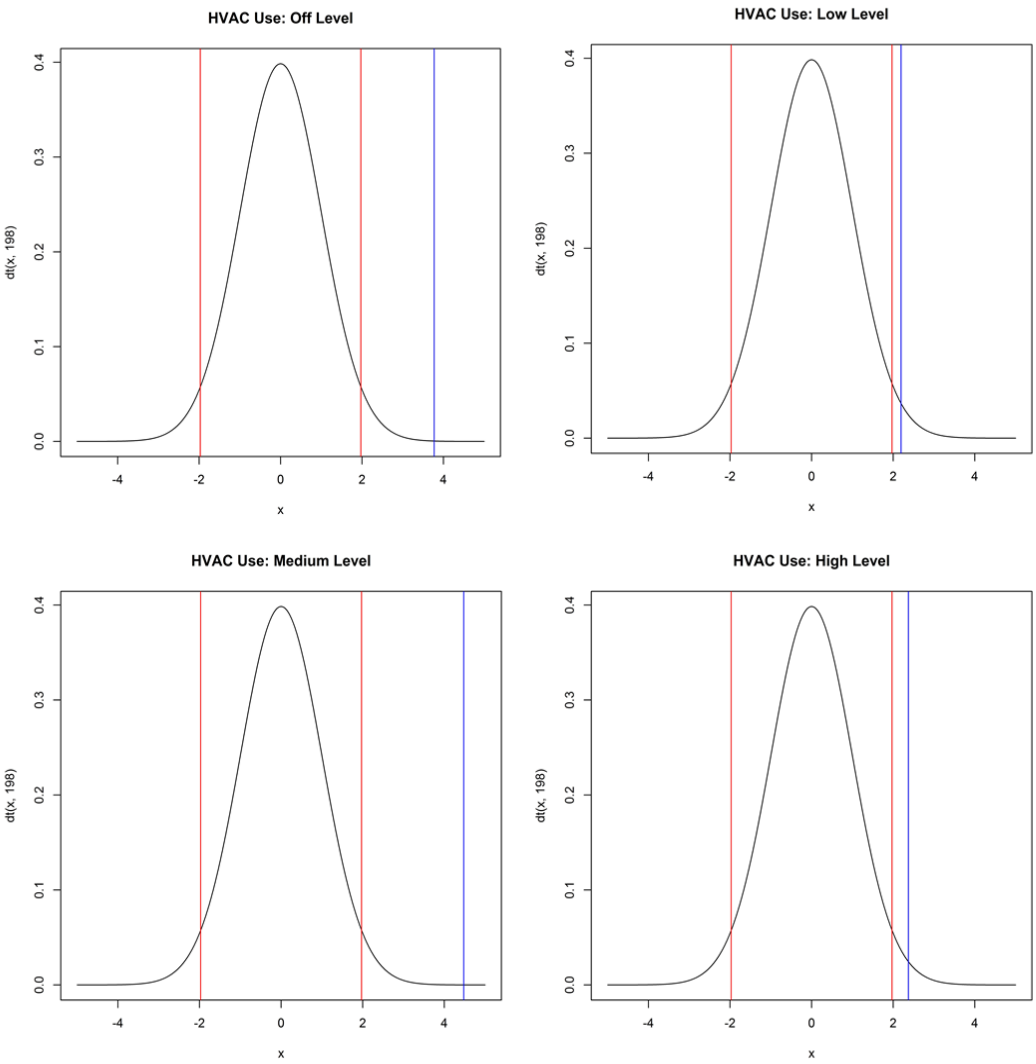

Figure B-18: Scenario I Results for Different HVAC Uses

Upon applying the Shapiro-Wilk test, the p-values generated for the datasets of all variables were greater than 0.05. Thus, it failed to reject that the data is normal. The

F-test was then applied and the corresponding outcome was implemented in the T-test. As shown in Table B-6, the tested or null hypothesis states that the results from both models are the same. However, the p-values generated by the T-test were less than 0.05, which rejected the aforementioned hypothesis. This is clearly shown in Figure B-18 where the blue lines (i.e. p-values) fell in the rejection zone, that is outside the area delimited by the red lines. Consequently, the p-values generated by the T-test were less than 0.05 which rejected the aforementioned hypothesis. The power of the T-tests applied was on average greater than 80%. Thus, when considering multiple behaviors of occupants, the emergent effect of these behaviors on the system was totally different than that of the single behavior. Therefore, it is important to consider multiple occupant behaviors to have a somewhat realistic model.

B.5.2 Scenario II: Control Model vs. No Window Model

In order to check the effect of the window on occupant behavior, the window variable was removed from the control model. The control model is assumed to be the multiple behavior model having all the properties discussed in Section B.4. When the window was removed, occupants had to always switch lights on in order to be satisfied visually. Moreover, occupants were always satisfied acoustically since there was no source of outside noise. However, the difference in the results of HVAC use were statistically analyzed and displayed both in Table B-7 and Figure B-19.

Table B-7: Scenario II Statistical Details

Scenario	Control Model vs. No Window Model							
Factor Tested	HVAC							
Level of Factor	Off Level		Low Level		Medium Level		High Level	
Dataset	Off_Cont	Off_NoW	Low_Cont	Low_NoW	Med_Cont	Med_NoW	High_Cont	High_NoW
Shapiro Test	0.12	0.032	0.42	0.7	0.79	0.57	0.079	4.10E-04
Variance Test	0.069		0.56		0.25		4.14E-05	
H0	Off_Cont ≥ Off_NoW		Low_Cont ≤ Low_NoW		Med_Cont ≥ Med_NoW		High_Cont ≤ High_NoW	
Ha	Off_Cont < Off_NoW		Low_Cont > Low_NoW		Med_Cont < Med_NoW		High_Cont > High_NoW	
T-test	3.94E-05		0.017		0.00052		1.42E-15	
Power	0.99		0.69		0.95		1	
Result	Reject H0		Reject H0		Reject H0		Reject H0	

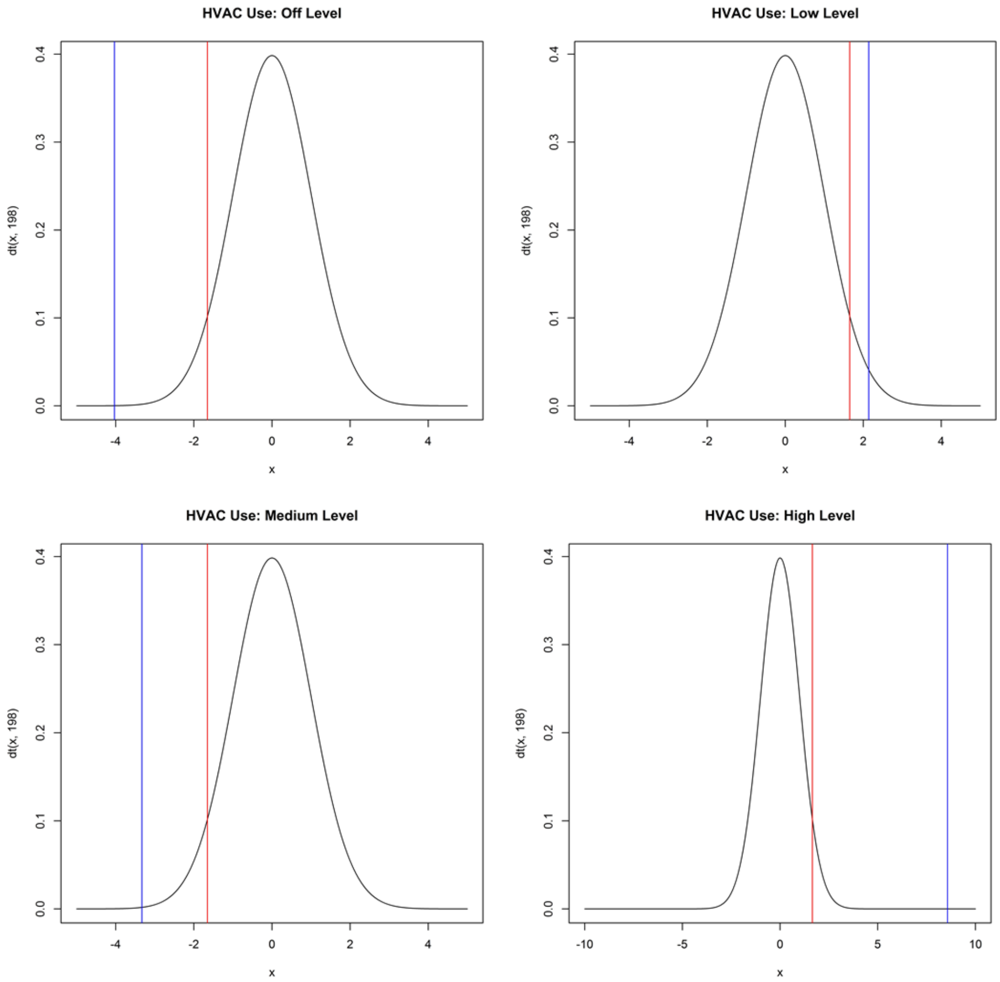

Figure B-19: Scenario II Results for Different HVAC Uses

When running the Shapiro-Wilk test, the results of all datasets generated a p-value greater than 0.05 except for the dataset of "HVAC off no window" case but it was assumed to be greater than 0.05. Thus, the test failed to reject that datasets belonged to a normal distribution. After that, the F-test of the first two pairs, (1) "HVAC off control" and “HVAC off no window” and (2) “HVAC low control” and “HVAC low no window”, yielded a p-value less than 0.05 rejecting the fact that the two datasets had equal variances which was taken into consideration when applying the T-test. On the other hand, the test for variances equality of the second pairs, (1) “HVAC medium control” and “HVAC medium no window” and (2) “HVAC high control” and” HVAC high no window”, generated a p-value greater than 0.05. Thus, it failed to reject that the two datasets had equal variance which was taken into consideration when applying the T-test. When applying the T-test, the results failed to reject that when window is removed, low and high levels of HVAC were used less than in the control model. On the contrary, the T-test results failed to reject that off and medium levels of HVAC were used more in the “no window” model than in the control model. These results are further confirmed in Figure B-19, where each of the blue lines (p-values) fell in the rejection zone of the respective null hypothesis, that is the smallest area under the curve bounded by the red lines. On the other hand, a common behavior of occupants in the control model includes opening the shades to be satisfied visually and increasing the HVAC level to be satisfied thermally because of the sun heat effect. However, when the window was removed, occupants did not have the option to open the shades. Therefore, they were not affected by the sun heat and did not have to increase the level of HVAC. Consequently, the low and high levels of HVAC use decreased and the off and medium levels of HVAC use increased. The power of T-test applied was on average greater than 0.9 which proved that the T-test is capable of rejecting the hypothesis tested 90% of the times when it is false which prove the reliability of the statistical results.

B.5.3 Scenario III: Control Model vs. Different Lights Level Model

In the third scenario, it was assumed that the office space is equipped with two light switches and an additional light switch was added to the control model. In other words, when being unsatisfied visually, occupants had the chance to (1) open the shades, (2) open the shades and turn half the lights on, (3) open the shades and turn all lights on, (4) keep the shades closed and turn half the lights on, or (5) keep the shades closed and turn all lights on. On the other hand, occupants in the control model had the chance to (1) open the shades while lights are off, (2) open the shades while lights are on or (3) keep the shades closed and turn the lights on. This variable was changed to check whether the addition of an intermediate light level would decrease the use of full light level. The statistical results are displayed both in Table B-8 and Figure B-20.

Table B-8: Scenario III Statistical Details

Scenario	Control Model vs. Different Light Levels	
Factor Tested	Lights	
Level of Factor	Full Level	
Dataset	On_Multi	Full_Diff
Shapiro Test	0.31	0.54
Variance Test	1.73E-11	
H0	On_Multi ≤ Full_Diff	
Ha	On_Multi > Full_Diff	
T-test	7.61E-08	
Power	1	
Result	Reject H0	

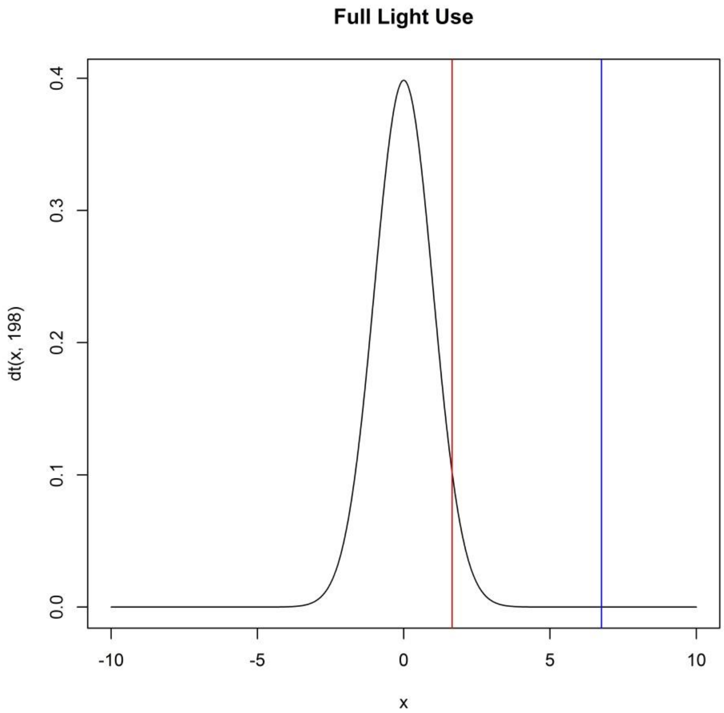

Figure B-20: Scenario III Results for Full Light Use

Normality testing for all datasets of the control model and of the different light levels model generated a p-value greater than 0.05. Thus, it failed to reject that these datasets followed a normal distribution. Moreover, equality of variances test yielded, as shown in Table B-8, a p-value less than 0.05, which was taken into consideration in the T-test. Figure B-20 shows the results of the applied T-test, where the blue line (i.e. p-value) fell in the rejection zone of the null hypothesis. Thus, it failed to reject that the full level of lights was used in the new model less than that in the control model. The power of T-test applied was 1 which proved that the T-test was 100% of the times capable of rejecting the hypothesis when it is false. Thus, it is highly recommended to have 2 switches in the office space rather than only one.

B.6. CONCLUSION AND FUTURE WORK

Energy consumption in academic buildings is a complex issue due to a wide variety of uses and energy services and therefore the energy demand of individual buildings need to be well understood. Researchers worked thereby on developing several tools that are capable of optimizing energy consumed in buildings . These tools were either developed to assess several design alternatives or incorporated occupant behavior to better comprehend its effect on energy use. However, they lack the ability to imitate a real world environment where different types of occupants target ultimate satisfaction and comfort on so many levels (i.e visual, thermal, and acoustic). As such, a new agent-based framework was proposed and designed in this paper to overcome the aforementioned limitations and study occupant multi-comfort level for building energy optimization. Moreover, the flexibility of the developed agent-based model facilitated the process of removing and adding new variables to test their effect on occupant behavior and on the model performance as a whole. For instance, the effect of having different occupant types within the space,no window or two light switches was studied and tested. In this case, results showed that (1) the presence of different occupant behavior types is deemed necessary for a more realistic overall model , (2) the absence of windows results in an acoustic satisfaction with an increase in HVAC off and medium level uses, and high lighting usage, and (3) the overall light usage decreases when two light switches instead of one are introduced.

While the proposed agent-based model has achieved promising results under different scenarios, it exhibits some limitations and further examination is needed to advance this line of research. Future research is needed to cover all components of the proposed framework and associated variables and parameters such as environmental conditions (temperature, humidity, etc.), indoor environment quality (IEQ), representative times of the day, occupants' clothing and activity levels, and different categories of occupants. Additional work is needed to implement a cost function and assess the overall cost of the emergent effect of occupant behavior on the system as well as model the leaving behavior of occupants using tracking technologies. Furthermore, the location-based components can be extended to track mobile occupants' cellphones connected over a Wi-Fi network. The authors will be also working on studying the effect of implementing new technologies and sensors in buildings on occupants' behavior and the system as a whole.

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