AN AGENT-BASED FRAMEWORK TO STUDY OCCUPANT MULTI-COMFORT LEVEL IN OFFICE BUILDINGS

Mohammad Barakat
Hiam Khoury

Department of Civil and
Environmental Engineering
American University of Beirut
P.O. Box 11-0236, Riad El Solh
Beirut 1107 2020, LEBANON

ABSTRACT

With the trend towards energy efficient buildings that diminish fossil fuel usage and carbon emissions, achieving high energy performance became a necessity. Allowing occupants to be actively involved during the design and operation phases of buildings is vital in fulfilling this goal without jeopardizing occupant satisfaction. Although different occupant behavior types were considered in prior research efforts, recent tools did not however examine simultaneously 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 the presence of different occupant behavior types is deemed necessary for a more realistic overall model, and the absence of windows results in an acoustic satisfaction with a decrease in (HVAC) use.

1 INTRODUCTION

With the expected increase in global population by 39% in 2035 (Dixit e. al., 2010), 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 (Yang et al., 2014). 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. (Yang et. al, 2014), 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 (Virote and Neves-Silva, 2012), and as such around 40% of the global energy is consumed by buildings (Pout et al., 2002). 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 (Energy Information Administration, 2010).

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 (Gul and Patidar, 2015). They usually focus on completing their job tasks rather than saving on energy (Andrews et al., 2013). 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 (Masoso and

Grobler, 2010) 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 objective of the paper is thereby to design a comprehensive agent based framework aiming at studying occupant multi-comfort level in academic buildings.

2 LITERATURE REVIEW

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. Researchers have observed that occupant behavior has a great influence on energy consumption at the operation phase (Azar and Menassa, 2012). 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 (Kavulya and Becerik-Gerber, 2012). Other previous work (Kwak et al., 2013) found that occupants consumed more energy when occupying large size rooms due to a higher HVAC and light power usage. In this case, energy efficient efforts were channeled toward creating efficient meeting schedules and reallocating occupants in the right rooms (Kwak et al., 2013). Accordingly, with occupants adopting energy conscious behaviors, energy consumption can be greatly reduced (Azar and Menassa, 2012). However, typical occupant adaptive behavior includes how an occupant adapts to changing environment conditions and sets comfort criteria. Therefore, researchers worked on enhancing occupant satisfaction level and improving indoor environment qualities through capturing their comfort levels using mobile cellphone applications (Jazizadeh et al., 2014). 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.

However, around 35% of the occupants are still not satisfied with the indoor environment qualities and the percentages of energy wasted are relatively still high (Asmar et al., 2014). As such, several new developed approaches and frameworks modeled occupant behavior and its effect on energy consumption, often using agent-based modeling (Railsback and Grimm, 2011). This simulation paradigm is a powerful technique mimicing real life systems by looking into its constituent units and testing what-if scenarios (Andrews et al., 2013). 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 (Bonabeau, 2002). Therefore, ABM (1) creates virtual agents that have the ability to interact with each other and their environment and accordingly make autonomous decisions, and (2) allows the examination of how collective system patterns develop from the adaptive behaviors of individual agents (Langevin et al., 2014).

Many researchers had a great interest in the commercial sector especially that occupants of these buildings do not usually have the incentive to save energy. For instance, Andrews et al. (Andrews et al., 2013) implemented a framework as an agent-based model of daily office occupant lighting use in order to test how well buildings are likely to perform given realistic occupants. This, in turn, helps measuring the usability of designs prior to the construction phase and thereby assessing whether design improvement is needed. Azar and Menassa (Azar and Menassa, 2012) developed an agent-based model to simulate occupant behavior and their impact on energy use in commercial buildings. More specifically, interactions between different office occupant agents having different energy behaviors were modeled vis-a-vis the energy use of the whole building. Lee and Malkawi (Lee and Malkawi, 2014) presented a new simulation methodology using agent-based modeling to simulate multiple occupant behaviors in a

commercial building and explore how they might adapt to changing thermal conditions in a way to reach thermal comfort or optimize energy savings.

Although the field of energy and buildings is evolving rapidly, existing approaches in the literature exhibit some limitations that should be overcome in order to achieve a reliable model capable of better mimicking real-life situations. Acoustic comfort of occupants was not considered. Only thermal and visual satisfaction levels were taken into consideration. When thermal and visual comfort levels were considered in previous research efforts, their simultaneous interaction was omitted. In other words, it was assumed that the behavior adopted to increase visual satisfaction is independent from that to increase thermal satisfaction. On the contrary, the state of certain variables in the system might affect more than one comfort level. The state of the shades, for example, can affect both thermal and visual comfort. Different occupant behaviors (i.e. green, neutral, non-green) within a multi-comfort scenario were not considered. Occupants might either have green, neutral or non-green behavior.

To address the aforementioned limitations, this paper aims at developing a comprehensive 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.

3   RESEARCH METHODOLOGY

The methodology adopted in this study is divided into two main tasks: (1) Abstraction of the agent-based model designed for studying occupant multi-comfort level in academic buildings, and (2) Implementation of the conceptual model using AnyLogic .

3.1   Agent-based Conceptual Model

Figure 1 presents the agent-based framework whereby occupants were the only agents considered. It is worth mentioning, that the area incorporated in the model is represented as an office space and occupant multi-comfort levels are only studied for the duration of the summer season's daytime hours. In this case, the occupant's adaptive comfort behavior is influenced by conditions related to both the system and themselves. These sets of conditions consist of (1) parameters that are defined at the start of the simulation and kept fixed throughout the simulation process and (2) variables that can change during the process according to rules and definitions (Borshchev and Filippov, 2004). Figure 2 depicts the aforementioned system and occupant parameters and variables.

In the first part of the framework (Figure 1), occupants within the space observe the space conditions to identify the internal and external factors (Component 1). Internal factors include Clothing (Clo) and Metabolic equivalent (Met) values which were considered because they both affect the occupant's thermal comfort (Component 2). Clo values define what the occupant is wearing (Indraganti et al., 2015) and a Met value is a physiological measure expressing the energy cost of physical activities (Rhee et al., 2015). 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.
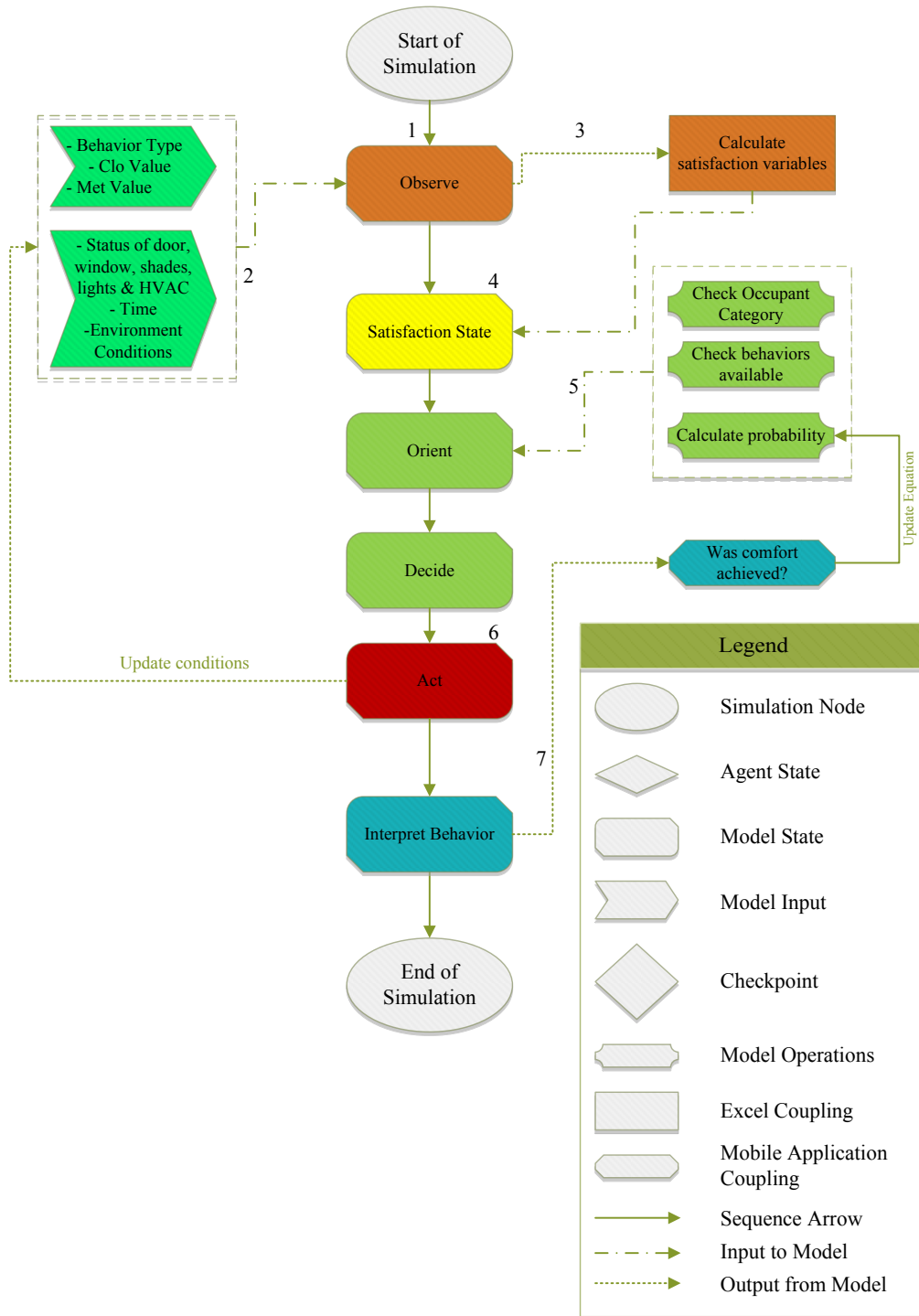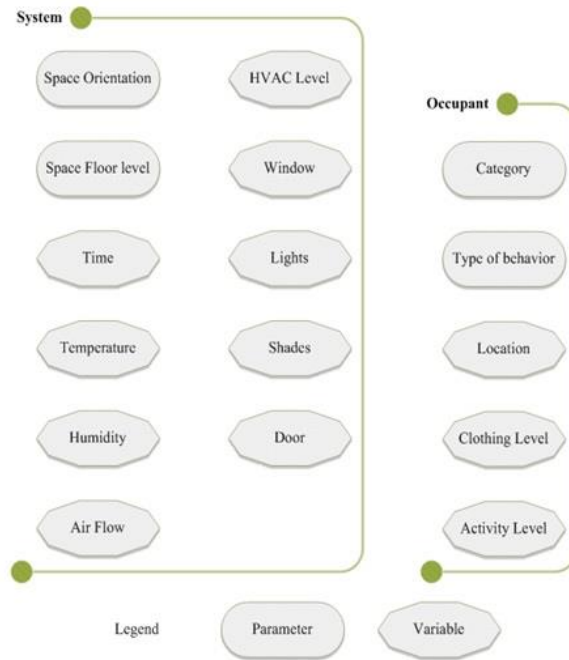
Figure 1: Proposed Framework.

Figure 2: Model Parameters and Variables.

Based on the internal and external factors observed, occupants analyze the situation by calculating the satisfaction variables. Table 1 mainly displays the direct effect of each factor on the different comfort levels (Component 3) using the " √ " symbol.

Table 1: 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	---	√	---

Based on the computed satisfaction variables, the occupant satisfaction state is updated (Component 4). According to the last recorded dissatisfied state, the occupant is then offered a set of possible behaviors that can enhance his/her satisfaction level. Given the agent-based modeling inherent nature, occupants interact with each other and decide upon certain behaviors, thereby updating the probability of certain comfort levels being reached within the studied space (Component 5). The occupants then act according to the decision taken, which in turn updates the system factors' conditions (Component 6). For instance, the HVAC level might increase or decrease, lights might be turned on, shades might be closed, etc. Finally, the behavior adopted is evaluated and interpreted to 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 (Component 7).

3.2   Agent-Based Model Implementation

In this section, the proposed agent-based framework was implemented using the multi-paradigm modeling tool, Anylogic (Borshchev and Filippov, 2004). Within Anylogic, all agents and common variables are usually defined in the Main window as shown in Figure 3. 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.
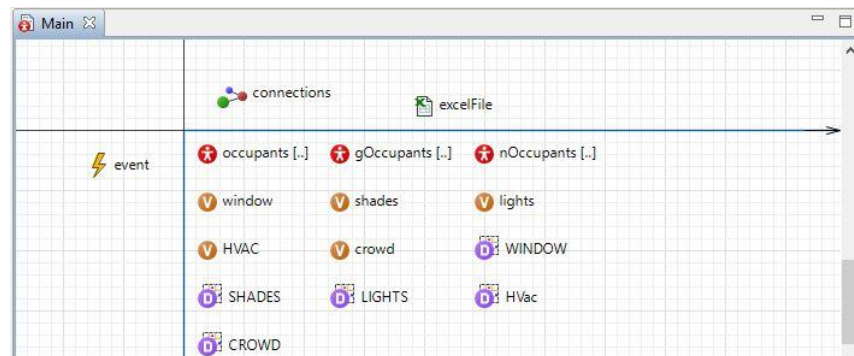

Figure 3: ABM Model Agents and Variables.

Variables specific to each agent were added on the Agent window. Figure 3 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 4 illustrates a multi-comfort agent statechart that is applicable to all agents (i.e. gOccupants, occupants, nOccupants) but with different behavioral properties. In this case, a satisfied state and four dissatisfied states were defined. More specifically, at the dissatisfied side of the statechart, many options exist. The occupant was considered to be dissatisfied visually, acoustically, or thermally. Moreover, the dissatisfied thermally state was subdivided into dissatisfied thermally hot and dissatisfied 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. Based on given conditions, the "Evaluate" event evaluates the current situation and determines the dissatisfaction state of the occupant. The event then sends a message (i.e. visual, hot, cold, or acoustic) to move the occupant from the satisfied state to the *dissatisfiedVisually,*

dissatisfiedThermHot, *dissatisfiedThermCold*, or *dissatisfiedAcoust* respectively. More specifically, the event checks dissatisfaction in the order of visual, thermal hot, thermal cold, and acoustic satisfaction.

As shown in Table 2, if the occupant is a green occupant, it was assumed 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 dissatisfied 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 dissatisfied 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 dissatisfied acoustically state was reached, and for all occupant types, there was an equal chance of closing the window or bearing the outside noise.

4   RESULTS AND STATISTICAL ANALYSIS

Upon running the simulation model for 10,000 iterations, the graphs shown in Figure 5 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.
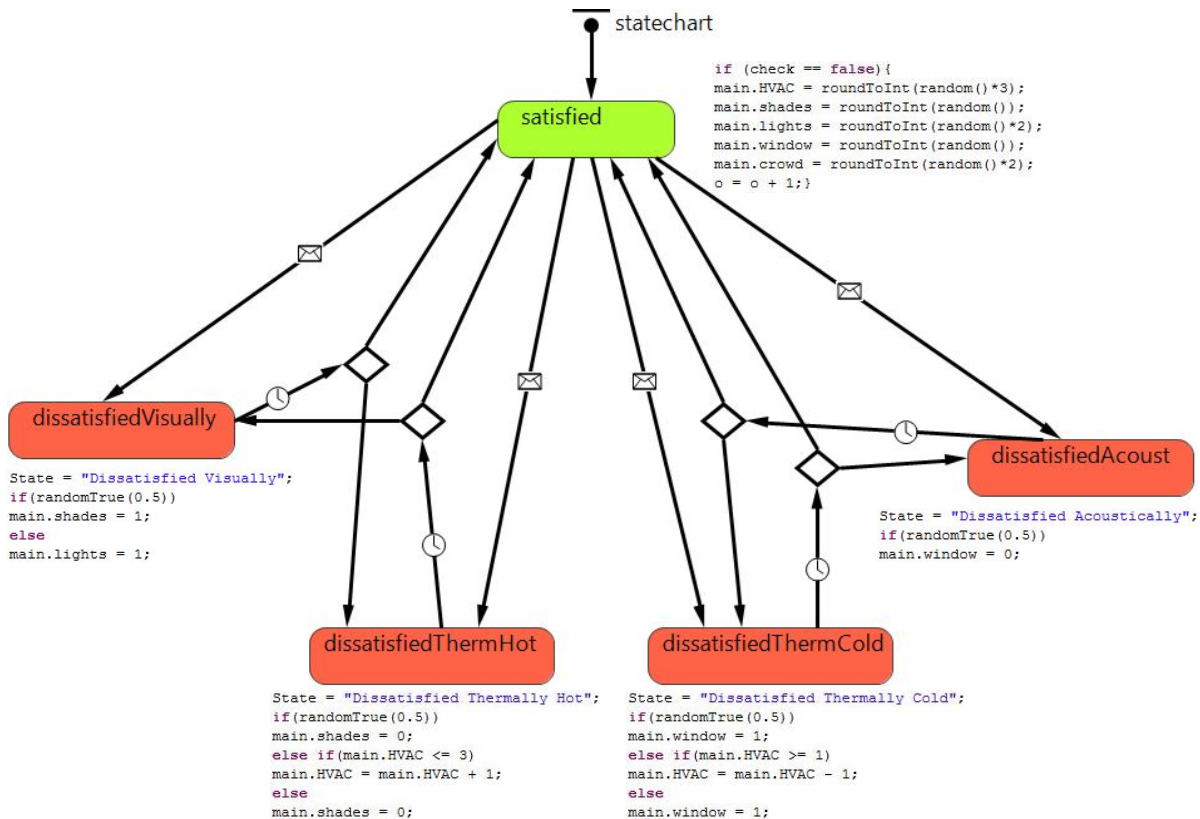

Figure 4: Multi-Comfort Agent Statechart.

Table 2: Probabilities of Behavior.

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

In order to analyze the results, RStudio was used (Gandrud,2013). It is an integrated development environment (IDE) for the R programming language that is used for statistical computing and graphics. More specifically, the probability of occurrence of each state was computed and stored 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, the Shapiro-Wilk test was carried out (Razali and Wah, 2011).
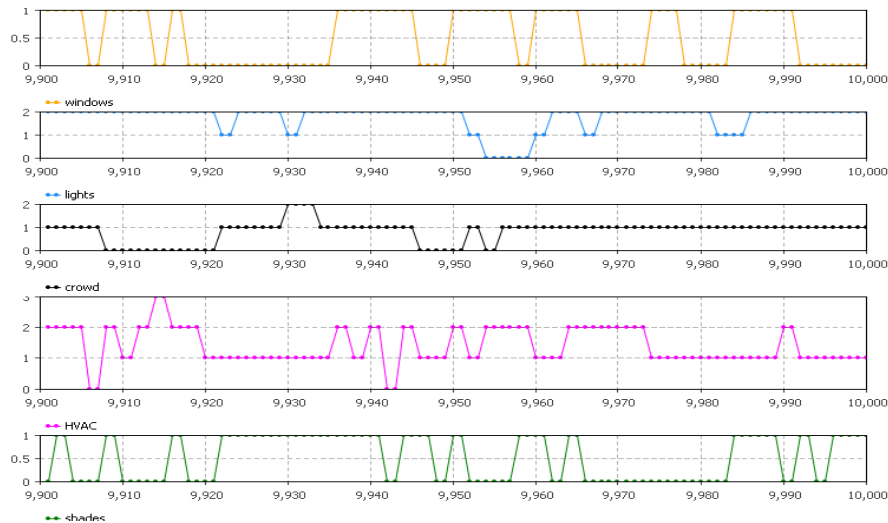

Figure 5: System Variables Output Graphs.

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 is 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 be rejected. After failing to reject normality, F-test is used to check whether two datasets compared against each other have equal variances (Shapiro and Wilk, 1965). 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 9) was used to test the hypothesis under question (Gardner and Altman,1986). 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 (Bridge and Sawilowsky, 1999).

In the following subsections, the aforementioned statistical analysis is applied on two different scenarios: (1) Single Behavior vs. Multiple Occupant Behavior and (2) Control Model vs. No Window Model, and tests' results serve as a proof-of-concept for the agent-based model.

4.1 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 in Table 3.

Table 3: 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	

Through rejecting H0, this scenario showed that 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.

4.2 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 3.

Table 4: 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	

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 in Table 4. This proved that when no window is available, the use of off and medium level increase where that of low and high levels decreased. This shows that 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.

5 CONCLUSIONS 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. The model flexibility allowed testing different scenarios. 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.

Future research is needed to cover environmental conditions (temperature, humidity, etc.), other indoor environment quality (IEQ) factors such as air quality, representative times of the day, and different categories of occupants. Additional work is needed as well to implement a cost function and assess the overall cost of the emergent effect of occupant behavior on the system.

REFERENCES

Andrew, C. J., Chandra Putra, H., and Brennan, C., 2013, "Simulation Modeling of Occupant Behavior in Commercial Buildings," Prepared by the Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA.

Azar, E. and Menassa, C., 2012, "Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings," *Journal of Computing in Civil Engineering.,* 26:506-518.

Azar, E. and Menassa, C., 2012, "A Comprehensive Analysis of the Impact of Occupancy Parameters in Energy Simulation of Office Buildings," *Energy and Buildings,,* 55:841-853.

Bonabeau, E., 2002, "Agent-based Modeling: Methods and Techniques for Simulating Human Systems," *Proceedings of the National Academy of Sciences*. 99(3):7280-7287.

Borshchev A., and Filippov, A., 2004. "AnyLogic—Multi-paradigm Simulation for Business, Engineering and Research," in *The 6th IIE Annual Simulation Solutions Conference*.

Bridge, P. D. and Sawilowsky, S. S., 1999. "Increasing physicians' Awareness of the Impact of Statistics on Research Outcomes: Comparative Power of the t-Test and Wilcoxon Rank-sum Test in Small Samples Applied Research," *Journal of Clinical Epidemiology,* 52:229-235.

Chen, D. and Gao, Z., 2011. "A Multi-objective Generic Algorithm Approach for Optimization of Building Energy Performance," *Computing in Civil Engineering (2011) American Society of Civil Engineers*, 51-58.

Dixit, M. K., Fernández-Solís, J. L., Lavy, S. and Culp, C. H., 2010. "Identification of Parameters for Embodied Energy Measurement: A Literature Review," *Energy and Buildings,* 42:1238-1247.

El Asmar, M., Chokor, A. and Srour, I., 2014. "Are Building Occupants Satisfied with Indoor Environmental Quality of Higher Education Facilities?" *Energy Procedia,* 50:751-760.

Gandrud, C., 2013. *Reproducible Research with R and R Studio.* CRC Press.

Gardner, M. J. and Altman, D. G., 1986. "Confidence Intervals Rather than P Values: Estimation Rather than Hypothesis Testing," *British Medical Journal (Clinical Research Edition),* 292(6522):746-750.

Gul, M. S. and Patidar, S., 2015. "Understanding the Energy Consumption and Occupancy of a Multi-Purpose Academic Building," *Energy and Buildings,* 87:155-165.

Indraganti, M., Lee, J., Zhang, H. and Arens, E. A., 2015. "Thermal Adaptation and Insulation Opportunities Provided by Different Drapes of Indian Saris," *Architectural Science Review,* 58:87-92.

Jazizade, F., Ghahramani, A., Becerik-Gerber, B., Kichkaylo, T. and Orosz, M., 2014. "Human-Building Interaction Framework for Personalized Thermal Comfort-Driven Systems in Office Buildings," *Journal of Computing in Civil Engineering,* 28:2-16.

Kashif, A., Le, X. H. B., Dugdale, J. and Ploix, S., 2011. "Agent Based Framework to Simulate Inhabitants' Behaviour in Domestic Settings for Energy Management." in *International Conference on Agents and Artificial Intelligence (ICAART)*, 190-199.

Kavulya, G. and Becerik-Gerber, B., 2012, "Understanding the Influence of Occupant Behavior on Energy Consumption Patterns in Commercial Buildings," *Computing in Civil Engineering (2012) American Society of Civil Engineers,* 569-576.

Khoury, H. M. and Kamat, V. R., 2009. "Evaluation of Position Tracking Technologies for User Localization in Indoor Construction Environments," *Automation in Construction,* 18:444-457.

Kim, J. B., Jeong, W., Clayton, M. J., Haberl, J. S. and Yan, W., 2015. "Developing a Physical BIM Library for Building Thermal Energy Simulation," *Automation in Construction,* 50:16-28.

Kwak, J., Varakantham, P., Maheswaran, R., Chang, Y., Tambe, M., Becerik-Gerber, B. and Wood, W., 2013. "TESLA: An Energy-saving Agent that Leverages Schedule Flexibility," in *Proceedings of the 2013 International Conference on Autonomous Agents and Multi-Agent Systems,* 965-972.

Langevin, J., Wen, J. and Gurian, P. L., 2014. "Simulating the Human-building Interaction: Development and Validation of an Agent-based Model of Office Occupant Behaviors," *Building and Environment.* 88:27-45.

Lee, Y. S. and Malkawi, A. M., 2014. "Simulating Multiple Occupant Behaviors in Buildings: An Agent-Based Modeling Approach," *Energy and Buildings,* 69:407-416.

Masoso, O. and Grobler, L. J., 2010. "The Dark Side of Occupants' Behaviour on Building Energy Use," *Energy and Buildings,* 42:173-177.

Outlook, A. E., 2010. "Energy Information Administration," *Department of Energy*.

Pout, C., MacKenzie, F. and Bettle, R., 2002. *Carbon Dioxide Emissions from Non-Domestic Buildings: 2000 and Beyond.* CRC, Construction Research Communications Limited.

Railsback, S. F. and Grimm, V., 2011. *Agent-Based and Individual-Based Modeling: A Practical Introduction.* Princeton University Press.

Razali, N. M. and Wah, Y. B., 2011. "Power Comparisons of Shapiro-wilk, Kolmogorov-smirnov, Lilliefors and Anderson-darling tests," *Journal of Statistical Modeling and Analytics,* 2:21-33.

Rhee, J. J., Sampson, L., Cho, E., Hughes, M. D., Hu, F. B. and Willett, W. C., 2015. "Comparison of Methods to Account for Implausible Reporting of Energy Intake in Epidemiologic Studies," *American Journal of Epidemiology,* 181:225-233.

Shapiro, S. S. and Wilk, M. B., 1965. "An Analysis of Variance Test for Normality (Complete Samples)," *Biometrika,* 591-611.

Yang, Z., B. Becerik-Gerber , N. Li, and Orosz, M., 2014. "A Systematic Approach to Occupancy Modeling in Ambient Sensor-rich Buildings," *Simulation,* 90:960-977.

AUTHOR BIOGRAPHIES

MOHAMMAD BARAKAT is a PhD student in Civil Engineering (majoring in Construction Management) at the American University of Beirut. He earned a B.E. and M.E. degrees in Civil and Environmental Engineering from the American University of Beirut in 2014 and 2015 respectively. Mr. Barakat's research interests involve Agent-Based and Discrete Event simulation, Building Information Modeling, and their applications in construction management besides their application in building energy studies to understand the impact of occupant behavior on energy consumptions in buildings. His email address is mob05@mail.aub.edu.

HIAM KHOURY is an Assistant Professor in the Department of Civil and Environmental Engineering (CEE) at the American University of Beirut (AUB). She earned a B.E. degree in Civil and Environmental Engineering from the Lebanese American University (LAU) in 2004, a M.S. and Ph.D. degrees in Civil and Environmental Engineering (majoring in Construction Engineering and Management) from the University of Michigan, Ann Arbor, MI, in 2005 and 2009 respectively. Dr. Khoury had the opportunity to be a guest researcher at the US National Institute of Standards and Technology (NIST), the US Army Construction Engineering Research Laboratory (CERL), and the George Washington University (GWU). Dr. Khoury's research interests encompass innovative simulation, computer and information technologies, and their applications in construction engineering and management, and other engineering fields, in addition to their applications in energy-based studies, in particular understanding the influence of occupant behavior in achieving energy-efficient buildings. Her email address is hk50@aub.edu.lb.