LIGHTING ENERGY LOAD PREDICTION FRAMEWORK USING AGENT-BASED SIMULATION AND ARTIFICIAL NEURAL NETWORK MODELS

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Abstract

Lighting is responsible for 17% of the total electricity consumption in commercial buildings in the United States. Investigating the lighting energy load provides the potential for more energy-saving in commercial buildings. Nonetheless, the development of lighting load prediction models has received limited attention in extant literature. This study proposes a framework to predict the lighting schedule and load in office buildings by integrating an agent-based model into an artificial neural network model. A small office building is used as a case study to simulate lighting load based on occupancy information using an agent-based model. Then, an artificial neural network model is developed to predict the simulated lighting energy load. The results illustrated that the accuracy of the prediction model could be as high as 92.8%. The developed model can be used by facility managers and engineers to accurately predict the lighting energy load in office environments.

Introduction

Buildings account for 72% of the energy used in the United States, where more than 80% of a building's life-cycle energy consumes during the occupation phase (Menassa, 2011). According to the U.S. Environmental Protection Agency (EPA), commercial buildings consume half of the total energy (Green, 2012). Specifically, lighting contributes to 17% of electricity use in commercial buildings, while in office buildings, it is as significant as 20% to 45% of total electricity consumption (EIA, 2017). Lighting is a crucial determinant of indoor environmental quality in buildings, as it significantly influences occupant satisfaction levels (Vosoughkhosravi *et al.,* 2022). Predicting the lighting energy load in office buildings is necessary for improving energy efficiency and increasing energy saving (de Bakker *et al.*, 2017).

It has also been stated that using occupancy sensors can reduce the lighting energy load by 20% to 60% in office buildings (Chung and Burnett, 2001). Although various studies investigated the lighting energy load and the feasibility of implementing occupancy sensors in specific buildings, a neglectable discrepancy between the actual and predicted lighting energy consumption has been observed due to underestimating the impact of occupant behavior (Hong *et al.*, 2016). Various methods and approaches have been used to simulate occupant behavior and its impact on building energy performance (Ardabili *et al.*, 2022). The agent-based modeling (ABM) simulation has gained more attention due to its capability to simulate the occupants' stochastic behavior (Kwok and Lee, 2011; Dong *et al.*, 2021). For instance, Liao et al. (2012) developed an ABM simulation model of occupancy dynamics with an unspecified number of occupants. Although their simulation model was effective in predicting occupancy schedules, it was only applicable to single-occupant office layouts. In another study, Azar and Menassa (2012) created an ABM model to predict the occupants' interaction with various energy use preferences. Also, Yang and Wang (2013) proposed a multi-agent-based model to optimize the building energy and provide thermal comfort for occupants in the building. In a recent study, Dziedzic et al. (2020) proposed a high-resolution, data-driven movement engine for occupants based on ABM that can simulate occupants' behavior and their different actions. In another study, Ding et al. (2019) investigated the energy behavior of occupants in shared university resident buildings. Since student–student and student–building system interactions are complicated, this study developed an agent-based simulation model regarding students as heterogeneous individuals focusing on simulation parameters such as students' basic information, the presence status in dorms, and appliance-using behaviors. This study concluded that occupancy is the most significant factor for dorms' energy consumption, and reducing the time of air conditioner use has the most significant impact on energy-saving.

Furthermore, Malik et al. (2022) conducted research to formalize the level of detail (LoD) required for occupant behavior representation in agent-based environments. This framework aimed to select the needed details in describing occupants in agent-based models and consider different occupants' characteristics in LoD to improve ABM simulation. Also, more information about agent-based modeling and simulation can be found in a study conducted by Stieler et al. (2022). They provided a systematic literature review, which indicates a classification for agent-based modeling and simulation (ABMS) in architecture using the individual entities being modeled as agents. In this regard, in each of the agent-based models uncovered in the selected literature, the representation of the entity of an agent in the model was proposed. Thus, a comprehensive classification for ABMs in architecture was provided in this research.

Besides, with the advancement of computational tools, Artificial Neural Network (ANN) models are getting have gained attention in predicting occupancy schedules and energy consumption based on historical data. For example, in a study by Deng and Chen (2019), occupant behavior was simulated by integrating an ANN model with building energy simulation tools to predict the HVAC energy consumption in an office building. In another study, Lee et al. (2019) investigated occupancy schedules to predict the energy consumption of single-person households in South Korea. They considered occupants' characteristics, such as age, gender, occupation, income, educational level, and occupancy period, to model energy consumption based on the ANN method. Their results represented a correlation between user characteristics and energy usage. Also, Amasyali and El-Gohary (2021) developed a predictive energy consumption model based on various machine learning algorithms. They concluded that ANN has a high performance in predicting the energy load. In addition, Chen et al. (2021) conducted a study to predict office building electricity demand using ANN. This study introduced an approach using ANN and fuzzy logic techniques to fit the building baseload, peak load, and occupancy rate with multi-variables of weather variables. They also verified their model with a case study of the University of Glasgow. Their results highlighted that the ANN with fuzzy model reduces the average RMSE by 42%, compared with the traditional power demand prediction models.

Predicting the occupancy schedule and its impact on building energy consumption is challenging. In this regard, the building energy consumption and energy saving potentials can vary case by case due to a high level of uncertainty (Abraham, Anumba, and Asadi, 2018). Therefore, case studies can play an essential role in simulating occupancy behavior and its impact on building energy consumption. However, it is difficult to generalize and apply the design principles from one case study to another. In addition, regarding predictive models, data-driven approaches such as ANN usually require a large set of input data that is usually unavailable during the design phase. Finally, developing lighting load prediction models, particularly in office spaces, has received limited attention in extant literature. Consequently, there is a pressing need for a precise lighting load model to effectively analyze energy consumption attributable to lighting.

To address these gaps, this study aims to predict lighting energy load in office buildings, considering occupant behavior, by integrating ABM and ANN models. First, an agent-based model is developed to simulate the occupancy schedule regarding lighting energy load based on three main occupant behavior of presence, movement, and interaction with the lighting system (i.e., turning lights on or off) in two scenarios: with or without having occupancy sensors. Then, an ANN model is trained based on the time series of the simulated occupancy schedules to predict lighting energy load in different scenarios based on three main inputs: time of the day, day of the week, and room number. A small office layout is used as a case study to evaluate the accuracy of the proposed model in different scenarios. This study contributes to the body of knowledge by providing researchers and professionals with a modeling and simulation tool to better understand occupancy schedules, lighting energy load, and occupancy sensors in office buildings. Practitioners can use the results of this study to integrate occupancy schedules into building energy simulation to accurately model building energy performance and potential energy savings.

Methodology

This study proposes a framework to simulate occupancy schedules and use it in predicting lighting energy load by integrating ABM and ANN models. To investigate the applicability of the proposed model, an example case study of a small rectangular shape office building is used. The office contains five single-occupancy offices, two bathrooms, one meeting room, and one lounge area, as well as a hallway. The schematic view of this office is shown in Figure 1.

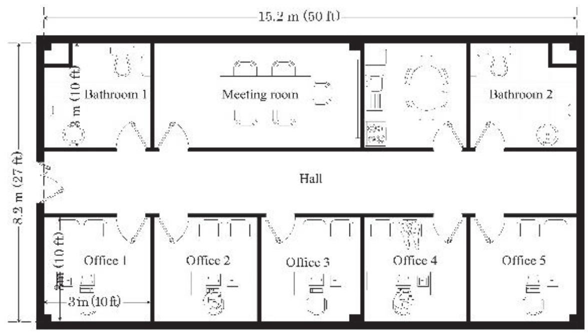

Figure 1: Office building layout for the case study

Several simplifying assumptions were considered for the example case. For example, all the rooms are the same size (except the meeting room, which is two times bigger) and have the same type of lighting fixture. In addition, natural lighting is not considered in this case study (i.e., rooms have no windows or blinds). Finally, only one type of occupancy pattern was considered in this study.

The lighting energy load predictive framework is demonstrated in Figure 2. In the first step, an ABM simulation model is developed based on occupant behavior parameters (i.e., number of occupants, occupants' presence, and occupants' movement) and building parameters (i.e., occupancy sensor status, lighting status, and building layout).

The ABM is designed to simulate occupant behavior by utilizing a range of predefined parameters. These parameters encompass the number of occupants for each type of occupancy, a probabilistic model for estimating the arrival and departure times of occupants within each occupancy category, a probabilistic model for determining the spatial positioning of occupants throughout the building for each occupancy type, and the interaction between occupants and the building itself, such as the likelihood of neglecting to turn off lights upon exiting a room. By incorporating this model with the building's layout and lighting characteristics, the result is a more accurate prediction of lighting energy consumption within the building, taking into account the influence of occupant behavior. The model can simulate the dynamic occupancy schedule in different scenarios:

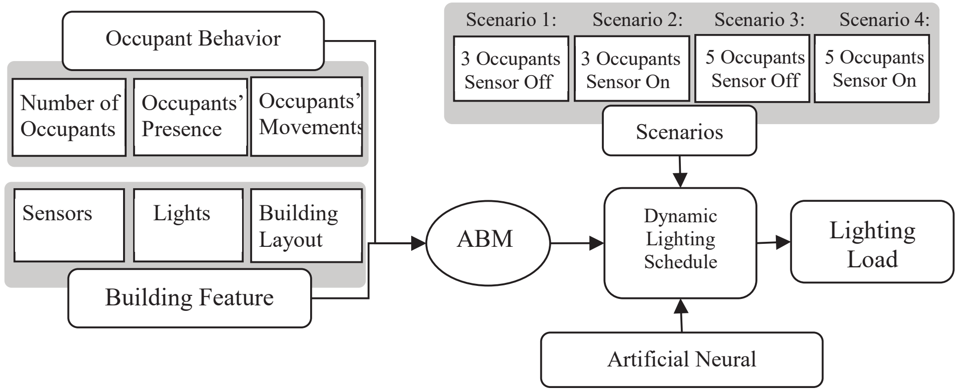

Figure 2: The proposed lighting energy load predictive framework

- Scenario 1: three occupants were considered to use the office building without any occupancy sensor;
- Scenario 2: three occupants were considered to use the office building with occupancy sensors installed;
- Scenario 3: five occupants were considered to use the office building without any occupancy sensor; and
- Scenario 4: five occupants were considered to use the office building with occupancy sensors installed.

The study employs four distinct scenarios to examine the effects of two critical variables on the ultimate models: 1) the number of occupants and 2) the implementation of occupancy sensors. It should be mentioned that in scenarios without any occupancy sensor, occupants might forget to turn off the lights with a predefined probability when they leave a room. Therefore, the lights might stay on until another occupant enters the room and turn them off when leaving. In scenarios with occupancy sensors installed, the lights will be turned off automatically when the room is unoccupied after a predefined time period. In both scenarios, occupants turn the lights on when entering a room.

In the second step, an ANN model is trained based on the simulated dynamic lighting schedule (as the developed ABM simulation output) to predict the building lighting energy load based on a time series function. In this regard, the cumulative total number of lighting features that remain on at each time step is computed for an entire day in order to determine the daily lighting energy load. The daily lighting energy consumption is then determined depending on the type of bulb utilized in each lighting fixture. The model is applied to the lighting status to find the lighting energy load in the example office building.

The two elements of the proposed lighting energy load predictive framework are as follows:

ABM simulation model

An ABM simulation model was developed to simulate the lighting energy use in the example office building considering different occupant behavior parameters. In this study, three key parameters of occupant presence, movement, and interaction with the lighting system were used to simulate the lighting schedule in the office building (Chen, Hong, and Luo, 2018; Micolier *et al.*, 2019; Norouziasl, Jafari and Wang, 2020; Khodabandelu and Park, 2021). The ABM model was simulated in NetLogo, an open-source software that visually simulated the agents and the environment (in which the agents were used to simulate the occupants while the environment was used to simulate the building). Various probabilistic and stochastic models were integrated into the ABM model to simulate these occupant behavior parameters based on predefined rules. For instance, the Markov Chain modeling technique was used to simulate the occupants' movement behavior. In the Markov Chain model, the probability of occurring an event is only dependent on the previous event (Wang, Yan, and Jiang, 2011), making it suitable for modeling the movement of occupants between different rooms. In addition, Gaussian distribution (Gilani *et al.*, 2016) functions were developed to model the occupants' arrival and departure events, meeting events, and lunch breaks. Besides, probabilistic models were used to simulate the occupants' interaction with the lighting system, such as turning the lights on/off and the forgetting probability of turning off the lights while leaving the room (Norouziasl, Jafari, and Wang, 2019).

ANN predictive model

Neural networks have been applied to many interesting problems in various areas of science, medicine, mathematics, and engineering, and in some cases, they provide state-of-the-art solutions (Krogh, 2008). In the current domain, an ANN Predictive Model can be used to determine the evolution of occupant interactions over time regarding the building systems (Jain, Mao, and Mohiuddin, 1996). In this study, the ANN was utilized to model the lighting schedule of an office building. In this regard, the simulated lighting schedule resulting from the ABM model was used to train the ANN model. The output of the ABM model represents the lighting status in each room based on the day of the week and the time of day. As was mentioned, the lighting status is marked by binary numbers; if the light is off, the lighting status is 0, while it is 1 when the light is on. The lighting configuration in the proposed office layout is contingent upon both the temporal aspects and the spatial positioning of the lighting fixtures. This implies that the illumination of the space is influenced by factors such as the time of day and the precise location of each lighting instrument, thereby affecting the overall lighting conditions and energy consumption within the office environment. Therefore, the ANN model was fed by three inputs: time of the day, day of the week, and the location of the room, in three layers: input layer, hidden layer, and output layer. For each scenario, the ANN model was trained by 80% of the data to predict lighting schedules to analyze the lighting status of different rooms in the office building and model a prediction for dynamic lighting schedules. Subsequently, the models were tested by 20% of the data. To indicate the performance of each model, different performance indexes, such as accuracy score, F1 score, and confusion matrixes, were provided. The models can predict the lighting status of each room based on binary numbers using the room ID and date and time information.

Model Inputs

The ABM model was developed based on two inputs: building features to simulate the example case study and occupant behavior parameters to model occupancy schedules. For the building features, the inputs were:

- Building area: The total area of the building was 1350 ft^2 (125.4 m^2), with 500 ft^2 (46.5 m^2) for the office and 500 ft^2 (46.5 m^2) for the bathrooms, meeting room, and break room
- Lighting fixtures: The required illuminance for office areas is 300–lumens per square meter. Considering that each 100-Watt incandescent lamp produces 1500 lumens, three lamps would be needed to provide the required illuminance of 2700–4600 lumens. Therefore, it was assumed that each lighting fixture had three 100-Watt incandescent bulbs.
- Occupancy sensor: Lighting occupancy sensors switch the lights off automatically once the occupant leaves a specific zone after a short delay. This study assumed a 60-second delay for each lighting occupancy sensor.

For the occupant behavior parameters, the inputs were:

- Arrival and departure time: An 8-hour working day was assumed, in which the occupants arrive at 8:00 a.m. and depart the building at 5:00 p.m. (one-hour lunch break) with 30 minutes variation using a Gaussian distribution.
- Meeting events: The probability of meeting occurrence was assumed to be 20% each day, with a start between 9:00 and 11:00 a.m. and with a duration of 30–60 min that follows a uniform distribution.
- Lunch break: The lunch break's start time was assumed to be 1:00 p.m. on average, with a standard deviation of 15 min, using a uniform distribution.
- Occupants' staying time: We assumed occupants would spend 65% of their time in their office, 8% in the bathroom, 5% in the other offices, 10% in the lounge, 7% in the meeting room, and 5% in the hall.
- Occupants' movement: The transition probability matrix that is assumed in this study based on the Markov Chain model is illustrated in Table 1. Since the occupants are not allowed to immediately re-enter the room they were previously occupying, the probability of moving from each room to the same room is equal to zero (diagonal of the matrix).
- Lighting switch forgetting probability: The probability of forgetting to switch off the lights when leaving the room was assumed to be 11%, according to a short survey performed by the authors.

Table 1: Transition probability matrix for the case study

	Own office	Other offices	Break room	Bathroom	Meeting room
Own office	0%	35%	15%	50%	0%
Other offices	75%	0%	10%	15%	0%
Break room	75%	15%	0%	10%	0%
Bathroom	75%	10%	15%	0%	0%
Meeting room	70%	10%	10%	10%	0%

The number of occupants and the application of occupancy sensors were changed based on the designed scenarios. After defining the input parameters, the simulation model was run to simulate the lighting schedules for each scenario. The simulation model was run for 20 business days from May 2, 2022, to May 27, 2022 (weekends were excluded from the simulation period). The size of the simulation time step was assumed to be one minute. For each scenario, the occupancy schedule and lighting status were extracted for each room based on the simulated time and date. Finally, the ANN model was trained to predict dynamic lighting schedules based on the simulation results. The ANN model contained three layers: the input layer, the hidden layer, and an output layer, connected through nodes. The model assumed a time series function for each room as input, while the output was the predicted lighting status.

Results and discussion

The ABM simulation results contain the lighting status of nine different rooms in 20 business days. The lighting energy load of the building was calculated by summing up the lighting energy load of each room. Finally, the ANN model is trained to predict the lighting energy load of the building for each of the four scenarios. Table 2 shows the results of these models.

Table 2: Dynamic Lighting Schedule Models

Scenario	Accuracy	F1 Score	Confusion Matrix		
			0	1	
1	84.4%	72.2%	33,252	2,904	0
			5,171	10,513	1
2	92.8%	81.0%	40,124	20,23	0
			1,712	7,981	1
3	82.0%	72.1%	30,455	2,774	0
			6,548	12,063	1
4	88.7%	78.8%	35,044	4,016	0
			1,860	10,920	1

As it is shown in Table 1, the trained model has an accuracy of higher than 82% (F1 score of higher than 72%) in all four scenarios. In addition, the second scenario (i.e., three occupants with occupancy sensors installed) has the highest accuracy (92.8%), while the third scenario (i.e., five occupants without any occupancy sensor) has the lowest accuracy (82.0%). As is shown, the developed model has a higher prediction accuracy in scenarios with occupancy sensors installed compared to scenarios without occupancy sensors. It is due to the fact that the use of occupancy sensors can automate the process of switching lights on/off, resulting in more predictable patterns by eliminating stochastic human behavior. According to Table 2, although the models with occupancy sensors installed show more accurate prediction results, the other models without any occupancy sensor also indicate acceptable performance, highlighting their high applicability in office buildings to predict lighting load energy.

Figure 3 illustrates the lighting status of two selected rooms (Lounge and office number 4) during the first three days of the simulation (from 5/2/2022 to 5/4/2022). Also, Figure 4 shows the lighting status of two selected rooms (Bathroom number 2 and office number 1) during the first three days of the simulation (from 5/2/2022 to 5/4/2022) in order to better visualize the results of the predictive model. The simulated values are shown in blue, while the predicted values are highlighted in red. According to the results, it can be realized that shared rooms, such as the lounge and bathroom, had lighting switches on during short time intervals (such as lunchtime), while office rooms had this status for long periods of time. It confirms the similarity between ABM simulation and the real behavior of occupants. In addition, the results indicate that ANN models have better performance in modeling the lighting status of occupied rooms, such as office buildings and meeting rooms.

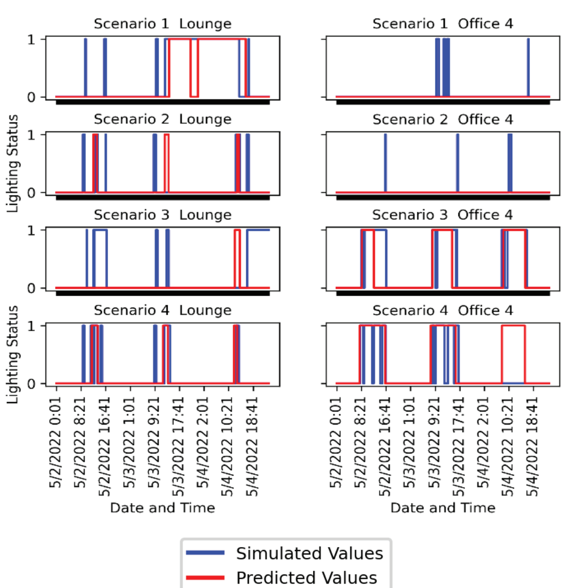

Figure 3: Dynamic Lighting Schedule of Lounge and Office 4 during the first 3 days

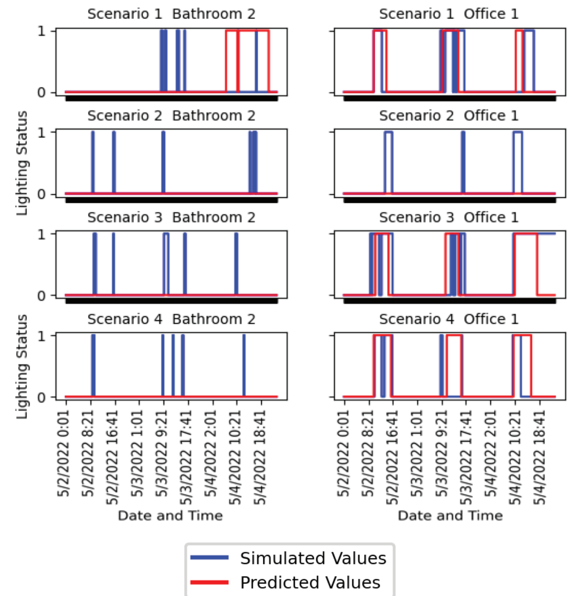

Figure 4: Dynamic Lighting Schedule of Bathroom 2 and Office 1 during the first 3 days

As mentioned, the required energy for each lighting fixture was estimated to be 300 Watts to provide enough illumination in each room. The ABM simulation results of the dynamic lighting schedule were used to calculate the simulated and predicted lighting energy load based on kilo Watt hour (kWh). Figure 5 shows the total lighting energy load of each room during the 20 working days.

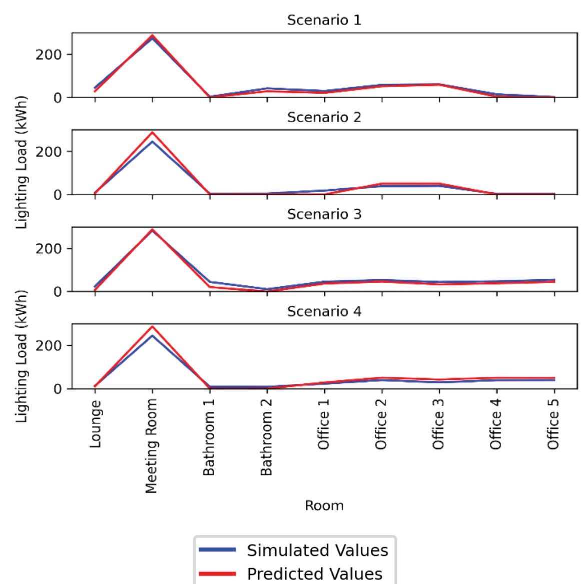

Figure 5: Total lighting energy load of different rooms

According to the results, the predicted lighting energy load pattern in each scenario follows the simulated lighting energy load pattern, which confirms the accuracy of dynamic lighting schedule models. Moreover, the meeting room has the highest lighting energy load in each scenario. It can be because of the number of lighting fixtures in the meeting room due to its size (which is twice of other rooms). Also, bathrooms have the lowest lighting energy load in each scenario. It could be because bathrooms were not used as frequently as in other rooms by occupants. Also, a lower lighting energy load was observed in all rooms in the scenarios with occupancy sensors installed (scenarios 2 and 4) compared to scenarios without any occupancy sensor (scenarios 1 and 3).

Figure 6 shows the total lighting energy load of each scenario. The results show that in scenarios with occupancy sensors installed, the lighting energy consumption was around 75% lower compared to scenarios without any occupancy sensor. It highlights the crucial role of occupancy sensors in minimizing lighting energy consumption in office buildings. In addition, as expected, by increasing the number of occupants from 3 to 5, the lighting energy consumption has increased by 15%.

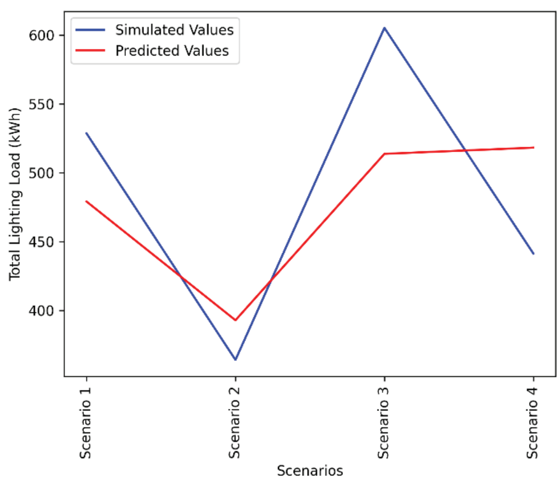

Figure 6: The total lighting energy load

Based on the results, the second scenario has the lowest amount of predicted lighting energy consumption during 20 working days (479.1 kW), while the fourth scenario has the highest amount of predicted lighting energy consumption (518.2 kW). Also, the lowest difference between the simulated lighting energy load and predicted lighting energy load is related to the second scenario (28.9 kW). The proposed lighting energy prediction framework has shown higher accuracy when the number of occupants is lower, and occupancy sensors are installed.

Conclusion

Accurately predicting lighting energy load can help control energy consumption and save energy in office buildings. This study introduced a framework to predict dynamic lighting schedules and lighting energy load in office buildings by integrating ABM and ANN models. The framework used an ABM model to simulate dynamic lighting schedules, and an ANN model to predict lighting energy load based on a time series function. A small office building was used as a case study to evaluate the accuracy of the proposed framework. The results showed an accuracy of 82.0% to 92.8% for predicting lighting energy load in different scenarios. In addition, it highlighted the essential role of occupancy sensors in reducing lighting energy consumption.

The proposed prediction framework can be used by practitioners to predict dynamic lighting schedules and lighting energy load in office buildings to on occupant behavior parameters, the building features data, and time and date. Such a framework can help reduce lighting energy consumption and save energy in office buildings by predicting the impact of installing occupancy sensors in reducing energy consumption.

Limitations and Future Works

A primary limitation of the present study is the relatively brief simulation time frame, which spans only 20 business days. Expanding the simulation's duration could yield more accurate results, particularly in the context of lighting, where seasonal variations and natural light play significant roles. Consequently, future research may benefit from extending the simulation period to encompass multiple seasons, thereby enhancing the overall modeling.

Another objective for subsequent research endeavors involves the development of a lighting load prediction model grounded in real-world data from Louisiana State University. To generate a more accurate representation of real-world lighting load modeling, the intention is to collect and incorporate lighting energy consumption data from a shared office. This data will then be utilized as input for the lighting load model, fostering a more realistic portrayal of the environmental factors at play.

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References

Abraham, Y. S., Anumba, C. J. and Asadi, S. (2018) 'Exploring agent-based modeling approaches for human-centered energy consumption prediction,' in Construction Research Congress 2018.

https://doi.org/10.1061/9780784481301.037

Amasyali, K. and El-Gohary, N. (2021) 'Machine learning for occupant-behavior-sensitive cooling energy consumption prediction in office buildings,' Renewable and Sustainable Energy Reviews, 142.

https://doi.org/10.1016/j.rser.2021.110714

Ardabili, S., Abdolalizadeh, L., Mako, C. Torok, B. and Mosavi, A. (2022) 'Systematic Review of Deep Learning and Machine Learning for Building Energy', Frontiers in Energy Research.

https://doi.org/10.3389/fenrg.2022.786027

Azar, E. and Menassa, C. C. (2012) 'Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings,' Journal of Computing in Civil Engineering, 26(4).

https://doi.org/10.1061/(ASCE)CP.1943-5487.0000158

de Bakker, C., Aries, M., Kort, H. and Rosemann, A. (2017) 'Occupancy-based lighting control in open-plan office spaces: A state-of-the-art review,' Building and Environment.

https://doi.org/10.1016/j.buildenv.2016.11.042

Chen, S. Ren, Y., Friedrich, D., Yu, Z. and Yu, J. (2021) 'Prediction of office building electricity demand using artificial neural network by splitting the time horizon for different occupancy rates,' Energy and AI, 5.

https://doi.org/10.1016/j.egyai.2021.100093

Chen, Y., Hong, T. and Luo, X. (2018) 'An agent-based stochastic Occupancy Simulator,' Building Simulation, 11(1).

https://doi.org/10.1007/s12273-017-0379-7

Chung, T. M. and Burnett, J. (2001) 'On the prediction of lighting energy savings achieved by occupancy sensors,' Journal of the Association of Energy Engineering, 98(4).

https://doi.org/10.1080/01998590109509317

Deng, Z. and Chen, Q. (2019) 'Simulating the impact of occupant behavior on energy use of HVAC systems by implementing a behavioral artificial neural network model,' Energy and Buildings, 198.

https://doi.org/10.1016/j.enbuild.2019.06.015

Ding, Z., Hu, Y., Li, M., Xu, X. and Zou, P. (2019) 'Agent-based model for simulating building energy management in student residences,' Energy and Buildings, 198.

https://doi.org/10.1016/j.enbuild.2019.05.053

Dong, B., Liu, Y., Fontenot, H., Ouf, M., Osman, M., Chong, A., Qin, S., Salim, F., Xue, H., Yan, D., Jin, Y., Han, M., Zhang, X., Azar, E. and Carlucci, S. (2021) 'Occupant behavior modeling methods for resilient building design, operation and policy at urban scale: A review,' Applied Energy, 293.

https://doi.org/10.1016/j.apenergy.2021.116856

Dziedzic, J. W., Yan, D., Sun, H. and Navakovic, V. (2020) 'Building occupant transient agent-based model – Movement module,' Applied Energy, 261.

https://doi.org/10.1016/j.apenergy.2019.114417

EIA (2017) CBECS 2012: Trends in Lighting in Commercial Buildings, U.S. Energy Information Administration.

https://www.eia.gov/consumption/commercial/reports/2012/lighting/

Gilani, S., O'Brien, W., Gunay, H.B. and Carrizo, J.S. (2016) 'Use of dynamic occupant behavior models in the building design and code compliance processes,' Energy and Buildings, 117.

https://doi.org/10.1016/j.enbuild.2015.10.044

Green, E. (2012) Buildings and their Impact on the Environment: A Statistical Summary, Saudi Med J.

https://archive.epa.gov/greenbuilding/web/pdf/gbstats.pdf

Hong, T., Sun, H., Chen, Y., Taylor-Lange, S. and Yan, D. (2016) 'An occupant behavior modeling tool for co-simulation,' Energy and Buildings, 117.

https://doi.org/10.1016/j.enbuild.2015.10.033

Jain, A. K., Mao, J. and Mohiuddin, K. M. (1996) 'Artificial neural networks: A tutorial,' Computer, 29(3).

https://doi.org/10.1109/2.485891

Khodabandelu, A. and Park, J. W. (2021) 'Agent-based modeling and simulation in construction,' Automation in Construction, 31.

https://doi.org/10.1016/j.autcon.2021.103882

Krogh, A. (2008) 'What are artificial neural networks?', Nature Biotechnology, 26.

https://doi.org/10.1038/nbt1386

Kwok, S. S. K. and Lee, E. W. M. (2011) 'A study of the importance of occupancy to building cooling load in prediction by intelligent approach,' Energy Conversion and Management, 52(7).

https://doi.org/10.1016/j.enconman.2011.02.002

Lee, S., Jung, S. and Lee, J. (2019) 'Prediction model based on an artificial neural network for user-based building energy consumption in South Korea,' Energies, 12(4).

https://doi.org/10.3390/en12040608

Liao, C., Lin, Y. and Barooah, P. (2012) 'Agent-based and graphical modelling of building occupancy,' Journal of Building Performance Simulation, 5(1).

https://doi.org/10.1080/19401493.2010.531143

Malik, J., Azar, E., Mahdavi, A. and Hong, T. (2022) 'A level-of-details framework for representing occupant behavior in agent-based models', Automation in Construction (139).

https://doi.org/10.1016/j.autcon.2022.104290

Menassa, C. C. (2011) 'Evaluating sustainable retrofits in existing buildings under uncertainty,' Energy and Buildings, 43(12).

https://doi.org/10.1016/j.enbuild.2011.09.030

Micolier, A., Taillandier, F., Taillandier, P. and Bos, F. (2019) 'Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling,' Engineering Applications of Artificial Intelligence, 82.

https://doi.org/10.1016/j.engappai.2019.03.008

Norouziasl, S., Jafari, A. and Wang, C. (2019) 'Analysis of Lighting Occupancy Sensor Installation in Building Renovation Using ABM,' in ASCE International Conference on Computing in Civil Engineering 2019.

https://doi.org/10.1061/9780784482421.075

Norouziasl, S., Jafari, A. and Wang, C. (2020) 'An agent-based simulation of occupancy schedule in office buildings,' Building and Environment, 186.

https://doi.org/10.1016/j.buildenv.2020.107352

Stielera, D. Schwinn, T., Leder, S., Maierhofer, M., Kannenberg, F., and Menges, A. (2022) 'Agent-based modeling and simulation in architecture,' Automation in Construction, 141.

https://doi.org/10.1016/j.autcon.2022.104426

Vosoughkhosravi, S., Dixon-Grasso, L. and Jafari, A. (2022) 'The impact of LEED certification on energy performance and occupant satisfaction: A case study of residential college buildings,' Journal of Building Engineering, 59.

https://doi.org/10.1016/j.jobe.2022.105097

Wang, C., Yan, D. and Jiang, Y. (2011) 'A novel approach for building occupancy simulation,' Building Simulation, 4(2).

https://doi.org/10.1007/s12273-011-0044-5

Yang, R. and Wang, L. (2013) 'Development of multi-agent system for building energy and comfort management based on occupant behaviors,' Energy and Buildings, 56.

https://doi.org/10.1016/j.enbuild.2012.10.025