Automation in Construction 107 (2019) 102917

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Combining context-aware design-specific data and building performance models to improve building performance predictions during design

Chanachok Chokwitthaya[a,*], Yimin Zhu[a], Robert Dibiano[b], Supratik Mukhopadhyay[c]

[a] Department of Construction Management, Louisiana State University, Baton Rouge 70803, USA
[b] Ailectric LLC., 7117 Florida Blvd, Baton Rouge 70806, USA
[c] Department of Electrical Engineering and Computer Science, Louisiana State University, Baton Rouge 70803, USA

ARTICLE INFO

Keywords:
Building performance models
Contextual factors
Occupant behaviors
Immersive virtual environments
Artificial neural network
Feature ranking

ABSTRACT

Building performance models (BPMs) such as building energy simulation models have been widely used in building design. Conventional BPMs may not be able to effectively address human- building interactions in new buildings still under design. The lack of such capability often contributes to the existence of building performance gaps, i.e., differences between predicted performance during design and actual performance of buildings. To improve the prediction accuracy of conventional BPMs, a computational framework is developed. It combines an existing BPM with context-aware design-specific data involving human-building interactions in new designs, using a machine learning approach. Immersive virtual environment (IVE) is used to capture data describing design-specific human-building interactions; and an artificial neural network (ANN) is used to combine data obtained from an existing BPM and an IVE to produce an augmented BPM. Additionally, the framework has the capability to rank influence of factors impacting human-building interactions using a feature ranking technique, which can help the design of future IVE experiments for better data collection.

The framework is tested using an application of a single occupancy office. An IVE of the office is created to simulate key artificial light use events during design. The Hunt model is selected as an existing BPM. The actual use of artificial lighting in the office is observed for one month using sensors to validate the effectiveness of the framework. The results of the application have shown the potential of the framework in improving the prediction accuracy of the Hunt model evaluated against data obtained from the actual office. The results verify the important role of context-aware design-specific data in improving the prediction of human-building interactions during design. In addition, the feature ranking technique is effective in identifying influencing factors impacting human-building interactions. Limitations of this study and future work are also discussed.

1. Introduction

According to the International Energy Agency (IEA), buildings in developed countries consume up to 40% of their total energy [1]. The significant consumption of fossil fuel-based energy has caused negative environmental impacts such as ozone layer depletion, global warming, and climate change [2]. In addition, studies have confirmed that decisions made during design phases significantly influence energy efficiency during building operations (e.g., [3,4]). Thus, improvements in decision support for building energy efficiency during design can contribute to the reduction of building energy consumption and enhancements in building energy performance [5].

Building performance models (BPMs) are decision-support tools assisting designers and engineers to understand, analyze, and optimize building performance during design. There are different types of BPMs, including simulation models of whole building energy consumptions [6], predictive models for the performance of building systems such as space heating [7] and air quality [8], and models of occupant interactions with building components such as light switches, blinds, windows, and thermostats [9] [10]. A number of research studies (e.g., [11] [12] [13] [14]) have successfully attempted to include human-building interactions in building performance modeling and predictions. Generally, such BPMs are constructed by collecting data of human-building interactions, and finding correlations between independent variables (e.g., temperature, illuminance, solar irradiance, and occupancy status) and dependent variables (e.g., human interactions with building components such as light switches, blinds, and windows). For instance, BPMs for predicting artificial lighting use (e.g., [11,15]) consider work area illuminance as an independent variable to predict whether occupants turn on artificial lighting at arrival. Arguably, not only work area

* Corresponding author.
E-mail addresses: cchokw1@lsu.edu (C. Chokwitthaya), yiminzhu@lsu.edu (Y. Zhu), robert@ailectric.com (R. Dibiano), supratik@csc.lsu.edu (S. Mukhopadhyay).

https://doi.org/10.1016/j.autcon.2019.102917
Received 14 February 2019; Received in revised form 16 July 2019; Accepted 21 July 2019
0926-5805/ Published by Elsevier B.V.

illuminance but also the location of light switches [16], interiors layouts [17], and occupancy statuses [18] have impact on occupant interactions with light switches. Human-building interactions (e.g., occupant responses to contextual factors and occupant habitual behaviors) are highly context-depended. Often, the context of existing buildings where data for developing BPMs are obtained differs from the context of a new building under design. Thus, the application of BPMs in a different context may significantly introduce large variances, and contribute to the discrepancies between predictions during design and actual performance during operations [19]. An alternative is to customize existing BPMs to address the context of buildings under design.

According to the Merriam-Webster dictionary, context is defined as "the interrelated conditions in which something exists or occurs." Contextual factors are often used to describe or model such interrelated conditions. In this paper, factors that may influence human-building interactions but are ignored in existing BPMs are considered as *"contextual factors"* in relation to the existing BPMs. There are evidences that human-building interactions are driven by contextual factors such as building conditions [20,21]. Moreover, multiple contextual factors may influence human-building interactions simultaneously [22]. Therefore, having the capability to consider human-building interactions in a specific context such as the context embodied in a new design may be one of the keys to significantly enhance the accuracy of BPMs.

Immersive virtual environments (IVEs), considered as multisensory computer-generated environments, have been effectively applied to various research in building design and engineering, such as emergency evacuation [23,24], building designs [25–27], and occupant behavior predictions [28,29]. IVEs have also been applied to studies related to human-building interactions and energy usages. For instance, Heydarian et al. [30] studied occupant lighting preferences in a single office using IVEs. Saeidi et al. [31] validated occupant light use behavior in IVEs and showed that IVEs were capable of replicating field experiences. Niu et al. [32] developed a framework to integrate building designs with IVEs to help building designers capture occupant preferences and identify context patterns. Studies have shown that human-building interactions are context-dependent. Since buildings under design do not physically exist, human-building interactions with buildings under design cannot be observed directly. To capture such human interactions, IVEs are proxies of reality that allow designers or researchers to observe such interactions. Overall, the main advantages of applying IVEs during design include replicating the context of buildings under design [31], allowing designers or researchers to control experimental conditions, and applying desired experimental contextual factors [33]. Therefore, IVEs have the potential to support designers or researchers to observe human-building interactions in simulated building context during design. However, IVEs have many limitations such as short experiment sessions, small data samples, and negative impacts on participants (e.g., cybersickness) [34], which make IVE-based experiments limited. The limitations of IVEs determine that it is difficult to continuously collect human-building interaction data in virtual environment for long time. IVE-based experiments for data collection are often highly focused and event/purpose-driven, therefore data collected using IVEs are not as comprehensive as data collected in reality using conventional occupancy data collection approaches (e.g., sensing, field studies, and surveys). Consequently, it is difficult to create comprehensive BPMs as general models, if only using data from IVE experiments. Thus, it is more feasible to bias a general model using observation data to fit a particular design than producing a general BPM only from observational data obtained from IVE experiments.

To enhance the prediction accuracy of existing BPMs, the authors have created a novel computational framework, which combines an existing model with observational data obtained from IVE experiments. Specifically, the framework preserves the general predictive power of an existing BPM, while addressing specific human-building interactions in the context of a new design identified by designers or researchers. As a result, the framework produces a more representative BPM specific to a building under design, and not as general as an existing BPM, to improve prediction accuracy.

In the following, the authors first discuss the research objective, and then provide an overview of the computational framework followed by the discussion of applying the framework to a single occupancy office. Based on the application, results, conclusions, and future work are then discussed.

2. Research objective

The objective of this study is to determine if the computational framework can potentially improve the prediction accuracy of BPMs during design. To achieve the objective, the authors apply the computational framework to the study of a single occupancy office. The framework produces an optimal BPM, which is called *an augmented BPM*. The application is designed to verify the effectiveness of the framework using *the augmented BPM*, which is achieved by testing a hypothesis.

The authors hypothesize that the computation framework can significantly improve the prediction accuracy of BPMs during design. To test this hypothesis, absolute errors are analyzed, including (1) the absolute error that measures the discrepancy between the predicted output of *an existing BPM* and actual data (E_1), and (2) the absolute error that measures the discrepancy between the predicted output of *an augmented BPM* and actual data (E_2).

The formulas for calculating E_1 and E_2 respectively are shown in Eqs. (1) and (2):

$$E_1 = |\text{ predicted outcome of } \textit{an existing BPM} - \text{actual data } | \tag{1}$$

$$E_2 = |\text{ predicted outcome of } \textit{the augmented BPM} - \text{actual data } | \tag{2}$$

Both errors are used to test the hypothesis as shown in the description below:

H_0: mean of E_1 – mean of E_2 = 0

H_1: mean of E_1 - mean of E_2 > 0

A one tailed *t*-test ($\alpha = 0.05$) is applied to investigate the statistically significant difference between the mean of E_1 and the mean of E_2.

3. Overview of the computational framework

The computational framework comprises of four main elements (see Fig. 1): (1) *an existing BPM*, (2) context-aware design-specific data, (3) computation, and (4) *an augmented BPM*. In theory, the framework is parametric and does not have any restrictions on the input datasets, because it only combines an existing BPM with context-aware design-specific data. Datasets associated with an existing BPM and context-aware design-specific data are inputs to the framework. Since the framework can be applied to any existing BPM and context-aware design-specific data, datasets applied in the framework do not need to be specified. In practice, there is a need to consider the cost associated with acquiring data using IVE experiments. In the following, details of components are discussed.

3.1. Existing building performance model

An existing building performance model (BPM) represents a model that already exists, and it does not necessarily capture important contextual factors of a new building design. For example, the Hunt model uses illuminance to predict the status of light switches. While it may be effective in general, the model cannot accurately predict artificial lighting usage, if a new design has a very different occupancy pattern from what the Hunt model is implicitly based on [11].

When a dataset represented by *an existing BPM* is needed, the computational framework provides a tool to generate such a dataset using statistical approaches, e.g., Monte Carlo simulations. The dataset is called *existing BPM dataset*.

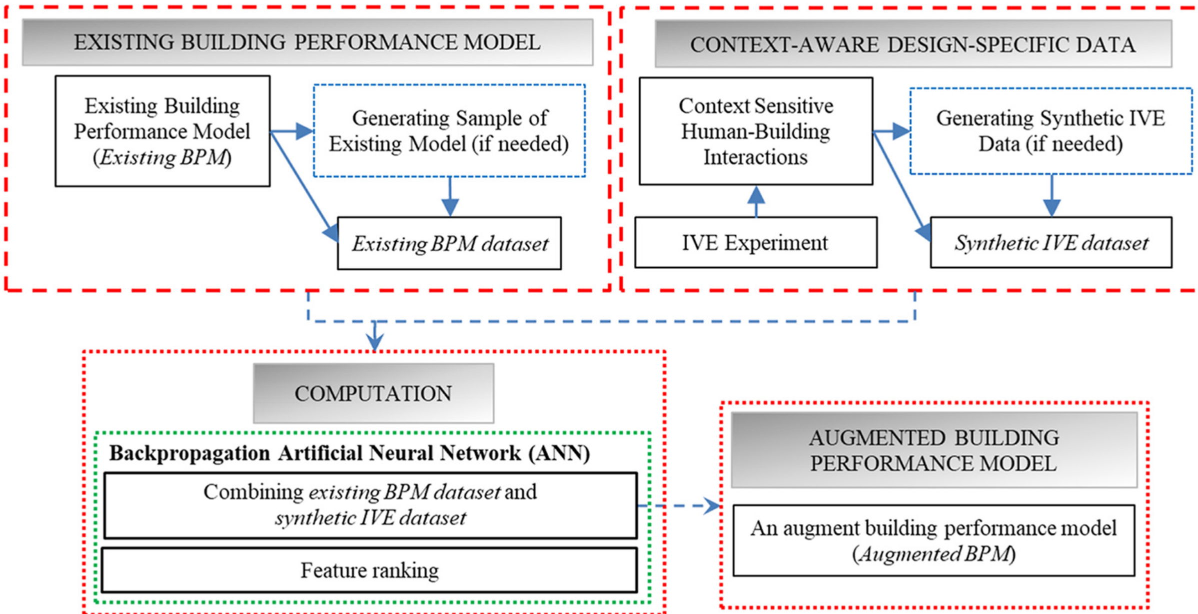


Fig. 1. Computational framework.

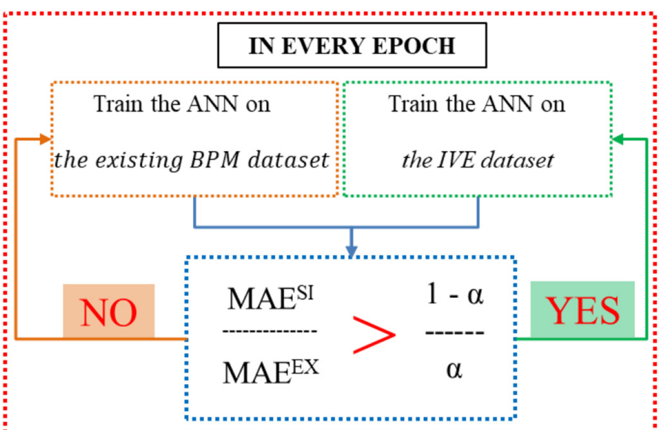


Fig. 2. Greedy heuristic algorithm.

3.2. Context-aware design-specific data

Context-aware design-specific data describe contextual factors in a set of specific events of a new design. For example, a designer may believe that how occupants interact with light switches at arrival in summer mornings is critical to a design purpose. The contextual factor, summer mornings, needs to be explicitly included in a BPM to observe occupant behaviors. The context-aware design-specific data are used to modify an existing BPM so that the BPM will better reflect the context of a new building under design. To construct context-aware design-specific data, an immersive virtual environment (IVE) is used as a tool to collect context specific data of a design, e.g., occupant's use of artificial lighting on a clear summer day. IVE-based experiments are often conducted with small samples in short period of time, leading to small IVE datasets [33,35,36]. To overcome this limitation, the framework provides an alternative solution to the small sample size issue by applying statistically data learning approaches such as Hidden Markov Model (HMM) to generate a large dataset, called *synthetic IVE dataset*.

3.3. Computation

Two major parts are included in the computation component, i.e., combining *the existing BPM dataset* and *the Synthetic IVE dataset*, and feature ranking.

3.3.1. Combining the existing BPM dataset and the synthetic IVE dataset

The purpose of combining *the existing BPM dataset* and *the synthetic IVE dataset* is to produce *an augmented BPM*. The authors applied an artificial neural networks (ANN) [37] to this process. Comparing to other methods such as Bayesian networks, regression models, Kalman filter, and other graphical models, ANNs provide several advantages for the computational framework. In many applications, ANNs have been proven that they are more accurate, flexible, and consistent in predictions than Bayesian networks [38], regression models [39] [40] [41], Kalman filter [42], and K-means [43]. ANNs have the capability to combine multiple datasets during training [44], e.g., the existing BPM dataset and the synthetic IVE dataset, while other graphical models may not offer or need complex algorithms to support such a function. Among graphical models, Bayesian networks offer the capability to combine multiple datasets, but they do not allow fine-grained control [45] (mixture ratio) over the combination of datasets. Unlike Bayesian networks, a greedy algorithm (see Fig. 2) can be used for fine-grained control to train an ANN with an appropriate mixture of two datasets.

To train the ANN for combining *the existing BPM dataset* and *the synthetic IVE dataset* based on a mixture ratio α (0 to 1), the authors use an efficient greedy heuristic algorithm (see Fig. 2). The algorithm uses the mean absolute error (MAE) to measure the effectiveness of ANNs trained on both datasets. Before training ANNs, *the existing BPM dataset* is split into *the existing BPM training dataset* and *the existing BPM testing dataset*. Similarly, *the synthetic IVE dataset* is split into *the synthetic IVE training dataset* and *the synthetic IVE testing dataset*. During training, two MAEs are calculated in every epoch. First, the MAE that measures the difference in the predictions of the ANN and *the synthetic IVE testing dataset* (MAE^{SI}). Second, the MAE that measures the difference in the predictions of the ANN and *the existing BPM testing dataset* (MAE^{EX}). The algorithm (Fig. 2) uses α to maintain the proportion of MAE^{SI} and MAE^{EX} based on the following equations:

$$\frac{MAE^{SI}}{MAE^{SI} + MAE^{EX}} \approx 1 - \alpha \tag{3}$$

$$\frac{MAE^{EX}}{MAE^{SI} + MAE^{EX}} \approx \alpha \tag{4}$$

The Eq. (3) is simplified by substituting value of $\mathrm{MAE}^{\mathrm{SI}}+\mathrm{MAE}^{\mathrm{EX}}$ in Eq. (4) and becomes $\frac{\mathrm{MAE}^{\mathrm{SI}}}{\mathrm{MAE}^{\mathrm{EX}}} \approx \frac{1-\alpha}{\alpha}$, which is used during training. During training, at every epoch, if $\frac{\mathrm{MAE}^{\mathrm{SI}}}{\mathrm{MAE}^{\mathrm{EX}}} > \frac{1-\alpha}{\alpha}$, the algorithm greedily attempts to reduce $\frac{\mathrm{MAE}^{\mathrm{SI}}}{\mathrm{MAE}^{\mathrm{EX}}}$ in this epoch by training ANNs on *the synthetic IVE training dataset* to reduce $\mathrm{MAE}^{\mathrm{SI}}$. Otherwise, in that epoch, ANNs are trained on *the existing BPM training dataset* to reduce $\mathrm{MAE}^{\mathrm{EX}}$. The training continues for a pre-specified number of epochs.

Several mixture ratios (α) may be used to combine *the existing BPM dataset* and *the synthetic IVE dataset* in the training. In the computational framework, the obtained results are called *updated BPMs*. The most accurate *updated BPM* when validated with reference data, i.e., data from a physical building is considered as *an augmented BPM*.

3.3.2. Feature ranking

Feature ranking is generally used to discern and discard weakly influent, irrelevant, and redundant features from a given set of features before performing further critical analysis [38]. Techniques that are often used to perform feature ranking can essentially be divided into three main categories, which are filter, wrapper, and embedded methods. The filter method directly uses properties of data to estimate the goodness of features and ignores the effects of the selected feature subsets on the performance of a classifier. Using the wrapper method, the estimation of the goodness of features is obtained by learning and evaluating the performance a classifier such as an ANN using only features of interest [39]. The embedded method is a combination of the filter and the wrapper methods. The embedded method uses the internal information of a classifier to analyze feature ranking [40]. However, there is no best method among the three [41]. In this study, the authors apply the feature ranking technique to rank the influence of factors impacting human-building interactions. The wrapper methods are selected since the ANN has been used as a classifier and the input data are classified into features of interest (e.g., occupancy, intermediate leaving, and illuminance).

4. Application of the computational framework

The application of the computational framework is focused on understanding the potential of the framework and validating the hypothesis. The prediction of artificial lighting usage in a single occupancy office is used for data collection and validation. The authors have monitored the physical office for a month to collect artificial lighting usage data. The data obtained from the physical office are used for two purposes: (1) creating an IVE simulating different contextual conditions for collecting human-building interaction data, and (2) validating *an augmented BPM*. An IVE is created by referring to the physical office, modeling conditions relevant to variables of a selected BPM, and contextual factors to be studied. The occupant who occupied the physical office has also participated in the IVE experiment. The Hunt model for predicting lighting usage is selected as *an existing BPM* [11]. After computation, the most accurate *updated BPM* is selected as *the augmented BPM*. Predicted results of *the augmented BPM* are compared with predicted results of *the existing BPM* to evaluate the effectiveness of the proposed framework. In the following, the authors explain the application in details.

4.1. Existing BPM and existing BPM dataset

The light switch BPM proposed by Hunt [11] is selected as *the existing BPM*. The selection of the Hunt model is based on several reasons: (1) it is used as a baseline model for many extended models predicting artificial light use [15,42,43], (2) it is cited as one of the major models by a recent paper in the field [44], and (3) the framework is generic, i.e., it can use the Hunt model or its expanded models as input. Moreover, the Hunt model has one independent variable (work area illuminance), allowing researchers to have more room to demonstrate the inclusion of other variables as contextual factors. It is expensive to collect data in IVE experiments for contextual factors, because all virtual scenes and stimuli about the contextual factors need to be designed and modeled. The more variables to include, the more expensive and time-consuming the experiments are. Therefore, to achieve the objective of this study, any well-accepted model ideally with a small set of input variables is acceptable.

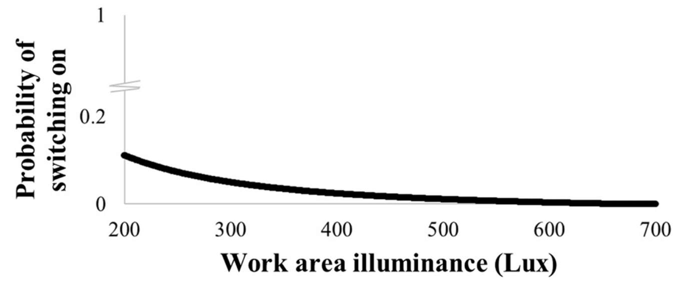


Fig. 3. Probability of switching on under work area illuminance of the Hunt model.

Hunt applied a field study approach to collect data of human-building interactions with light switches. He observed occupant light switching behaviors in six different rooms including multi-person offices, school classrooms, and open-plan teaching area for six months. He deployed time-lapse photography to capture the lighting status in the rooms every 8 min throughout the day and night. Using Probit regression analysis, the Hunt model predicts artificial lighting status based on work area illuminance (lux) (Fig. 3) [11].

Monte Carlo (MC) simulation is used to generate independent and identically distributed (IID) samples from the Hunt model. The input is work area illuminance, which is randomly generated following a uniform distribution. The output of MC simulation is probabilities of switch on under various work area illuminance levels. The input and output are arranged into pairs of work area illuminance and the corresponding probability of switch on. This data set is referred to as *existing BPM dataset*.

4.2. Context-aware design-specific data

4.2.1. Physical Environment

A single occupancy office located on the campus of a major state university in the south-central region of the USA is selected as the actual environment for the application (Fig. 4). The office occupant is a 30–40-year-old male faculty member. The dimension of the office is 9 ft wide by 12 ft long and 10 ft high (Fig. 6). Various sensors are placed in the office to measure the lighting illuminance (lux), the artificial lighting status (on, off), and the occupancy pattern (occupy, non-occupy) from September 23rd to October 27th, 2016. Two Onset UX90–005 HOBO occupancy/light runtime data loggers are placed above the door (sensor #1 in Fig. 6) and the work area (desk) (sensor #2 in Fig. 6) respectively to identify the occupancy pattern and the lighting status (on/off). Two Onset U12-012 HOBO temperature/relative humidity/light/data loggers are place at the work area (sensor # 3 in Fig. 6) and windows (sensor # 4 in Fig. 6) respectively to specifically measure the work area and outdoor light intensity respectively. The sensors are set to collect data every 5 s.

The data collected from the physical environment are used to construct the IVE experiment. The authors have observed major patterns of the occupant interactions (i.e., human-building interactions) with the office lighting system along with information of contextual factors, namely occupancy status, length of intermediate leaving, work area illuminance, and outdoor illuminance. The major patterns of the occupant's interactions with the office lighting system are mapped into 128 events, including (1) 25 event of arrival at the office, (2) 40 events

Fig. 4. The physical environment.

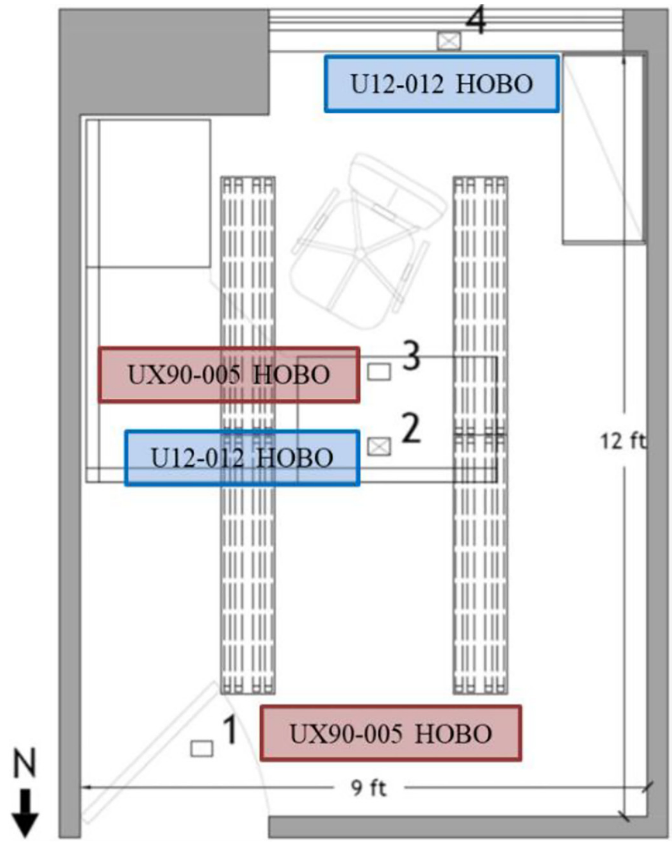


Fig. 6. The layout of the physical environment and the locations of the sensors.

of intermediate leaving, (3) 40 events of returning from the intermediate leaving, and (4) 36 events of departure. The IVE experiment is constructed based on the information of these events for data collection and validation.

The data also form a baseline for evaluating *an augmented BPM*, i.e., the probabilities of switching on when the occupant arrives at the office. Fig. 7 shows that the occupant always turns on the light regardless of the minimum work area illuminance based on sensor data.

4.2.2. Immersive virtual environment (IVE) and experiment

The IVE configuration is illustrated in Fig. 5. The IVE experiment are structured based on three main factors including (1) the considerations of the cost of developing IVE models and conducting experiments, (2) the obtained occupancy data from the physical environment, and (3) the Spatial-Temporal Event-Driven (STED) modeling approach [33]. The STED designs IVE experiment by modeling critical events during a day in chronological order, which comprises of four main components, namely states, contexts, events, and human-building interactions.

Based on the three main factors, states, contexts, events, and human-building interactions are defined:

- States are light switch conditions, which include switch on and off.
- Contexts are conditions of the independent variable and the contextual factors in Table 1. The independent variable is work area illuminance considered in Hunt model. The contextual factors are outdoor illuminance, occupancy, and intermediate leaving statuses. The occupancy statuses comprise of occupy and non-occupy. The intermediate leaving statuses are non, short, and long leaving. The work area and outdoor illuminance are categorically defined. There are two major constraints for illuminance to be designed as categorical. First, the STED defines variables in IVE experiments as discrete. Although a small interval between minimum and

Fig. 5. The IVE configuration.

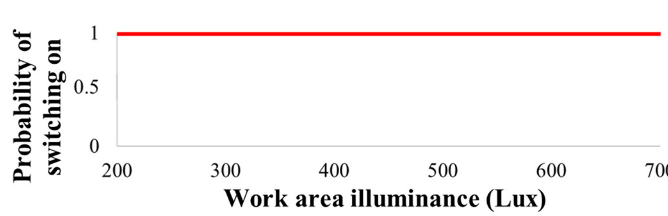


Fig. 7. Probability of switching on under work area illuminance (physical environment).

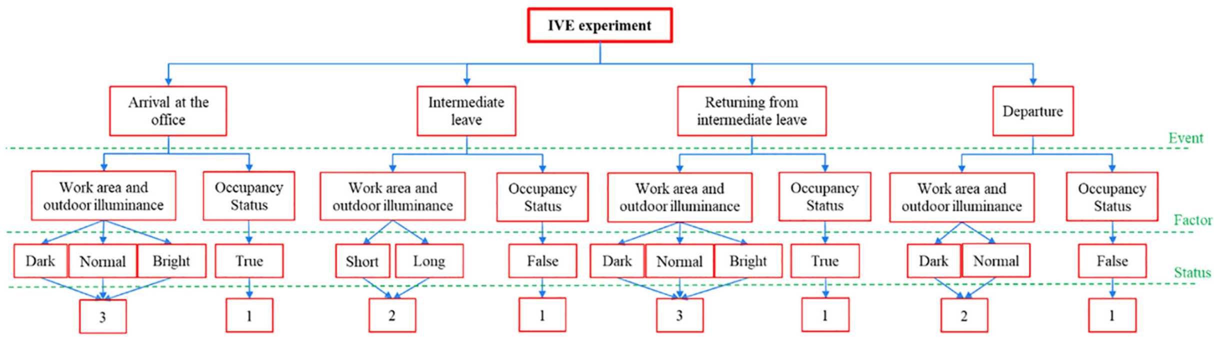


Fig. 8. Diagram of factors included in the IVE experiment.

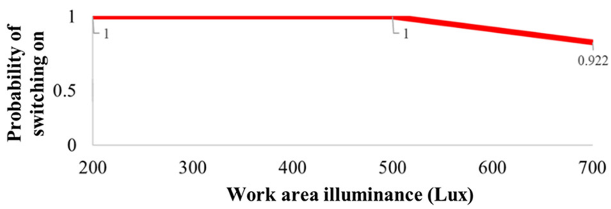


Fig. 9. Probability of switching on under work area illuminance (HMM).

maximum illuminance levels may be defined to simulate continuous illuminance, it will unnecessarily increase the number of IVE experiments. Second, due to the limitations of IVE technologies, typically an IVE experiment session will only last for about 40 min. Participants may not be able to tolerate in IVEs for a long period of time to simulate continuous illuminance as in physical environments. Levels of the work area illuminance are defined by applying the recommended lighting levels from the U.S. General Services Administration (GSA) [45], which 500 lx is the recommended light level at work area when performing office tasks. Accordingly, a darker level is defined as 200 lx and brighter level is defined as 700 lx based on the average of minimum and maximum natural light during work time (8:00 am – 5:00 pm). Although the levels of the work area illuminance are maintained as dark (200 lx), normal (500 lx), and bright (700 lx), the levels of the outdoor illuminance are respected to the sun locations and directions depended on the

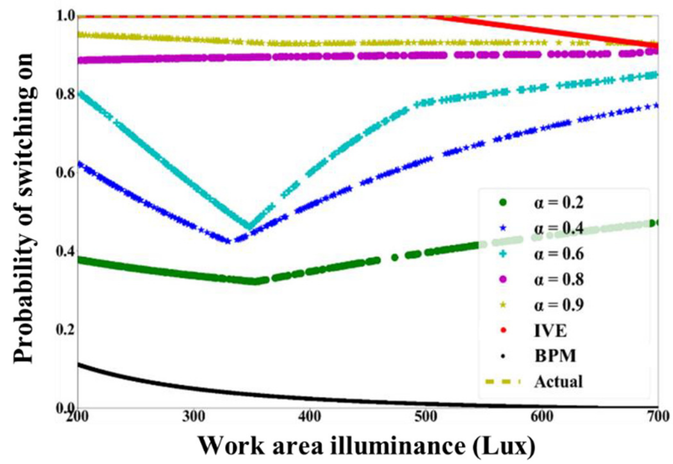


Fig. 11. Observations of *updated Hunt models* obtained from the computational framework using various mixture ratio (α).
****IVE = the synthetic IVE dataset.*
BPM = the existing BPM dataset.
Actual = the actual data from the physical environment.

times of the day in the experiment. Therefore, if the outdoor illuminance is dark, normal, and bright, the work area illuminance without artificial lighting is assigned as dark, normal, and bright

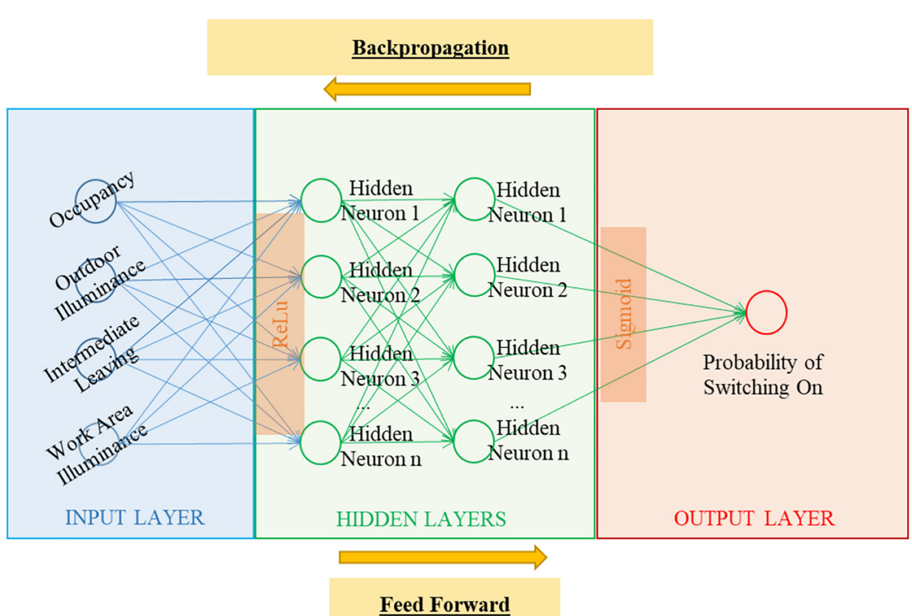


Fig. 10. Scheme of artificial neural networks (ANNs) of the computational framework.

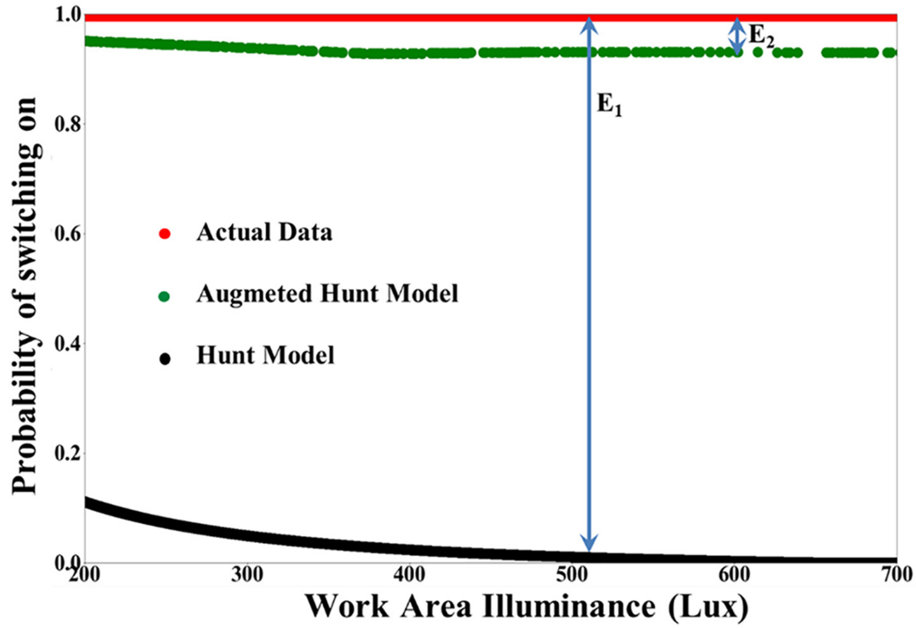


Fig. 12. The hypothesis testing.

respectively.

- Events are occurrences of contexts that trigger the occupant to change or maintain the states as shown in Table 3. There are five critical events considered during a day in the IVE experiments, including initial events before arrival at the office, arrival at the office, intermediate short leave or long leave, returning from the intermediate short leave or long leave, and departure.
- Human-building interactions are interactions of the occupant on light switch.

In each event, the situations of contextual factors and independent variable included in the Hunt model (see Table 1) are exposed to the participant. Visual (e.g., outdoor conditions) and auditory (e.g., reminders) cues are used to inform the participant about outdoor conditions and length of leaving or staying in the office respectively. Examples of cues are shown in Table 2. The participant is asked to interact with the light switch, which he may switch on, switch off, or maintain the light switch. Then, data of occupancy status, work area and outdoor illuminance, and intermediate leaving status along with the light status in each event are collected throughout the sequence (see Table 3). The participant is the same person who occupies the physical office. The participant uses a head-mounted display (HMD) to experience the IVE and participate in the experiment. The experiment is divided into two sessions and each session lasts about 70 min in total. The study has been approved by the local Institutional Review Board (IRB).

Table 1
Contextual factors and independent variable in the application.

Contextual factor	Status
Occupancy	Occupancy (True) Non-occupancy (False)
Outdoor illuminance	Dark Normal Bright
Intermediate leaving	Short intermediate leave Long intermediate leave

Independent variable	Status
Work area illuminance	Dark (200 lx) Normal (500 lx) Bright (700 lx)

4.2.2.1. Determinations of data points in the IVE experiment. Fig. 8 illustrates the diagram of factors included in the IVE experiment. Based on Fig. 8, events of the arrival, intermediate leave, returning from intermediate leave, and departure include 3, 2, 3, and 2 alternatives respectively, which lead to $3 \times 2 \times 3 \times 2 = 36$ unique

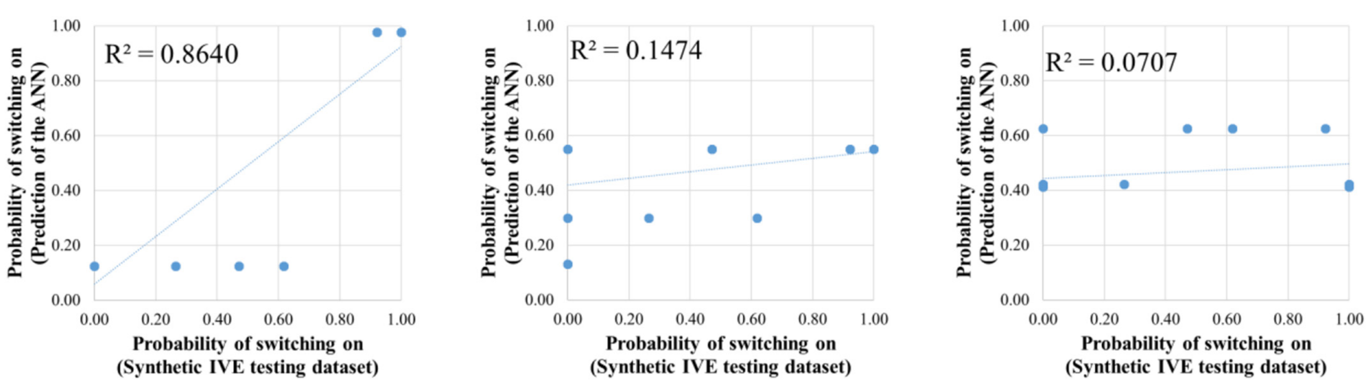
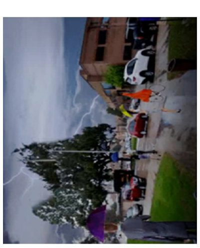


Fig. 13. Plots of probability of switching on obtained from the synthetic IVE testing dataset and prediction of the ANN.

Table 2
Examples of virtual and auditory cues used in the IVE experiment.

Event	Arrival at the office	Intermediate short leave	Intermediate long leave	Returning from the intermediate leave	Departure
Virtual cue	 (V1)	–	–	 (V2)	–
Auditory cue	You have arrived at your office. Please pick your most preferred your lighting choice for at least 2 h of office work. (A1)	Your package is just delivered. Please go and quickly pick it up from the department office. (A2)	It is now 9:20 a.m. and you need to go and teach your class which takes about 1.30 h. You may or may not change the light status as you leave. (A3)	It is 11:15 a.m. and you have arrived at your office. Please pick your most preferred your lighting choice for at least 2 h of office work. (A4)	It is 5:30 p.m. now and you decide to go home. You may or may not change the lighting status of your office as you leave. (A5)

combinations (called "*sequences*"). To construct the IVE experiment, 36 sequences, and cost of developing IVE and conducting experiment are taken into an account. First, each sequence is extracted and assigned to four events (2nd-5th data point of each sequence in Table 4). Second the initial events are appended to each sequence (1st data point of each sequence in Table 4). The initial events are not included in the sequence diagram in Fig. 8 because it results in doubly increasing the number of total data point and excessive experimental time. Appending the initial events to the sequence s relieves the number of total data point and excessive experimental time as well as maintain the uniqueness of the 36 sequences. Therefore, a total data point is 180 (i.e., 36 (sequence s) × 4 (data points in each sequence) + 36 (data points from each initial event)).

4.2.3. Generating synthetic IVE data

Due to the fact that the data sample from the IVE experiment is small and the IVE data represented a sequence of events, the authors decide to employ a Hidden Markov Model (HMM) Baum-Welch algorithm [46] to generate a synthetic dataset based on data from the IVE experiment (i.e., increasing the number of independent and identically distributed (IID) samples). The advantages of the HMM are that it has the ability to statistically learn information about observed parameters to estimate for non-observable parameters [47], and recognize sequential patterns of provided data [48].

The HMM Baum-Welch algorithm [46] learns the relationship of the participant's light switch interactions and the factors influencing the interactions. The HMM assumes that the current state (S_t) impacts the next state (S_{t+1}). The hidden state happening at time t + 1 (S_{t+1}) is dependent only on the hidden state happening at time t (S_t) [49] [50]. The change in hidden states from time t to time t + 1 is called state transition. The probability of state transitions can be calculated and simplified as a transition probability matrix. The observations depend on the hidden state variables, and therefore the probability density function of observations is dependent on the hidden state variables [50]. The observation probabilities can be expressed in a matrix form as an observation probability matrix. The HMM is trained by using the distribution of hidden states and observations from the transition and observation probability matrices. After training, the HMM are executed to generate IID samples.

From the 180 data points obtained from the IVE experiment, the hidden states and the observations of events are classified. The statuses of the light switch are classified as the hidden states. The statuses of the other variables, namely occupancy status, intermediate leaving, and outdoor and work area illuminance are classified as observations. Each observation as a vector is encoded to an ordinal variable for training the HMM. non-occupancy, short intermediate leave, dark work area illuminance, and normal outdoor illuminance are represented as "no + short + dark + dark" and encoded by using a single value such as "*1*". The transition and observation probabilities are calculated. The HMM is trained to learn the relationship between the hidden states and observations from the transition and observation probabilities. After training, the HMM is executed to generate the statuses of the light switch and variables in Table 1. The complete analysis of HMM for the case study can be found in [51]. To obtain the variables corresponding to the Hunt model, probabilities of switching on upon arrival based on work area illuminance are computed (Fig. 9). The probabilities of switching on upon arrival are calculated and paired with the IID samples of variables in Table 1 generated by the HMM and called *synthetic IVE dataset*.

4.3. Computation

4.3.1. Artificial neural network (ANN)

The ANN (Fig. 10) is a three-layered perceptron network including input, two hidden, and output layers. Input in the input layer includes occupancy status, intermediate leaving, and minimum work area

Table 3
The sequence of the IVE experiment.

Event	Sequence of IVE Experiment in a Day			
	Light Status Before Interaction	*Virtual and Auditory Cues Exposed to the Participant*	*Interaction*	*Light Status After Interaction*
Arrival at the Office	Initial light status	*V1* and *A1*	Participant interacts with light switch	Light status of the event
Intermediate Leave	Light status of the previous event	Short (*A2*) Long (*A3*)	Participant interacts with light switch	Light status of the event
Returning from Intermediate Leave	Light status of the previous event	*V2* and *A4*	Participant interacts with light switch	Light status of the event
Departure	Light status of the previous event	*A5*	Participant interacts with light switch	Light status of the event

Table 4
Details of IVE experimental days.

Sequence	Initial (1st data point of each sequence)		Arrival at the office (2nd data point of each sequence)		Intermediate leave (3rd data point of each sequence)		Returning from intermediate leave (4th data point of each sequence)		Departure (5th data point of each sequence)	
	Light switch	Occupancy	Illuminance	Occupancy	Intermediate leave	Occupancy	Illuminance	Occupancy	Illuminance	Occupancy
1	On	False	Bright	True	Long	False	Bright	True	Normal	False
2	Off	False	Bright	True	Long	False	Bright	True	Dark	False
3	On	False	Bright	True	Long	False	Normal	True	Normal	False
4	Off	False	Bright	True	Long	False	Normal	True	Dark	False
5	On	False	Bright	True	Long	False	Dark	True	Normal	False
6	Off	False	Bright	True	Long	False	Dark	True	Dark	False
7	On	False	Bright	True	Short	False	Bright	True	Normal	False
8	Off	False	Bright	True	Short	False	Bright	True	Dark	False
9	On	False	Bright	True	Short	False	Normal	True	Normal	False
10	Off	False	Bright	True	Short	False	Normal	True	Dark	False
11	On	False	Bright	True	Short	False	Dark	True	Normal	False
12	Off	False	Bright	True	Short	False	Dark	True	Dark	False
13	On	False	Normal	True	Long	False	Bright	True	Normal	False
14	Off	False	Normal	True	Long	False	Bright	True	Dark	False
15	On	False	Normal	True	Long	False	Normal	True	Normal	False
16	Off	False	Normal	True	Long	False	Normal	True	Dark	False
17	On	False	Normal	True	Long	False	Dark	True	Normal	False
18	Off	False	Normal	True	Long	False	Dark	True	Dark	False
19	On	False	Normal	True	Short	False	Bright	True	Normal	False
20	Off	False	Normal	True	Short	False	Bright	True	Dark	False
21	On	False	Normal	True	Short	False	Normal	True	Normal	False
22	Off	False	Normal	True	Short	False	Normal	True	Dark	False
23	On	False	Normal	True	Short	False	Dark	True	Normal	False
24	Off	False	Normal	True	Short	False	Dark	True	Dark	False
25	On	False	Dark	True	Long	False	Bright	True	Normal	False
26	Off	False	Dark	True	Long	False	Bright	True	Dark	False
27	On	False	Dark	True	Long	False	Normal	True	Normal	False
28	Off	False	Dark	True	Long	False	Normal	True	Dark	False
29	On	False	Dark	True	Long	False	Dark	True	Normal	False
30	Off	False	Dark	True	Long	False	Dark	True	Dark	False
31	On	False	Dark	True	Short	False	Bright	True	Normal	False
32	Off	False	Dark	True	Short	False	Bright	True	Dark	False
33	On	False	Dark	True	Short	False	Normal	True	Normal	False
34	Off	False	Dark	True	Short	False	Normal	True	Dark	False
35	On	False	Dark	True	Short	False	Dark	True	Normal	False
36	Off	False	Dark	True	Short	False	Dark	True	Dark	False

illuminance. Output in the output layer is the probability of switching on. The hidden layers of the model are generated using 300 hidden neurons with rectified linear unit activation function (ReLU) since it has been shown to have better fitting ability than the sigmoid function in similar applications [38]. To prevent overfitting, elastic net regularization (combination of L1 (Laplacian) and L2 (Gaussian) penalties) [52] is used. The sigmoid activation function is applied to the neuron at the output layer because the values of outputs are probabilities. The loss function of the model is binary cross entropy (logistic regression). The learning rate and regularization are 10^{-6}.

Before input data can be used by the ANN, they are normalized first to ensure compatibility between *the existing BPM dataset* and *the synthetic IVE dataset*. Since the Hunt model has only illuminance as an independent variable, contextual data for the Hunt model, e.g., occupancy, intermediate leaving, and outdoor illuminance are randomly generated according to the available occupancy, intermediate leaving, and outdoor illuminance of *the synthetic IVE dataset*. For instance, since occupancy status in *the synthetic IVE dataset* includes non-occupancy and occupancy, the data of occupancy in *the existing BPM dataset* are randomly generated with non-occupancy and occupancy. Corresponding to the status of intermediate leaving in *the synthetic IVE dataset*, the data of intermediate leaving in *the existing BPM dataset* are randomly generated with non-leave, short intermediate leave, and long intermediate leave.

After normalization, inputs and outputs of *the existing BPM dataset* and *the synthetic IVE dataset* are defined as shown in Fig. 10. *The existing BPM dataset* and *the synthetic IVE dataset* are divided into training datasets (i.e., *the existing BPM training dataset* and *the synthetic IVE training dataset*) and testing datasets (i.e., *the existing BPM testing dataset* and *the synthetic IVE testing dataset*) based on an 80–20 split. Five percent of the inputs of *the synthetic IVE training dataset* is changed to White Gaussian noise to prevent overfitting during training.

4.3.2. Training algorithm

To initialize the ANN model, *the existing BPM training dataset* is used to train the ANN for 60,000 epochs to allow the ANN to accurately learn the probability distribution of *the existing BPM dataset*. After initializing, to train the ANN on a mixture of *the existing BPM training dataset* and *the synthetic IVE training dataset* with a mixture ratio (α), the efficient greedy heuristic algorithm (Fig. 2) is used. The training continues for 400,000 epochs. To understand the impact of the mixture ratio on the prediction accuracy of *updated Hunt models*, mixture ratios (α) from 0 to 1 with an interval of 0.1 are used to generate a sequence of *updated Hunt models*. After training, the *existing BPM testing dataset* are used as inputs to acquire outputs (the probabilities of switching on) through the trained ANN. The inputs (i.e., the inputs of *the existing BPM testing datasets*) and the obtained outputs are paired to construct *updated Hunt models*. Among all *updated Hunt models*, the best performing one with the highest prediction accuracy relative to the actual data is considered as *the augmented BPM*, *the augmented Hunt model* in this case.

4.3.3. Feature ranking

Factors such as occupancy status, intermediate leaving, and work area illuminance have a different level of impact on predictions [33]. Thus, it is important to have a method to determine the relative importance of such factors. The feature ranking technique is used to evaluate the influence of factors on predictions. To perform feature ranking in the ANN, the ANN is trained using *the synthetic IVE training dataset*, which is modified by considering only one specific factor of interest, at the input layer. The probability of switching on is selected as the output in the output layer. For example, the ranking of occupancy status is analyzed by training an ANN using *the synthetic IVE training dataset* that is modified to have the occupancy status as the only input factor and the probability of switching on as the output in the ANN. The ANN is trained using the similar scheme as mentioned in Fig. 10.

The correlation of determinations (R^2) is used as a statistical measurement of the linear relationship between expected outputs, i.e., probability of switching on of *the synthetic IVE testing dataset*, and predicted output (i.e., the probability of switching on obtained from prediction by the ANN). R^2 provides a measure of how accurate expected outputs are learned by the ANN [53]. The value of R^2 ranges from 0 to 1, in which 1 means the probability of switching on can be predicted without error. Therefore, a higher R^2 means a factor has more influential impact on the prediction of switching on.

5. Results

5.1. Updated Hunt models

Fig. 11 presents *updated Hunt models* (each with a different α), plotting the probability of switching on versus work area illuminance ranging from 200 lx to 700 lx. In addition, *the existing BPM dataset*, *the synthetic IVE dataset*, and the actual dataset obtained from the physical office are also presented. Some observations can be made from Fig. 11:

- The prediction accuracy of *updated Hunt models* improves as α increases; and
- Significant improvements in terms of prediction accuracy of *the updated Hunt models* can be visually noticed when α is from 0.2 to 0.8. However, when α is > 0.8, the rate of the improvement is not as obvious as when α is ≤0.8.
- When α = 0.2, 0.4, and 0.6, the probability of switching on decreases when the work illuminance is lower than around 350 lx and then increases when the work illuminance is higher than 350 lx. These behaviors occur because of several reasons. One of the main reasons is that the synthetic IVE dataset is categorical, which includes work area illuminance at 200, 500, and 700 lx. At α = 0.2, 0.4, and 0.6, the weight of the existing BPM dataset is stronger than the synthetic IVE dataset especially in the region around 350 lx. The existing BPM biases the probability of switch on toward itself. At α = 0.8 and above, the weight of the existing BPM dataset becomes weaker than the synthetic IVE dataset. Updated Hunt models tend to follow behaviors of the synthetic IVE dataset. However, α between 0.6 and 0.8 are not observed in the study.
- The observations have demonstrated the potential of the proposed framework to generate *updated Hunt models* that are better than the original. The observations have also shown that α, a measure for mixing the two datasets, may have a relationship with the prediction accuracy of *updated Hunt models*. Finding an optimal α can help an application to reach a desired level of prediction accuracy.

5.2. Hypothesis testing

The updated Hunt model with a mixture ratio α of 0.9 is considered *the augmented Hunt model* since it has the best predictive ability among all generated *updated Hunt models*.

To validate the hypothesis, 500 data samples are randomly drawn from *the existing BPM testing dataset*, in which the occupancy status is "true" and the intermediate leaving status is set to "none-leave" to be consistent with the Hunt model. *The augmented Hunt model* and the original Hunt model are both tested on this dataset and their predicted outputs are recorded. Then, 500 samples are drawn from the actual dataset under identical conditions (occupancy, intermediate leaving, and work area illuminance).

To test the hypothesis, Eqs. (1) and (2) are used to determine E_1 and E_2 as shown below:

E_1 = | The probability of switching on from the prediction of *the existing BPM dataset* –
The probability of switching on from the actual data |
E_2 = | The probability of switching on from the prediction of *the augmented Hunt model* –
The probability of switching on from the actual data |

Statistical one-tailed t-test is used to identify the statistically significant difference between the mean of two errors, i.e., E_1 and E_2 (Fig. 12). The hypothesis is:

H_0: mean of E_1 – mean of E_2 = 0

H_1: mean of E_1 - mean of E_2 > 0

From Table 5, the result of the one tailed t-test shows that the P-

Table 5
The summary of *t*-test analysis.

Absolute T-value	Degree of freedom	P-value	H_0
617.94	998	< 0.05	Reject

value is smaller than 0.05; therefore, the null hypothesis is rejected. The result can be interpreted that the mean of E_1 is significantly higher than the mean of E_2. It can be concluded that the probabilities of switching on estimated by *the augmented Hunt model* are significantly closer to the actual data than those estimated by the original Hunt model. This result implies that combining data reflecting design-specific contextual factors with data from the Hunt model can generated *an augmented Hunt model* with higher prediction accuracy than the original Hunt model.

5.3. Feature ranking analysis

Fig. 13 shows the plot of the probability of switching on obtained from *the synthetic IVE testing dataset* and the prediction of the ANN, and the coefficient of determination (R^2) for occupancy status (a), leaving status (b), and work area illuminance (c). It is assumed that occupancy status, leaving status, and work area illuminance are independent to each other. The results of R^2 in Fig. 13 show that the most influential factor is occupancy status ($R^2 = 0.8640$). The leaving status and the work area illuminance are respectively less important factors. This result is consistent with other studies (e.g., [54,55]), which suggests that the feature ranking analysis has the potential to identify influential factors.

6. Limitations of the study

Even though the potential of the framework has been shown through its application to the case, major limitations of the study can be found in the following aspects:

- At this stage, the framework does not have the capability to determine an optimal mixture of data from an existing BPM and context-aware design-specific data. Therefore, a series of mixtures has been applied to show the impact of mixing data from two different sources. However, it is ideal to have an approach allowing designers or researchers to quickly determine an optimal mixture depending on the goal of building performance.
- The study uses a single occupancy office as a case study. In addition, the participant's habitual behavior is very unique, affecting the observational data significantly. The case has well demonstrated the potential of the computational framework, because on one hand it shows the deviation of human-building interactions from predictions, on the other hand it demonstrates the potential of the computational framework to bias a general model to fit a specific design. However, more cases such as different types of occupants and multi-occupancy offices need to be studied.
- The limitations of virtual reality technologies determine that it is difficult to continuously collect human building interaction data in virtual environment for long time. Hence, data collection using IVEs are not continuous. For example, only a limited set of illuminance data is collected in IVE experiments.

7. Conclusions and future work

In this paper, a computational framework has been discussed. The framework combines design-specific contextual factors with an existing BPM to produce *an augmented BPM* with better prediction accuracy. An immersive virtual environments (IVE) is used to capture data related to design specific contextual factors. The framework is applied to a lighting use study, in which the Hunt model is chosen as the existing BPM. An ANN combines data from the Hunt model with the data obtained from the IVE experiment (context-aware design-specific data) to generate *an augmented Hunt model*. Results show that *the augmented Hunt model* produces better predictions than the original Hunt model. Although the Hunt model is selected in this study, the framework is not designed specifically to the Hunt model.

Several conclusions can be made based on the application of the framework to the prediction of light switch status of a single occupancy office:

- Design-specific contextual factors play an important role in predicting human-building interactions. Other studies [19] [56] [57] have concluded similarly, which corroborates this study.
- The framework has demonstrated the potential of integrating design-specific contextual factors with *an existing BPM* to generate *an augmented BPM*, which produces better predictions than the original BPM. However, it has to be noted that this study has not offered an approach to determine the α of *the augmented BPM*. Future work is needed to determine such an approach.
- The framework relies on an IVE to collect data related to design-specific contextual factors. As pointed out by previous studies, using an IVE as a data collection tool has its limitations [58]. Although the most matured IVE capability, visual simulation, is mainly applied in this study, visual simulation alone cannot simulate all kinds of human-building interactions. Other capabilities such as simulating acoustic and thermal comfort of an indoor space should be developed and incorporated in the future.
- Feature ranking has the potential to identify important factors influencing predictions. The proposed method effectively identify that occupancy status strongly affects the predictions of light switch status as confirmed by many researches (e.g., [54] [55]). The ability to identify most influencing factors can help designs of IVE experiments for better data collection.

The contributions of the study are as follow:

- The main contribution of the study is the computation framework that biases an existing BPM to better fit the context of a building under design. The case study has demonstrated the potential of the framework to improve performance predictions. This approach is different from conventional approaches where in general BPMs often developed using data of existing buildings are applied to buildings under design. Due to the uniqueness of each building and the context-dependent nature of occupant behaviors, BPM developed using conventional approaches often fail to produce accurate predictions. Thus, the computational framework offers new possibilities to assists designers or researchers to improve performance predictions during building design.
- An additional contribution of the framework is to assist designers or researchers in integrating contextual factors related to a new design with an existing BPM. To adopt the framework for a building under design, designers or researchers need to select an existing BPM, identify contextual factors that are relevant to the design, and then collect context-aware design-specific data addressing specific human-building interactions in the context of the design using IVEs. There is no restriction on the BPM or the contextual factors to be considered. In most cases, it depends on the knowledge or experience of designers or researchers to make decisions. To a user, the computational framework is treated as a black box after the BPM and the contextual factors are determined, i.e., a user only uses an augmented model produced by the framework to generate predictions, which better address the context of a building under design.
- The framework is intended for use during a design stage, especially when a designer has several design options and need to determine the performance of a building under design.

In the future, the framework needs to be validated in different indoor environments. The data in this study are collected from a single occupancy office. Other types of spaces including homes and multi-occupancy offices and other types of occupant needs and preferences should be studies as well. Moreover, the framework needs to be improved to allow designers or researchers to use performance targets (e.g., building benchmarks, building standards, arbitrary building data, and energy consumptions) as the guide for combining data from an existing BPM and context-aware design-specific data [59]. This step is important because it makes the framework practical. It will help designers or researchers to obtain appropriate mixtures without trying many mixture ratios as shown in this study. The framework will help designers or researchers to compare different design alternatives using performance targets as a guide. From the comparison, designers or researchers will be able to determine which design alternative should be selected in order to obtain an overall optimal design. In addition, uncertainties due to the limitations of IVE technologies need to be considered in the future improvement of the computational framework.

Acknowledgments

This paper was partially supported by the Louisiana Board of Regents Award No. LEQSF (2016-17)-RD-C-07 and the U.S. National Science Foundation Award #1640818. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Louisiana Board of Regents or the National Science Foundation.

References

[1] R.K. Jain, K.M. Smith, P.J. Culligan, J.E. Taylor, Forecasting energy consumption of multi-family residential buildings using support vector regression: investigating the impact of temporal and spatial monitoring granularity on performance accuracy, Appl. Energy 123 (2014) 168–178.
[2] I. Dincer, Environmental impacts of energy, Energy Policy 27 (14) (1999) 845–854.
[3] V. Granadeiro, J.P. Duarte, J.R. Correia, V.M.S. Leal, Building envelope shape design in early stages of the design process: integrating architectural design systems and energy simulation, Autom. Constr. 32 (September) (2013) 196–209.
[4] W. Wang, R. Zmeureanu, H. Rivard, Applying multi-objective genetic algorithms in green building design optimization, Build. Environ. 40 (11) (2005) 1512–1525.
[5] P. Hoes, J.L.M. Hensen, M. Loomans, B. De Vries, D. Bourgeois, User behavior in whole building simulation, Energy and Buildings 41 (3) (2009) 295–302.
[6] H.T. Pao, Comparing linear and nonlinear forecasts for Taiwan's electricity consumption, Energy 31 (12) (2006) 1793–1805.
[7] M. Aydinalp, V.I. Ugursal, A.S. Fung, Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks, Appl. Energy 79 (2) (2004) 159–178.
[8] B. Blocken, C. Gualtieri, Ten iterative steps for model development and evaluation applied to Computational Fluid Dynamics for Environmental Fluid Mechanics, Environ. Model. Softw. 33 (0) (2012) 1–22.
[9] J.A. Love, Manual switching patterns in private offices, Lighting Research & Technology 30 (1) (1998) 45–50.
[10] A.I. Rubin, B.L. Collins, R.L. Tibbott, Window blinds as a potential energy saver-a case study, NBS Building Science Series 112 (1978) 89.
[11] D.R.G. Hunt, Predicting artificial lighting use - a method based upon observed patterns of behavior, Light. Res. Technol. 12 (1) (1980) 7–14.
[12] G.R. Newsham, Manual control of window blinds and electric lighting: implications for comfort and energy consumption, Indoor and Built Environment 3 (3) (1994) 135–144.
[13] J.F. Nicol, Characterising occupant behavior in buildings: towards a stochastic model of occupant use of windows, lights, blinds heaters and fans, Seventh International IBPSA Conference, 2001, pp. 1073–1078.
[14] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, S. Gilani, Development and implementation of an adaptive lighting and blinds control algorithm, Build. Environ. 113 (2017) 185–199.
[15] C.F. Reinhart, Lightswitch-2002: a model for manual and automated control of electric lighting and blinds, Sol. Energy 77 (1) (2004) 15–28.
[16] D. Lindelöf, N. Morel, A field investigation of the intermediate light switching by users, Energy and Buildings 38 (7) (2006) 790–801.
[17] A.C. Kunduraci, T. Kazanasmaz, Assessing Manual Lighting Control in Offices, (2016) Conference: SBE16 Smart Smart Metropoles at: Istanbul.
[18] A. Mahdavi, A. Mohammadi, E. Kabir, L. Lambeva, Occupants' operation of lighting and shading systems in office buildings, J. Build. Perform. Simul. 1 (1) (2008) 57–65.
[19] G. Branco, B. Lachal, P. Gallinelli, W. Weber, Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data, Energy and Buildings 36 (6) (2004) 543–555.
[20] T. Hong, S. D'Oca, W.J.N. Turner, S.C. Taylor-lange, An ontology to represent energy- related occupant behavior in buildings part I: introduction to the DNAs framework, Build. Environ. 92 (2015) 764–777.
[21] V. Fabi, R.V. Andersen, S. Corgnati, B.W. Olesen, Occupants' window opening behaviour: a literature review of factors influencing, Build. Environ. 58 (2012) 188–198.
[22] J.F. Nicol, M.A. Humphreys, B. Olesen, A stochastic approach to thermal comfort - occupant behavior and energy use in buildings, ASHRAE Trans. 110 (PART I) (2004) 554–568.
[23] M. Kinateder, M. Müller, M. Jost, A. Mühlberger, P. Pauli, Social influence in a virtual tunnel fire - influence of conflicting information on evacuation behavior, Appl. Ergon. 45 (6) (2014) 1649–1659.
[24] M. Kobes, I. Helsloot, B. De Vries, J. Post, Exit choice, (pre-)movement time and (pre-)evacuation behaviour in hotel fire evacuation - behavioural analysis and validation of the use of serious gaming in experimental research, Procedia Engineering 3 (December 2010) (2010) 37–51.
[25] C. Mackie, J. Cowden, D. Bowman, T. Walid, Desktop and immersive tools for residential home design, Proceedings of CONVR Conference on Construction Applications of Virtual Reality, 2004, pp. 63–70.
[26] D. Tutt, C. Harty, JJourneys through the CAVE: the use of 3D immersive environments for client engagement practices in hospital design, Proceedings 29th Annual Association of Researchers in Construction Management Conference, ARCOM 2013, No. September, 2013, pp. 111–121.
[27] Y. Hong, P. Michalatos, LumiSpace: A VR architectural daylighting design system, SIGGRAPH ASIA 2016 Virtual Reality Meets Physical Reality: Modelling and Simulating Virtual Humans and Environments, 2016, pp. 1–2.
[28] J.H. Kwon, J. Powell, A. Chalmers, How level of realism influences anxiety in virtual reality environments for a job interview, Int. J. Hum. Comput. Stud. 71 (10) (2013) 978–987.
[29] C. Chokwitthaya, S. Saeidi, Y. Zhu, R. Kooima, The impact of lighting simulation discrepancies on human visual perception and energy behavior simulations in immersive virtual environment, Congress on Computing in Civil Engineering, Proceedings, 2017–June 2017.
[30] A. Heydarian, J.P. Carneiro, D. Gerber, B. Becerik-Gerber, Immersive virtual environments, understanding the impact of design features and occupant choice upon lighting for building performance, Build. Environ. 89 (2015) 217–228.
[31] S. Saeidi, T. Rizzuto, Y. Zhu, R. Kooima, Measuring the effectiveness of an immersive virtual environment for the modeling and prediction of occupant behavior, Sustainable Human-Building Ecosystems - Selected Papers From the 1st International Symposium on Sustainable Human-Building Ecosystems, 2006 2015, pp. 159–167.
[32] S. Niu, W. Pan, Y. Zhao, A virtual reality integrated design approach to improving occupancy information integrity for closing the building energy performance gap, Sustain. Cities Soc. 27 (2015) 275–286.
[33] S. Saeidi, C. Chokwitthaya, Y. Zhu, M. Sun, Spatial-temporal event-driven modeling for occupant behavior studies using immersive virtual environments, Autom. Constr. 94 (May) (2018) 371–382.
[34] Y. Zhu, S. Saeidi, T. Rizzuto, A. Roetzel, R. Kooima, Potential and challenges of immersive virtual environments for occupant energy behavior modeling and validation: a literature review, Journal of Building Engineering 19 (2018).
[35] P.S. Bordnick, K.M. Graap, H.L. Copp, J. Brooks, M. Ferrer, Virtual reality cue reactivity assessment in cigarette smokers, CyberPsychology & Behavior 8 (5) (2005) 487–492.
[36] D.A. Das, K.A. Grimmer, A.L. Sparnon, S.E. McRae, B.H. Thomas, The efficacy of playing a virtual reality game in modulating pain for children with acute burn injuries: a randomized controlled trial, BMC Pediatr. 5 (1) (2005) 1.
[37] C.M. Bishop, Neural Networks for Pattern Recognition, Oxford university press, 1995.
[38] Y. Sun, X. Wang, X. Tang, Deep learning face representation from predicting 10,000 classes, Cvpr (2014) 1891–1898.
[39] P. Bermejo, J.A. Gámez, J.M. Puerta, A GRASP algorithm for fast hybrid (filter-wrapper) feature subset selection in high-dimensional datasets, Pattern Recogn. Lett. 32 (5) (2011) 701–711.
[40] Y. Saeys, T. Abeel, Y. Van de Peer, Robust feature selection using ensemble feature selection techniques, Joint European Conference on Machine Learning and Knowledge Discovery in Databases, 2008, pp. 313–325.
[41] A. Jović, K. Brkić, N. Bogunović, A review of feature selection methods with applications, 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2015 - Proceedings, 2015, pp. 1200–1205.
[42] P. Correia da Silva, V. Leal, M. Andersen, Occupants interaction with electric lighting and shading systems in real single-occupied offices: results from a monitoring campaign, Build. Environ. 64 (Rsece 2006) (2013) 152–168.
[43] D. Bourgeois, C. Reinhart, I. Macdonald, Adding advanced behavioural models in whole building energy simulation: a study on the total energy impact of manual and automated lighting control, Energy and Buildings 38 (7) (2006) 814–823.
[44] D. Yan, X. Feng, Y. Jin, C. Wang, The evaluation of stochastic occupant behavior models from an application-oriented perspective: using the lighting behavior model as a case study, Energy and Buildings 176 (2018) 151–162.
[45] U.S. general services administration, [Online]. Available: https://www.gsa.gov/node/82715 , Accessed date: 6 July 2019.
[46] L.E. Baum, An inequality and associated maximization technique in statistical estimation for probabilistic functions of Markov process, Inequalities 3 (1972) 1–8.
[47] J. Picone, Continuous speech recognition using hidden Markov models, ASSP Magazine, IEEE 7 (July 1990) (1990) 41.

[48] S. Luhr, S. Venkatesh, G. West, H.H. Bui, Duration Abnormality Detection in Sequences of Human Activity, PRICAI, 2004, pp. 983–984 no. February.
[49] Z. Ghahramani, An introduction to hidden Markov models and Bayesian networks, Int. J. Pattern Recognit. Artif. Intell. 15 (1) (2001) 9–42.
[50] I. Visser, Seven things to remember about hidden Markov models: a tutorial on Markovian models for time series, J. Math. Psychol. 55 (6) (2011) 403–415.
[51] C. Chokwitthaya, Y. Zhu, R. Dibiano, S. Mukhopadhyay, A Machine Learning Algorithm to Improve Building Performance During Design, (2019) (Manuscript submitted for publication).
[52] Zou Hui, H. Trevor, Regularization and variable selection via the elastic net, Journal of the Royal Statistical Society: Series B (Statistical Methodology) 67 (2) (2005) 301–320.
[53] S. Kalogirou, Artificial neural networks for the prediction of the energy consumption of a passive solar building, Energy 25 (5) (2000) 479–491.
[54] Y. Gu, The Impacts of Real-time Knowledge Based Personal Lighting Control on Energy Consumption, User Satisfaction and Task Performance in Offices, (2011), p. 157.
[55] J. Yang, M. Santamouris, S.E. Lee, Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings, Energy and Buildings 121 (2016) 344–349.
[56] C. Demanuele, T. Tweddell, M. Davies, Bridging the gap between predicted and actual energy performance in schools, World Renewable Energy Congress XI, September 2010, pp. 1–6.
[57] A.C. Menezes, A. Cripps, D. Bouchlaghem, R. Buswell, Predicted vs. actual energy performance of non-domestic buildings: using post-occupancy evaluation data to reduce the performance gap, Appl. Energy 97 (2012) 355–364.
[58] Y. Zhu, S. Saeidi, T. Rizzuto, A. Roetzel, R. Kooima, Potential and challenges of immersive virtual environments for occupant energy behavior modeling and validation: a literature review, Journal of Building Engineering 19 (January) (2018) 302–319.
[59] C. Chokwitthaya, E. Collier, Y. Zhu, S. Mukhopadhyay, Improving prediction accuracy in building performance models using generative adversarial networks (GANs), arXiv Preprint arXiv:1906.05767, 2019 June 13, p. 2019.