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Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis

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Abstract

The objective of this paper is to discover the emergent energy performance and determinants of energy waste in buildings. Electricity consumption in the U.S. attributes to 73% of energy waste in buildings and much of this waste is due to improper design, operation, and use of appliances. In particular, the operation or use phase of buildings and the way occupants behave significantly contribute to energy waste. Understanding the determinants of energy waste during the operation phase of buildings is a challenging task due to the complex interactions between the occupants, building units, and appliances. To decode these complex interactions and facilitate a better understanding of the determinants of energy waste, a simulation approach is used in this study. An agent-based simulation model was developed to capture the diverse attributes and dynamic behaviors of building occupants at the interface of human-building-appliance interactions. The application of the proposed model is demonstrated in a case study. Using simulation experiments, the interactions between occupant, building unit and appliance on energy consumption were investigated. The simulation model also was used for estimating determinants of energy waste. In addition, the simulation model includes a visualization interface that facilitates communication of strategies between the buildings users and facility managers. The results will highlight the significant attributes and effective strategies for energy waste reduction at the interface of human-building-appliance interactions. This information has potentially significant implications for building designers, facility managers, and users through a better understanding of emergent energy performance of buildings.

Peer-review under responsibility of the organizing committee of ICSDEC 2016

Keywords: human building appliance interaction; building energy; agent-based modeling; emergent energy perfromance; occupant behavior; energy efficiency

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1. Introduction

Energy waste is a major sustainability challenge in buildings in urban areas. During the last decade, primary energy consumption has been increasing annually and the building sector accounts for significant part of energy consumption nationally and globally. Buildings consume 20-40% of primary energy in developed countries [1]. In the United Kingdom, buildings are responsible for 39% of energy consumption which is slightly higher than average energy consumption in other European countries (37%). Similarly, in the United States, 41% of total energy consumption and 74% of energy used for electricity in 2014 were from the residential and commercial building sectors [2]. Accordingly, several studies have been conducted to investigate ways to improve energy efficiency and reduce energy wastes in buildings. However, improving the energy performance of buildings has remained as a major challenge due to the complex nature of buildings and lack of information related to energy factors, occupancy, and occupant decision indicators [3-5]. In particular, occupant behaviors have been identified as one of the major determinants of energy waste in buildings. Accordingly, various studies have investigated phenomena influencing occupant behaviors and its impact on energy waste [6,7]. The operation phase of buildings and the way occupants behave significantly contribute to energy waste. Occupant behaviors affect the decisions in the operation of appliances and contribute to energy consumption and waste in buildings. Despite the growing literature in this area, there is a gap in knowledge regarding occupant-building-appliance interactions and its impact on energy performance of buildings. In fact, building energy performance can be investigated from two aspects: baseline energy performance and emergent energy performance, as shown in Fig. 1. Baseline energy performance is influenced by factors such as building materials, climate zones, and building envelope. Emergent energy performance is affected by the dynamic behaviors at the interface of occupant-building-appliance interactions. In order to better understand emergent performance, there is a need for understanding how different attributes of occupants, buildings, and appliances lead to certain behaviors and how the interactions between the occupants, building, and appliance cause energy waste. To address this important gap in the body of knowledge, the objective of the study presented in this paper is to utilize simulation to investigate emergent energy performance in buildings.

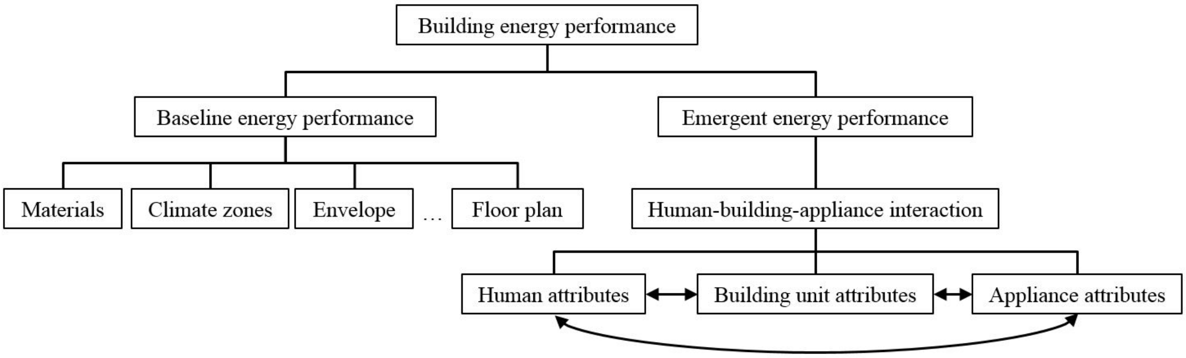


Fig. 1. Building energy performance

2. Research Objectives

Understanding the determinants of energy waste during the operation phase of buildings is a challenging task due to the complex interactions between occupant behaviors, building unit characteristics, and appliance characteristics. The main objective of this paper is to discover the emergent energy performance and its influencing factors in order to investigate human-building-appliance interactions and to estimate determinants of energy waste in buildings. This study utilizes a simulation approach to decode these complex interactions and facilitate a better understanding of the determinants of energy waste. An agent-based simulation model is developed to capture the diverse attributes and dynamic behaviors of building occupants at the interface of human-building-appliance interactions. The application of the proposed model is demonstrated by using a case study, described later in the paper. The impacts of several different factors, such as occupant schedules, workload, and energy literacy levels of occupants are investigated during the simulation experiments. In addition, the simulation model includes visualization interfaces, such as 3D animation, 2D animation, and statistics features, which facilitate the communication of strategies between the buildings users and facility managers.

3. Methodology

In this section, an agent-based modeling simulation (ABMS) approach is proposed to capture and model interactions between occupants, buildings units (rooms) and appliances. The model can help to explain the occupant interactions with building units and appliances, how agents communicate and coordinate with their environment and appliances and how these interactions affect energy consumption. The model captures the interactions of all these features by modeling building units and appliances as individual agents interacting with occupants. Additionally, the model can provide the effect of different energy literacy levels of occupants on energy use. The ABMS captures the energy literacy level of occupants, appliances and room features such as natural lighting and ambient temperature.

3.1. ABMS using Anylogic

The ABMS is constructed using AnyLogic 7.1. AnyLogic is a simulation software package that uses the Java programming language to create agent-based models, in addition to other simulation methodologies [8]. The tool provides graphical animations in addition to statistical functions to generate simulations, which made it ideal for our use. Additionally, AnyLogic's Process Modeling Library is used to simulate an office's work schedule in the studied building environment, an office setting.

3.1.1. Case study

The model is demonstrated using a hypothetical case study. The case study's environment is a single floor office building with 7 regular office rooms, a conference room, and a kitchen with copy machine area as shown in Fig. 2. Two different types of office rooms are depicted including: (1) an office with a window, which has a positive Natural Lighting attribute, and (2) an office without windows, which has no Natural Lighting. Table 1 summarizes the information about the building units, occupants and appliances in this study. The Process Modeling Library was used to model a typical workday for permanent occupants of the office, called a *Resident Occupants* in the model. Their behaviors and schedules were modeled as shown in Fig. 2. This flowchart shows how all typical workers start work in the same manner on weekdays but then branch off to different tasks, which can include team meetings in the conference room, running errands to adjacent offices and staying in their own respective office to do solo-work. Then, based on their task demands, workers have the choice to move to the break room for a lunch break, or continuing work in their own office. At the end of a workday, the workers go back to their office to pack up and then go home as denoted by the second to last node on the flowchart. The delay at the end of the flowchart denotes time spent outside of the office until the new workday.

3.1.2. Agents and their attributes

To observe interactions between the three main agent types in this study, *resident occupants*, *building units*, and *appliances*, the ABMS models different types of agents with their attributes. In the simulation, each *resident occupant* had a semi-randomized work schedule to perform different task demands and movement trajectories in addition to lighting and temperature comfort levels. When the *resident occupant* is present in office, energy consumption is determined based on appliance and lighting energy usage. The instances of energy waste occur if the *resident occupant* leaves the room and forgets to turn off the light or *appliance*(s). The likelihood of such instances depends on the occupant attributes such as the level of energy literacy. For example, an energy literate occupant has less possibility to leave the light on when leaving the office compared to an energy illiterate occupant. The lighting comfort level would determine if the occupant decides to use artificial light in a room with windows. The use of natural lighting also depends on the energy literacy of the occupant. The energy literate occupant has a greater likelihood to use natural lighting to meet the comfort level. On the other hand, the energy illiterate person always uses the artificial lighting. Table 1 presents agents and their related attributes that are considered in the model. For instance, each building unit has an associated natural lighting level (due to windows or lack thereof) and a *resident occupant* has a lighting comfort level that can be met by the natural lighting level of the room along with the aid of an artificial lighting appliance that consumes energy. Similar relationships are made by heating and cooling appliances and regular appliances. Using proper algorithm the rules associated with occupant behaviors are realized and implement in order to simulate the impact of different building, occupant, and appliance attributes on the energy performance of the building.

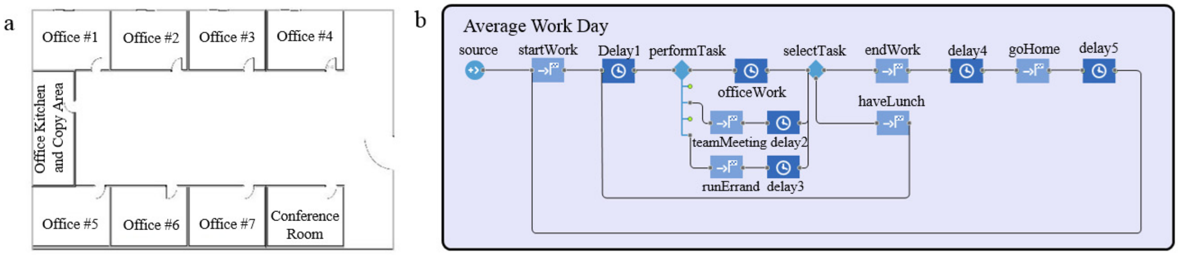


Fig. 2. (a) A floor plan of case study (left) and (b) Average work day schedule flowchart generates a semi-random schedule for workers.

Table 1. Agents and their attributes.

Building Units (rooms)	Resident Occupants (workers)	Appliances
Natural lighting levels	Lighting comfort levels	Lighting consumption and waste percentages
Heating and cooling characteristics	Heating and cooling comfort levels	HVAC system consumption information
Number of appliances	Appliance usage information levels	Energy consumption information
Number of resident occupants	Energy literacy	Differing energy consumption information

3.1.3. Agents UML diagrams

As mentioned previously, the simulation models resident occupants, appliances, building units, and the interactions between them. The class diagram in Fig. 3 depicts these agents and their associated connections. This case study includes the *Appliances*, *ResidentOccupants*, and *BuildingUnits* classes, in addition to *Main*, which runs the simulation. Shown here are the first three classes or agents.

In the Fig. 3, the *ResidentOccupants* class depicts an office worker, along with his or her personal attributes, such as office, energy literacy, and personal comfort levels for lighting, and heating and cooling. It is possible to change these preferences by setting the energy literacy attribute to true or false or by manually setting the levels through the *setComfortLevels* function as shown in *ResidentOccupants* class. The relationship line presents how, depending on which room the *ResidentOccupants* is currently in, the occupancy will affect the status of the *BuildingUnit* through the *useLight* and *useAppliances* function. The *BuildingUnits* class uses the *turnOnAC*, *turnOffAC*, and *useApps* functions after being called by the *useLight* and *useAppliances* function from the *ResidentOccupants*. The functions of *turnOnAC* and *turnOffAC* affect the energy consumption levels from the Appliances class for the appliances in the *BuildingUnits*. Appliance energy consumption levels are then increased through the use functions in the *Appliances* class.

The states diagram in Fig. 4 shows the flow of execution of the simulation when the resident occupant moves from his or her office to the kitchen (breakroom) for lunch. The occupant first enters his office and proceeds to turn on lights, appliances, and air conditioning based on his *task demands* and his heating, cooling and lighting *comfort levels*. These levels are affected by the occupant's *energy literacy* levels which can positively or negatively impact the usage levels of appliances in the room.

At this point, the total energy consumption in kWh of appliance agents in the room is increased if the appliances are being utilized. This information is individually collected by the office, simulating sensors in the room, such as a lighting sensor or a temperature sensor that would accumulate consumption information from different appliances. Finally, the consumption information, *collectKwhConsumption*, is gathered by the main class in the simulation and it is further used for statistics and analysis of the buildings energy consumption. The next step of the simulation is *setLight/Temp/appliances* function, which shows the resident occupant setting the light and appliances for the breakroom; it indicates that the occupant has gone to lunch. As stated before, the appliances in the breakroom adjust their kWh levels and later this data is collected by the break room and then the main class. The same scenario occurs when the resident occupant moves to the conference room for a meeting.

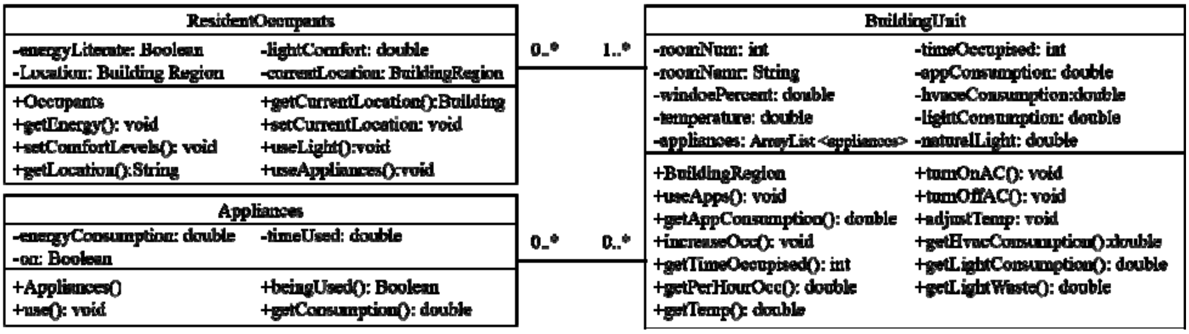


Fig. 3. Class diagram for the energy efficiency ABMS

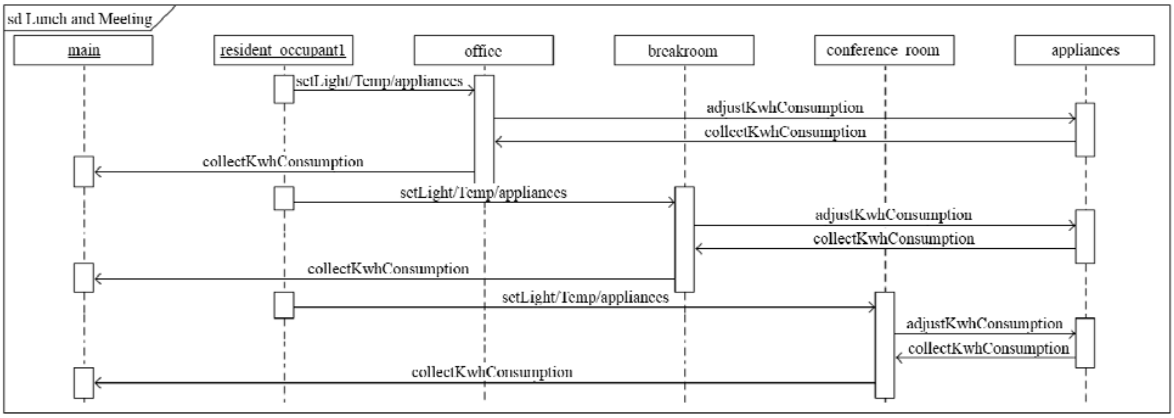


Fig. 4. State diagram depicting an occupant going to his office, then to lunch and followed by a meeting

3.2. Case study scenarios

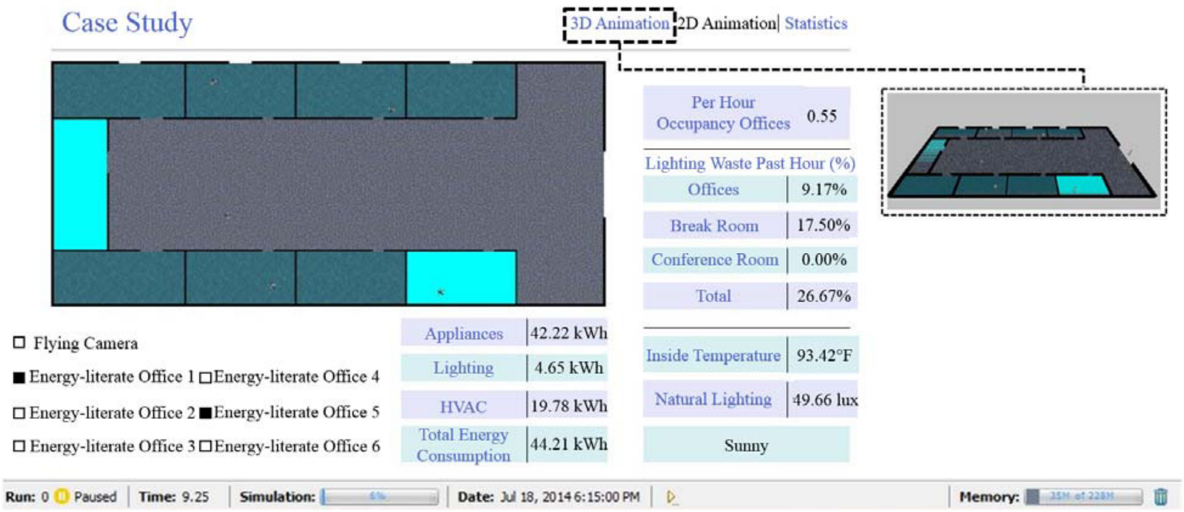
In this study, four scenarios are performed to demonstrate the model and investigate the occupant-building unit-appliance interactions. The resident occupants are classified as either energy-literate users or energy-illiterate (wasteful) users based on their energy efficiency concerns. Their energy consumption behaviours directly impact the use of appliances in their currently occupied room. Furthermore, occupants can be assigned to occupy one of two building unit types: (1) an office with window and (2) an office without a window. Different building units influence the availability of natural lighting which can also affect lighting comfort levels of occupants. To sum up, scenario 1 and 2 consider energy-literate occupants in the two different building units. Likewise, scenario 3 and 4 examine energy-illiterate occupants in the different building units. The summary of scenarios is provided in table 3.

In each scenario, the energy consumption levels of appliances, lighting and HVAC units in an office are estimated. The energy-literate person is modeled to utilize artificial lighting only when the lighting in the room is below his or her comfort level. Since the occupant is classified as energy-literate, his lighting comfort level will be lower than someone who is an energy-illiterate person. In addition, he will utilize appliances less and have a temperature comfort level that reduces the consumption of the offices HVAC system. On the other hand, an energy-illiterate person has a lighting comfort level that is higher than an energy-literate person, causing him to use more artificial lighting since this type of occupant will always turn on a light, even if he or she occupies a room with a window.

4. Results

In this section, the results of ABMS scenarios are analyzed. As mentioned earlier, AnyLogic can simply create a 3D visualization interface of the building environment with office characteristics, such as doorways and windows. A screenshot from the AnyLogic software showing the model's layout and simulation features is presented in Fig. 5. As shown in the layout, the break room is located to the left side of the building and is highlighted in a bright blue color. Another room with the same color on the bottom right corner is the conference room. The entrance and exit of the office is on the outermost wall to the right as previously predicted in Fig. 2.

At the instance of the simulation shown in Fig. 5, the model is able to detect the energy consumption of appliances, lighting, and HVAC units as well as total energy consumption in kWh. There are other features detailed by the simulation such as natural lighting levels, heating and cooling energy consumption, indoor temperature, and outside weather conditions. The model also has the ability to set the energy literacy levels of resident occupants for an experiment. Furthermore, there are options of visualization modeling using AnyLogic. The model can show 2D animation, 3D animation, and dynamic statistic display of energy consumptions.



Per Hour Occupancy Offices	0.55

Lighting Waste Past Hour (%)

Offices	9.17%
Break Room	17.50%
Conference Room	0.00%
Total	26.67%

Appliances	42.22 kWh
Lighting	4.65 kWh
HVAC	19.78 kWh
Total Energy Consumption	44.21 kWh

Inside Temperature	93.42°F
Natural Lighting	49.66 lux

Sunny

☐ Flying Camera
☒ Energy-literate Office 1 ☐ Energy-literate Office 4
☐ Energy-literate Office 2 ☒ Energy-literate Office 5
☐ Energy-literate Office 3 ☐ Energy-literate Office 6

Run: 0 Paused | Time: 9.25 | Simulation: 6% | Date: Jul 18, 2014 6:15:00 PM | Memory: 35M of 228M

Fig. 5. Model layout and simulation presents users of offices #1 and #5 are selected as energy-literate persons, and users of office #2 and #6 are energy-illiterate.

The screenshot in Fig. 5 shows the simulated office with different energy efficiency levels for the occupants of different offices based on the four scenarios in this study. In particular, the resident occupants of office #1 (with a window) and #5 (no window) are specified as energy-literate persons, while the resident occupants of offices #2 (with a window) and #6 (no window) are introduced as energy-illiterate persons. Table 3 summarizes the total energy consumption in kWh for all scenarios. The results show that energy-literate occupants consumed approximately 35% less energy than their energy-illiterate counterparts in all cases as expected. Furthermore, it can be observed that having natural light in an office can decrease the total energy consumption by 8% regardless of the occupant behaviors. However, it is found that an energy-illiterate person in an office with a window (see scenario 3) still consumes more energy than an energy-literate person in an office without windows (scenario 2). These results highlight the coupled impacts of building unit and occupant attributes on the emergent energy performance of the building.

Table 2 summarizes lighting waste produced by the different scenarios described above. It is not surprised to see that there is not energy waste in the scenarios 1 and 2 and also that energy-literate occupants are the only indecisive behavior who produces waste. The interaction of energy-illiterate person to the building unit can be pointed out here. The windowless office in scenario 4 produces 30% more waste than another office occupied by the same type of energy behaviors. The graph in Fig. 6 presents the dynamic outcomes of the total energy consumption over time in all scenarios. The total energy usage is increasingly aggregated from the morning to the evening in all cases. Both energy-literate occupants exhibit the similar levels of energy used throughout the day as shown by their comparable slopes in the graph. On the other hand the energy-illiterate occupant in the office without a window had the steepest slope than the other occupants which shows his increased energy expenditure.

The results support the significant impacts of occupant behaviors to the total energy expenditure of the building. It also identifies the critical interactions between occupants, building units and appliances that should be considered. The understanding of complex interactions can lead to an opportunity for future energy efficiency and energy waste reduction plan.

Table 2. Scenarios summary and results.

Scenario	1	2	3	4
Occupant	Energy-literate person		Energy-illiterate person	
Building unit	Office with window	Office without window	Office with window	Office without window
Energy consumption (kWh)	92.73	101.70	141.91	154.44
Total light waste (kWh)	0	0	19.17	25

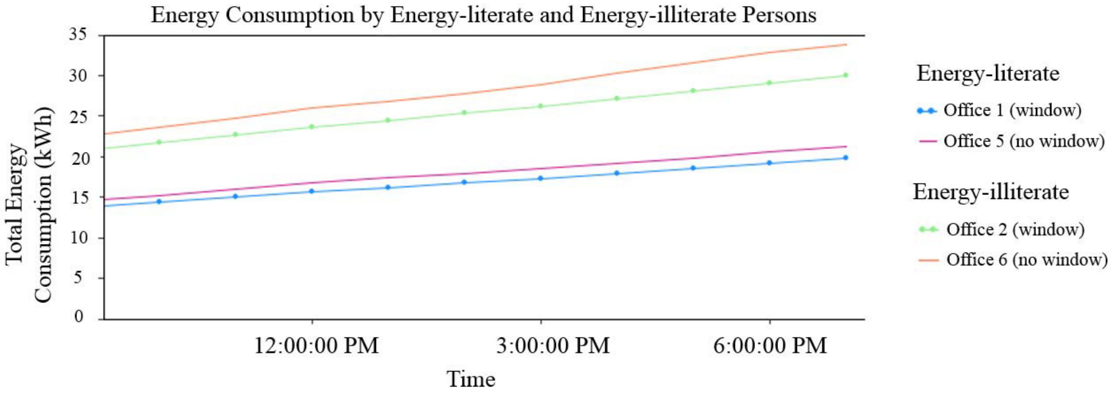


Fig. 6. Energy consumption of 4 effects at the end of two workdays, with energy-literate and illiterate occupants.

5. Conclusion

This study investigates the emergent energy performance of an office building in order to identify opportunities for energy waste reduction in buildings. The focus of the analysis is on investigating occupant-building-appliance interactions and their impact on building energy waste. This study utilizes an ABMS approach to decode occupant behaviors in regards to energy expenditure in buildings. The model can demonstrate how these interactions affect energy expenditure and how they can change based on occupant features such as energy literacy levels and work schedule. For instance, the results shows that if an occupant is energy-literate person, he or she will perform best in an office with a window because the occupant would take advantage of the natural lighting of the room and tentatively does not waste energy by turning on artificial light when it is bright and sunny outside. An energy-illiterate person would always use the artificial lighting in any cases, even when it is not necessary due to the adequate light coming through the window. Hence, this preliminary study shows the importance of considering occupant-building-appliance interactions in assessing the emergent energy performance in buildings. These complex interactions are not fully considered in previous studies. According to the results of this study, further investigation of occupant-building-appliance interactions holds the key to unlock numerous opportunities for energy waste reduction in buildings.

4. Future work

In an ongoing plan, the model will be extended to create a more robust methodology and incorporate more scenarios that will include how peer effect influences occupants and their energy consumption. Moreover, the model is planned to integrate Partially Observable Markov Decision Processes (POMDP) in order to assess occupant behaviors with limited observational data. Thus, the model will be able to simulate agents using unique utility functions to demonstrate how agents in a building mutually influence each other in differing energy efficiency scenarios [9].

Additionally, in order to automatically identify energy-literacy levels, data from a sensor network will be incorporated to capture real-time information about occupants rather than taking the passive approach of surveying occupant behaviors for their perception of their literacy levels. Thus, real-life data collected from a non-invasive sensor network that records actual occupancy and indoor temperature, lighting, and energy consumption information will be integrated into the simulation [10,11]. This will significantly help to fine-tune our simulation parameters and more precisely estimate energy consumption in buildings.

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