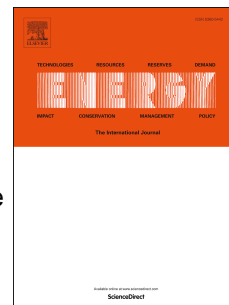


Journal Pre-proof

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PII: S0360-5442(24)00668-6

DOI: <https://doi.org/10.1016/j.energy.2024.130896>

Reference: EGY 130896

To appear in: *Energy*

Received Date: 13 November 2023

Revised Date: 1 February 2024

Accepted Date: 1 March 2024

Please cite this article as: Zhang C, Luo Z, Yacine R, Zhao T, Enhancing building energy consumption prediction introducing novel occupant behavior models with sparrow search optimization and attention mechanisms: A case study for forty-five buildings in a university community, *Energy* (2024), doi: <https://doi.org/10.1016/j.energy.2024.130896>.

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Enhancing building energy consumption prediction introducing novel occupant behavior models with sparrow search optimization and attention mechanisms: A case study for forty-five buildings in a university community

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Abstract: The escalating energy and environmental crises underline the imperative for sustainable cities and societies. For effective and real-time energy management, this study proposes an enhanced building energy consumption prediction system. It introduces a novel concept named region-wide occupant energy-use behavior probability and incorporates it into the input system, which better reflects real-time and complex energy-occupant-environment interactions in buildings. In addition, it integrates the squeeze-and-excitation attention mechanism, sparrow search algorithm, and convolutional neural network processes for optimizing data processing and hyperparameter selection. Validation in seven sample buildings demonstrates the proposed prediction system has a better balance between time and accuracy, reducing 36.32% MAPE and 31.20% CV-RMSE on average compared to all other prediction systems, only with 118.354s of extra time consumption increase compared to the least time-consuming method. Furthermore, this study discusses methods for selecting suitable input systems and algorithms based on building type, data collection conditions, accuracy, and time consumption. Finally, the enhanced prediction is applied to forty-five buildings in a university community, yielding a 12.35% MAPE and a 0.1707 CV-RMSE on average, reaffirming its superiority and practicality.

Keywords: University community; Building energy consumption prediction; Region-wide occupant behavior probability; Squeeze-and-excitation attention mechanism; Sparrow search algorithm; Priority selection

Highlights

1. An enhanced energy consumption prediction including improving input and algorithm is proposed.
2. It introduces occupant energy-use behavior probability as inputs.
3. It introduces SSA, SE attention, and CNN modules for improving training algorithms.
4. It discusses the performance comparison of proposed algorithms and other advanced algorithms.
5. Method for selecting suitable inputs and algorithms in different buildings is presented.

Nomenclature section

Nomenclature	
ANN	Artificial neural network
AC	Air conditioning
ACO	Ant colony optimization
AR	Autoregressive model
ARIMA	Autoregressive integrated moving average
BPNN	Back-propagation neural network
CNN	Convolutional neural network
CO ₂	Carbon dioxide
CV-RMSE	The coefficient-of-variation of root mean square error
DE	Deep ensemble model
DT	Decision tree
EUI	Electrical consumption intensity
GA	Genetic algorithm
HVAC	Heating, Ventilation and Air Conditioning
LSTM	Long short-term memory (neural network)
MAE	The mean absolute error
MAPE	The mean absolute percentage error
PI	Performance improvement
PSO	Particle swarm optimization
R ²	The coefficient of determination
RF	Random forest
RMSE	The root mean square error
RNN	Recurrent neural network
ROEBP	Region-wide occupant energy-use behavior probability
SE	Squeeze-and-excitation (attention mechanisms)
SSA	Sparrow search algorithm
SVM	Support vector machine
TIME	The whole algorithm realization duration from initial data import to the completion of evaluation index outputs
XGBoost	Extreme gradient boosting
Variables and symbols	
M_b	The values of the evaluation indices before input or algorithm improvement.
M_a	The values of the evaluation indices after input or algorithm improvement.
p	The time index (if p is 2, then T_{p-1} , T_p , and T_{p+1} are $T_{1:00}$, $T_{2:00}$, and $T_{3:00}$).
q	The code of each energy equipment.
N	The total number of all equipment.
M_0	The times of the one kind of energy-use actions.
M_q	The times of the total all energy-use actions.
T	Time.
ΔT_0	The time difference between t_n and t_{n+1} (In this study, ΔT_0 will be 1 h).

ΔT_q	The usage time of the q th equipment during the period $T_p - T_{p+1}$.
S	The mathematical measure of psychology.
I	The physical parameter (external stimulus).
P	The energy-use behavior probability.
x	The environmental parameter.
x_1	The indoor air temperature.
x_2	The outdoor solar radiation intensity.
x_3	The indoor carbon dioxide concentration.
n	The number of sparrows in SSA.
d	The dimension of the variables in SSA.
t	The current iteration in SSA.
i	The code of sparrows ($i=1,2,\dots,n$) in SSA.
j	The code of dimension ($j=1,2,\dots,d$) in SSA.
$iter_{max}$	A constant with the largest number of iterations in SSA.
α	A random number between 0 and 1 in SSA.
R_2	The alarm value (range: 0–1) in SSA.
ST	The safety threshold (range: 0.5–1) in SSA.
Q	A random number that obeys a normal distribution in SSA.
X_p	The best position currently occupied by the producer in SSA.
X_{worst}	The current global worst position in SSA.
β	The step control parameter (a random normally distributed value with mean 0 and variance 1) in SSA.
f_g	The global best fitness values for the current state respectively in SSA.
f_w	The global worst fitness values for the current state respectively in SSA.
ϵ	A very small constant to avoid the equation being meaningless if the divisor is 0 in SSA.
u	The influencing factor of socket-related behaviors.
f,g,h,t	The mapping relation symbol.

1 Introduction

1.1 Background

The global energy landscape is significantly impacted by the energy consumption of buildings, amounting to over one-third of total energy consumption worldwide ^[1]. This figure surges to more than 40% in the United States and European Union ^[2], and peaks at 45.5% in China ^[3]. These statistics underscore the urgency of effectively managing building energy consumption and carbon emissions. Real-time and accurate energy management technologies are fundamental to addressing this challenge, which needs an online accurate energy consumption prediction system with high accuracy. Especially, This necessity is further underscored by the increasing complexity of energy supply, propelled by emerging technologies such as distributed energy systems, which makes supply-demand matching more challenging. Therefore, precise and immediate energy consumption prediction at an hourly scale has become a critical cornerstone for energy network scheduling, as supported by empirical evidence ^[4–10].

1.2 Review on building energy consumption prediction

Building energy consumption prediction can be approached through three primary approaches: physical modeling methods, data-driven methods, and combinatorial methods. The physical modeling method, which utilizes simulations through software such as Energyplus, forecasts energy consumption by incorporating climate zones, building geometry, occupant activity schedules, and various equipment parameters. Nonetheless, these methods are limited in their effectiveness for online prediction applications because of challenges in representing real-time interactions among occupants, energy systems, and environment in buildings ^[11]. In addition, some researchers have raised concerns about the accuracy of physical methods, suggesting that they may be insufficient ^[12]. Additionally, although optimization methods such as using Bayesian have been explored ^[13], limits on the online application may also exist. And the combinatorial methods, integrating aspects of physical modeling and data-driven approaches, aim to improve performance. However, this approach faces some challenges such as a lack of theoretical hypotheses and standardized nomenclature, determination of the optimal order of each component in the hybrid model, and a shortage of unified software solutions ^[14–15]. Similar to physical modeling, the use of software can compromise online prediction performance. Considering the aims, this study will specifically focus on data-driven methods.

Data-driven methods rely on sufficient data and principally entail the development and selection of suitable inputs and effective algorithms. This study attempted to summarize and analyze some recent studies in this area as follows.

Concerning the input system, the possible parameters include indoor environmental parameters ^[16–17] (e.g., indoor air temperature); outdoor meteorological parameters ^[16–18] (e.g., outdoor air temperature); occupant-related parameters ^[16, 18–19, 21–22, 26–29] (e.g., occupancy); equipment-related parameters ^[19–20, 25, 28, 30] (e.g., heating and cooling set point); time-based elements ^[16,18]; and building information parameters ^[23–24] (e.g., building geometry). Moreover, in individual building energy consumption

prediction, certain broader indicators such as cultural background, residential income, building geometry, and shape are less influential and often excluded from the prediction model. Conversely, indoor and outdoor environmental parameters, time characteristics, occupant behavior characteristics, and equipment operating parameters are crucial for achieving high prediction efficiency in data-driven building energy consumption prediction.

However, despite the wealth of parameters available for forecasting building energy consumption, significant challenges persist. One primary challenge pertains to the uncertainty and reduced effectiveness of occupant-behavior-related parameters. Specifically, first, evaluating the intricate interactions among energy systems, occupants, and environment in buildings employing existing parameters remains challenging. For example, occupancy merely indicates presence rather than actions, and schedules may be challenging to apply in real-time. Furthermore, AC temperature setting values have a limited impact on non-air-conditioning energy consumption. Consequently, these oversimplified parameters present limited utility when addressing buildings with irregular energy consumption and complex occupant behaviors. Second, available occupant behavior parameters prove difficult to capture the comprehensive use and regulation of all equipment by all occupants within the building currently. Given numerous instances of multiple ACs, lamps, sockets, and other types of equipment in a building, their intricate usage and interactions have not been appropriately parameterized. Third, many related parameters may raise privacy concerns. Finally, these existing occupant-related parameters may not be effectively integrated with energy consumption prediction algorithms.

Consequently, there is a pressing requirement to propose some parameters that can more effectively characterize and reflect the complex real-time energy-human-environment interactions and can be seamlessly integrated into the energy prediction algorithm system. Moreover, for practical utility, it is essential to offer implementable calculation models using data that can be collected without privacy violations.

Concerning the algorithms and their optimizations, the domain of data-driven building energy consumption prediction involves the application of various successful algorithms and their optimizations. These algorithms include artificial neural network (ANN), back-propagation neural network (BPNN)^[31], recurrent neural network (RNN)^[34], convolutional neural network (CNN)^[33], long short-term memory neural network (LSTM)^[34], support vector machine (SVM)^[35], multiple linear regression^[35], autoregressive integration and moving average (AIRMA)^[36], decision tree (DT)^[38], and genetic algorithm (GA)^[37]. Statistical analyses of relevant studies^[39] reveal that ANN, SVM, and DT have been used in 47%, 25%, and 4% of studies respectively, while statistical algorithms account for the remaining 24%. Notably, these algorithms without optimization modules generally have poor prediction accuracy. To address these inadequacies, various optimizations have been employed in the pursuit of enhanced prediction accuracy. First, the data processing process can be optimized by analyzing and digging into input data features^[40, 42–43]. Second, the hyperparameter optimization

selection process can be optimized algorithmically, for example, by using swarm intelligence algorithms to determine optimal values for the weights and thresholds of neural networks ^[44–49]. Finally, it can also be optimized with a combination of multiple algorithms. For example, Liang et. al. combined the deep ensemble (DE) model and the autoregressive (AR) model ^[41].

However, despite the abundance of existing research in this field, current algorithms face common challenges that necessitate further refinement. These challenges include but are not limited to prolonged computation times, low prediction accuracy, and limitations in their applicability to various building types. For instance, some swarm intelligence algorithms may require excessive iteration time, while some algorithms may constrain predicted values around mean estimates, resulting in poor identification of peaks and valleys.

Consequently, there is a pressing requirement to develop comprehensive algorithms that integrate fundamental and optimization algorithms, striking a better balance between prediction accuracy and time consumption compared to previous algorithms. The optimized algorithm should not only strive for improved prediction accuracy but also aim to minimize additional time consumption.

1.3 Targets and works

To address the above challenges, this study proposes an advanced system for predicting building energy consumption. The system incorporates innovative occupant energy-use behavior models and enhanced algorithms with the CNN process, sparrow search optimization, and attention mechanisms. Initially, this study scrutinizes the proposed prediction system in detail across seven sample buildings and subsequently extends the improved system to encompass a total of forty-five buildings within a university community.

First, this study introduces a novel concept named region-wide occupant energy-use behavior probability (ROEBP) as a crucial input feature. It delineates the definition, resolution method, and simplified models. Based on recent studies on AC-related behavior and socket-related behavior, this study additionally supplements the studies with an exploration of light-related behavior. Together, these form a comprehensive framework to reflect the complete probability of occupant energy-use behavior in a building. The application of the ROEBP model facilitates more effective real-time energy-human-environment interactions and can be seamlessly integrated into the prediction system, thereby improving prediction accuracy.

Second, this study introduces the CNN-LSTM-Attention algorithm, which involves the integration of CNN into LSTM to extract complex features among multiple input variables collected for building energy demand forecasting and storing complex irregular trends. This approach also involves the incorporation of the Squeeze-and-Excitation block attention mechanism (SE-Attention) into LSTM for optimizing key hyperparameters, such as weights, thresholds, and learning rates. Moreover, this study also compares the prediction performance of the proposed CNN-LSTM-SE with other advanced

machine learning algorithms, including LSTM-SSA, RF, XGBoost, etc. (XGBoost: extreme gradient boosting, RF: random forests).

Finally, this study conducts a comparative analysis to determine suitable combinations across three dimensions: input systems, algorithms, and buildings. This is based on the diversity of building energy consumption characteristics, the challenges of data collection, and performance and time requirements.

The remaining sections are organized as follows. Section 2 presents the data collection process and dataset, key algorithmic details, and the computation process of ROEBP. Section 3 presents the results and discussions of occupant behavior modeling and energy consumption forecasting in seven sample buildings in Sections 3.1–3.2, where it also includes a detailed comparison of the proposed combination of inputs and algorithms and other combinations. Moreover, Section 3.3 discusses some advanced machine learning algorithms including random forests, support vector machines, and extreme gradient boosting. Finally, the application of the proposed energy consumption prediction methods to all forty-five buildings is detailed in Section 3.4. Sections 4 and 5 present the limitations and conclusions.

2 Methodology

2.1 Sample buildings and related data collection

This study initially focused on analyzing enhanced prediction systems using a selection of seven sample buildings. Subsequently, this analysis encompassed an extended study involving forty-five buildings within a university community. Essential information pertaining to the seven sample buildings will be shown in Table 1, while details for the remaining buildings are provided in Appendix B. The campus buildings primarily comprise dormitories, laboratories, office buildings, educational buildings, libraries, and scientific-research buildings encompassing research laboratories and offices of graduate students and supervisors. Notably, the energy consumption pattern within the dormitory buildings appears relatively uniform. The dormitories on the target campus do not possess ACs and are subject to restricted electricity usage (powering off after 22:30). Therefore, the dormitory buildings within this particular campus may not be representative of typical structures. Moreover, given the prevalence of research on dormitory and residential buildings, this study opted to focus on several characteristic office buildings, educational buildings, libraries, and scientific-research buildings as research cases (Buildings A–G). These buildings exhibit an Electrical consumption intensity (EUI) exceeding 30 kWh/m² and are equipped with a comprehensive array of energy-consuming apparatus. Moreover, these seven buildings offer a wealth of pertinent data encompassing energy usage, environmental impact, and occupier-related information which is vital for this study's objectives.

It is important to note that these buildings operate under three control modes. Category a entails unrestricted all equipment controlled by all occupants, without intervention from administrators. In Category b, all occupants in buildings can process free equipment control, with administrators

responsible for verifying and subsequently turning off the equipment post building closure. Category c entails the designated administrators' control of all ACs, while all other equipment can remain under the free control of all occupants in buildings. Moreover, administrators are tasked with verifying and turning off the equipment after the buildings are closed.

Table 1 The seven sample buildings in this study

Code	Type	Energy items	Heating and cooling systems	Control modes	EUI (kWh/m ²)
Building A	Scientific research	Sockets, lighting, ACs	Heating: District heating system with municipal hot water and using ACs as a supplement Cooling: Split ACs	Category a	75.76
Building B	Office	Sockets, lighting, ACs	Heating: District heating system with municipal hot water and using ACs as a supplement Cooling: Variable refrigerant flow multilink ACs	Category a	44.89
Building C	Scientific research	Sockets, lighting, ACs	Heating: District heating system with municipal hot water Cooling: Centralized ACs	Category b	41.55
Building D	Library	Sockets, lighting, ACs	Heating: District heating system with municipal hot water Cooling: Centralized ACs	Category c	30.54
Building E	Library	Sockets, lighting, ACs	Heating: District heating system with municipal hot water and using ACs as a supplement Cooling: Centralized ACs	Category c	60.09
Building F	Education	Sockets, lighting	Heating: District heating system with municipal hot water Cooling: None	Category b	62.74
Building G	Education	Sockets, lighting	Heating: District heating system with municipal hot water Cooling: None	Category b	37.76

Energy data were collected from building energy consumption monitoring platforms^[52–54]. These sample buildings were equipped with an energy-consumption monitoring and management system. This system can comprehensively record the current, voltage, and energy consumption changes in all energy-use items and branches while uploading related data to cloud platforms. An illustration of the system is shown in Figure 1(a). Indoor environmental data were obtained from ceiling-mounted sensors installed in the buildings, with at least one sensor placed in each room and corridor. These sensors can simultaneously record four parameters: indoor air temperature, indoor air humidity, indoor CO₂ concentration, and indoor PM_{2.5} concentration. The installation locations and equipment schematics are shown in Figure 1(b). Outdoor meteorological data were collected from the China Meteorological Science Data Center^[55], which serves as a sharing portal for basic public meteorological data.

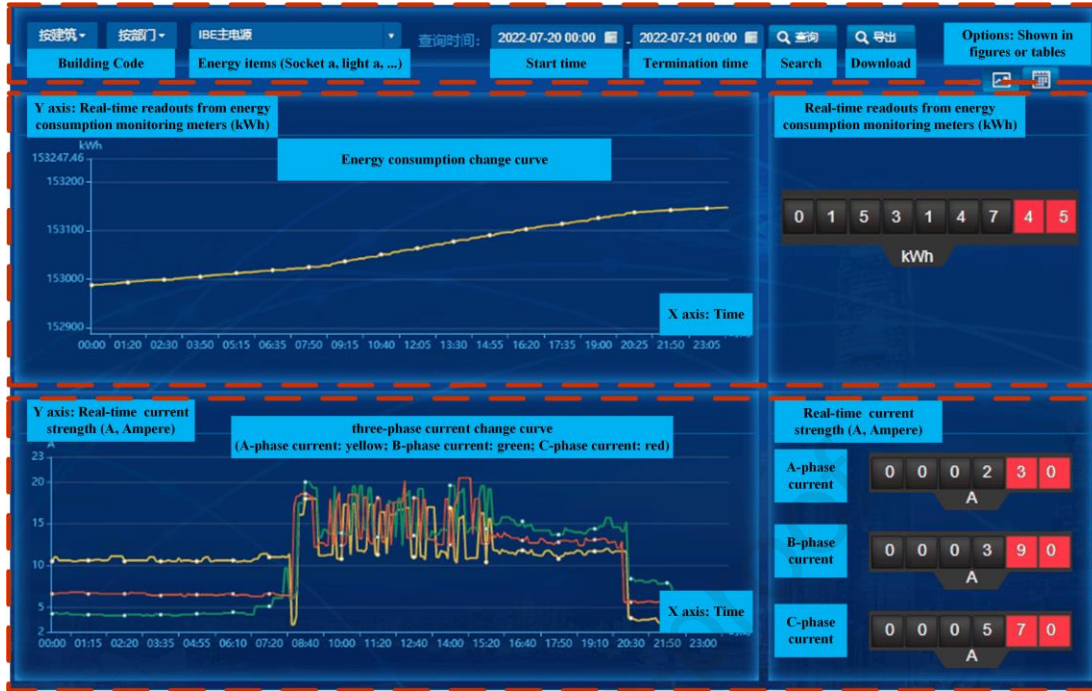


Figure 1(a) The monitoring and management of building energy consumption

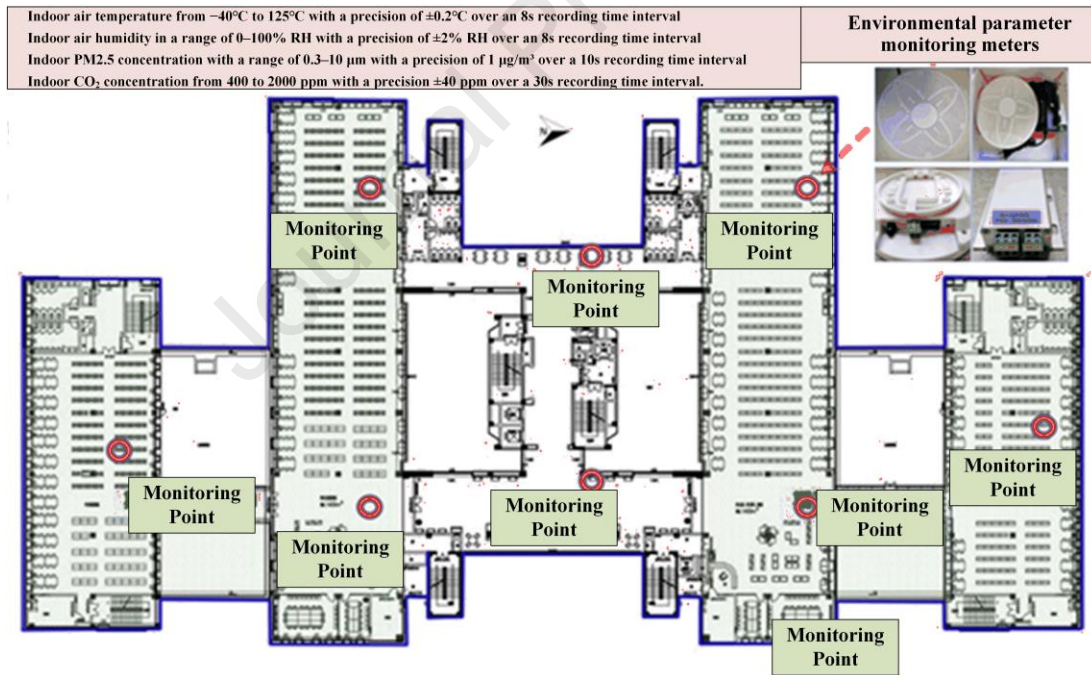


Figure 1(b) The monitoring and management of building indoor environmental parameters

Occupancy and the number of occupants were obtained from the automatic access control system or similar monitoring systems (installed in Buildings A, B, C, F, and G), as well as the seat reservation system (installed in Buildings D and E) and were collected on an hourly basis, as shown in Figure 1(c). However, in some buildings, the occupancy-related data were incomplete using the above systems. Therefore, this study considered the occupancy or number of occupants using indoor CO₂ concentration

in these buildings, an alternative method that has been proven effective in many studies [56-60].

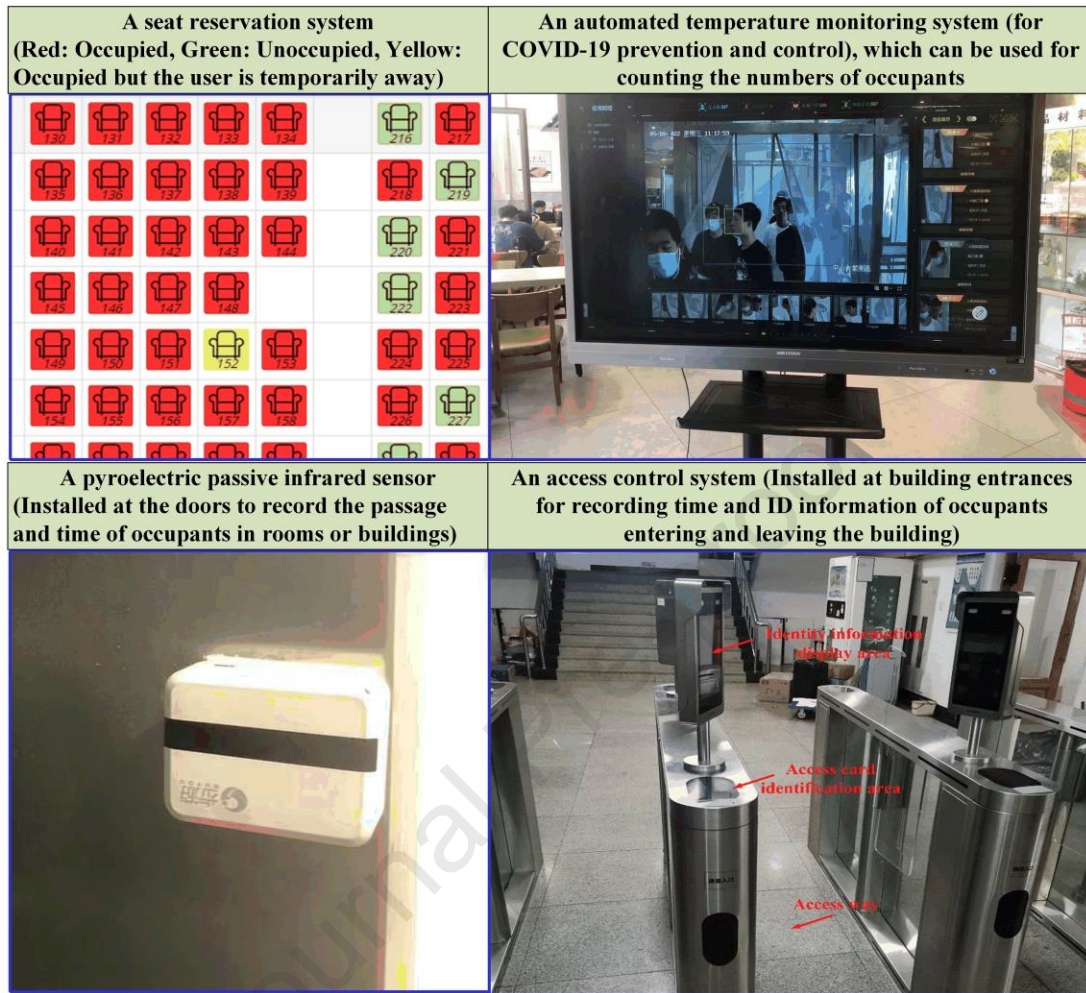


Figure 1(c) The monitoring and management of occupancy (or number of occupants)

Figure 1 Different parameter monitoring systems in this study [61, 96-97]

All data were collected on an hourly scale in 2021. As for the period of a year, it generally includes vacation days, exam days, and non-exam days. Non-exam days are when faculty and students conduct their daily classes, while exam days occur at the end of each semester referring to the period when final exams are prepared and administered. As for the day of a period, it can be categorized into weekdays and weekends. As for the time of one day, it generally includes working hours, transition hours, and nighttime. For example, in Building C (operating time: 7:00–23:00), working hours are from 09:00 to 22:00 and transition hours are from 07:00 to 09:00 and from 22:00 to 23:00 (two hours after opening and one hour before closing). Nighttime spans from 23:00 to 07:00 the following day. The time division schematic is shown in Figure 2 [61, 96-97].

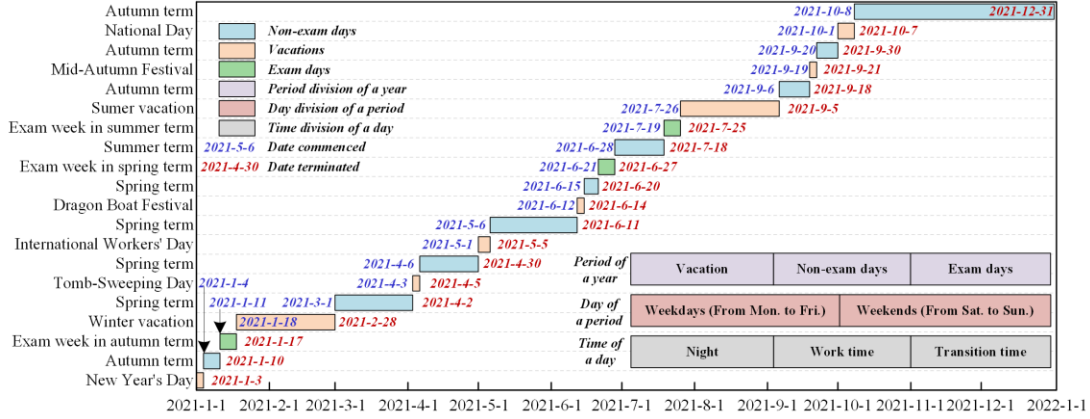


Figure 2 The Gantt Chart of time division in 2021 [61, 96–97]

2.2 ROEBP models

The detailed process of the ROEBP model can also be found in previous studies [61, 96–97]. However, for the sake of completeness of this study, the relevant definitions and solutions of this concept are still described in Section 2.2.

2.2.1 Definition and principle of proposed ROEBP models

Recent research [61–68] suggests that occupant behavior constitutes a comprehensive concept that includes occupant presence, movement, and various actions. Occupant presence can be reflected by occupancy or number of occupants or indoor CO₂ concentration. Moreover, this study aims to introduce energy-use behavior features to enhance existing energy consumption prediction systems. Therefore, rather than focusing on the occupant movement, it centers on the comprehensive energy-use intensity of all equipment over a specific period. Various parameters have been proposed to measure these energy-use behaviors, and the occupant behavior probability can be widely recognized.

Taking AC-related actions as an example, the novel proposed equation denoting the probability of various actions is expressed as equation (1). Furthermore, to demonstrate the effectiveness of the occupant probability model developed in this study, this study also introduces equation (2), which denotes the traditional approach for solving behavior probabilities [92].

$$P_{(T_p-T_{p+1})} = \frac{\sum_{q=1}^n \Delta T_q}{n \times \Delta T_0} \quad (1)$$

$$P_{(T_p-T_{p+1})} = \frac{\sum_{q=1}^n M_q}{n \times M_0} \quad (2)$$

Where P is the occupant behavior probability. p is a time index (e.g., if p is 2, then T_{p-1} , T_p , and T_{p+1} are $T_{1:00}$, $T_{2:00}$, and $T_{3:00}$, respectively). q represents the code of each AC. n is the total number of all ACs (e.g., if a building has 10 ACs, then n is 10 with j numbered from 1 to 10). M_q and M_0 represent the times of the AC-related actions and total actions. ΔT_0 represents the time difference between t_n and t_{n+1} (in this study, focusing on hourly energy consumption, ΔT_0 will be 1 h),

and ΔT_q represents the usage time of the p th AC during the period $T_p - T_{p+1}$.

The probabilistic model presented in this study offers a departure from the traditional approach, which determines the probability of certain actions by considering the ratio of the total count of certain actions to the overall total count of actions. Instead, the probabilistic model presented in this study leverages the proportion of the duration of certain actions to the total duration as the probability. In proposing this novel concept (equation 1), this study builds upon established literature regarding modeling occupant behavior (equation 2). To elucidate the differences between equations (1) and (2), consider the following example: when predicting AC energy consumption between 13:00 and 14:00, Scenario A assumes that occupants commence AC usage at 13:01 and continue until 14:00, while Scenario B assumes that occupants commence AC usage at 13:59 and continue until 14:00. When focusing on the period from 13:00 to 14:00, using the traditional equation (equation 2) would yield a uniform occupant behavior probability of 1/1, failing to distinguish between Scenario A and B. In contrast, adopting the proposed equation (equation 1) would yield occupant behavior probabilities of 1/60 and 59/60 for Scenario A and B, respectively.

This alteration presents two distinct advantages. First, it provides a more accurate reflection of occupant behavior towards energy-consuming equipment, particularly by highlighting the intensity of equipment usage. Second, it can be flexibly utilized to model probabilities at different time-scale levels, such as examining hourly, daily, or monthly behavior probabilities. Conversely, the traditional method tends to model probability at larger time scales which may fail when assessing probabilities at an hourly time-scale or below, as occupants may be unlikely to replicate the same behavior frequently in a single hour (e.g., turning a light on and off multiple times within an hour would constitute a low probability event). In addition, similar methodologies akin to this study for solving probabilities using the ratio of behavior duration time to total time have been discussed and validated in some recent studies ^[61, 96–97].

2.2.2 Modeling and solving method of proposed ROEBP models

Regarding occupant energy-use actions, they can be primarily classified into three categories ^[61]: environment-related, time-related, and random behaviors. The methods for deriving probabilities for these different behaviors are outlined below in detail.

(1) Environment-related behavior: External stimuli play a crucial role in equipment control behavior under environment-related behavior. For instance, in some buildings, AC control depends on thermal comfort which is linked to indoor and outdoor air temperature, while lighting control depends on indoor illumination, which is correlated with outdoor solar radiation. The direct correlation among environmental stimulus, psychological changes, and behavior probability will be presented in equations (4–5), and equation (5) can be further expanded into equation (6). This mapping relationship follows no fixed patterns but normally includes linear functions, logistic functions, exponential functions, and alternative types ^[73–75].

$$S = k \times \Delta I^n \quad (4)$$

$$P \propto \Delta S \quad (5)$$

$$P_{(T_p-T_{p+1})} = f(I_{T_{p-1}-T_p}) = [aI + b], \left[\frac{a+b(I-I_0)^n}{1+(I-I_0)^n} \right], \dots, etc. \quad (6)$$

Where S represents a mathematical measure of psychology. I represents a physical parameter (external stimulus). Exponents k and n have different values for different senses. x represents the environmental parameter. This model has predominantly found applicability in behaviors related to AC and lighting. The factors (external stimuli) influencing AC-related behavior often encompass indoor air temperature [63], outdoor air temperature [65], etc., with indoor air temperature being identified as the most impactful factor (several researchers have found indoor air temperature to be a more reliable predictor than outdoor air temperature for occupant behaviors related to AC and window [72]). Furthermore, the external stimulus regarding lighting-related behavior typically corresponds to the average indoor or work desk illuminance [64–65]. Nonetheless, since most illuminance meters are handheld devices that can be challenging to monitor online for extended periods, as well as some with studies suggesting that illuminance can be inferred from outdoor solar radiation intensity [66–67], this study attempts to utilize solar radiation intensity as the primary influencing factor in determining lighting-related behaviors which are also successfully applied in a recent study [61].

(2) Time-related behavior: Time and time-related events play a crucial role in equipment control behavior under time-related behavior. For example, in some buildings, ACs or lights are activated upon the arrival of the initial occupant and deactivated when the last occupant leaves. The occupant behavior probability model is expressed as equation (7).

$$P_{(T_1-T_2)} = \begin{cases} 1, & \text{some time or time – related events} \\ 0, & \text{other time} \end{cases} \quad (7)$$

(3) Random behavior: This category of behavior may be random and unaffected by specific and uniform physical parameters that influence equipment control behavior, such as charging cell phones, utilizing microwave ovens, and watching TV. The occupant behavior probability model is demonstrated as equation (8).

$$P_{(T_1-T_2)} = g(\text{some uncertain factors}) = g(u) \quad (8)$$

Where u represents the influencing factor. Although these influencing factors are not universally recognized, some studies have proposed some parameters. For example, some researchers suggested parameters such as the waiting time from the last action to the present action, drawing from the human dynamics theory proposed by Barabási [29]. Other parameters include indoor CO₂ concentration referring to recent studies [61, 96–97], and psychosocial factors such as attitudes and personal norms [62]. In this study, indoor carbon dioxide concentration will be selected. The decision stems from the strong correlation between the number of occupants and occupant behavioral characteristics. Generally, occupants' identities and behavioral logics are similar in similar buildings, and both have a strong impact on the building energy consumption [95]. Considering indoor CO₂ concentration can signify fluctuations in the

number of occupants and the difficulty of data acquisition, this study attempts to characterize overall occupant behaviors by indoor CO₂ concentration. That is, the independent variable u was selected as indoor CO₂ concentration when solving for the probability of random socket-related behaviors. This method has also been substantiated by recent studies [61, 96–98]. Moreover, g represents the mapping function, akin to equation (6), primarily encompassing some statistical models [73–75] such as logistics, quadratic, sigmoid, and probity functions [62], and even machine-learning algorithms [68].

In conclusion, this study identified the actual control patterns in sample buildings with reference to recent studies [61–68]. Besides time or time-related events being the control strategies for behaviors, AC-related and lighting-related behaviors primarily comprise environment-related behaviors, notably influenced by indoor air temperature and outdoor solar radiation intensity respectively [61, 63, 65]. Additionally, socket-related behavior constitutes random behaviors, with CO₂ concentration as the indirect indicator reflecting behavior [61].

Furthermore, it is noteworthy that previous research on human behavior has primarily focused on room situations with indoor parameters confined to the room. However, this study expands the scope to the building level, where indoor environmental parameters are measured as the average values across all rooms and corridors in a building. While modeling the behavior probability in each room (using the behavior probability and temperature in that specific room) can provide more precise results, it would fail to reflect the overall energy-use behavior in the overall building, making it challenging to utilize the model for building energy consumption forecasting. Conversely, modeling the behavior probability for the entire building (using the average behavior probability and temperature values across all rooms) can better represent the energy-use behaviors of the overall building, albeit at the cost of a relatively vague probabilistic model. Moreover, several studies have demonstrated the feasibility of using averages in modeling [61, 70–71, 96–97], and some studies also suggest that while certain applications necessitate high accuracy, others like HVAC often do not [69]. Thus, considering that the primary objective of this study is to reflect the occupant energy-use behavior intensity across a specific period for using the probability in energy consumption prediction, rather than to precisely characterize human behavior in thermal comfort simulation, this study deems it effective to adopt the average values.

2.3 Related algorithms and optimizations

2.3.1 CNN and LSTM

Given the conventional nature of both LSTM and CNN as classical neural network architectures, this study does not detail the mathematical derivation process. It will focus solely on presenting the hyperparameter selection process [76–77]. The program has been implemented using MATLAB.

Regarding the key hyperparameters for CNN, the maximum number of iterations (MaxEpochs) is set to 100, and the initial learning rate (InitialLearnRate) is established as 0.005. Additionally, LearnRateDropPeriod and LearnRateDropFactor are configured as 80 and 0.8 respectively (The

learning rate is multiplied by a factor every time a certain number of periods elapse, where the multiplication factor is LearnRateDropFactor and the number of periods is LearnRateDropPeriod.). As for the LSTM module, MaxEpochs is 1000, InitialLearnRate is 0.01, LearnRateDropPeriod is 800, and LearnRateDropFactor is 0.8. L2 Regularization is employed in both CNN and LSTM to evade overfitting ^[78]. Traditional batch gradient descent can be computationally intensive, while stochastic gradient descent may not converge easily. Thus, this study resorts to Mini-batch gradient descent, with a MiniBatchSize of 24 for CNN and 240 for LSTM (Typically, MiniBatchSize represents a multiple of 2 between 0 and the maximum number of iterations.). Moreover, the ReLU function (Linear rectification function) will serve as the activation function in the CNN process, with a convolutional kernel size of 64 ^[99]. Meanwhile, the *tanh* function will serve as the activation function in the LSTM process. The neurons of LSTM are set to 32 and the hidden layers are set to 2 (Note: In some algorithms with SSA and SE attention modules, SSA and SE will be used to determine the optimal number of hidden layers instead of setting it to 2 directly).

2.3.2 Sparrow search algorithm

The optimization of hyperparameters often employs swarm intelligent techniques encompassing various classical methods such as ACO and PSO. This study refers to some existing tests ^[79–80] and uses the SSA due to its superior performance. The step is shown in Figure 3.

The location vectors of all sparrows are shown in equation (9), and their corresponding fitness values are shown in equation (10). Sparrow populations are divided into two categories: producers and scroungers. Producers assume the task of searching for food and guiding the movement of the entire population. The locations of the producers are updated according to equation (11). In contrast, scroungers monitor producers more frequently. Once a producer has found abundant food, scroungers immediately leave their current position to compete for the food. If successful, they acquire the producer's finding immediately; if not, they continue to monitor the producers. The equation for updating the positions of the scroungers is shown in equation (12). Moreover, this algorithm assumes some sparrows that are aware of the danger accounting for 10% to 20% of the total population. The initial positions of these aware sparrows are randomly generated within the population, with their subsequent positional updates detailed in equation (14).

$$X = \begin{pmatrix} x_{1,1} & \cdots & x_{1,d} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,d} \end{pmatrix} \quad (9)$$

$$F_X = \begin{pmatrix} f([x_{1,1}, x_{1,2}, \dots, x_{1,d}]) \\ f([x_{2,1}, x_{2,2}, \dots, x_{2,d}]) \\ \dots \\ f([x_{n,1}, x_{n,2}, \dots, x_{n,d}]) \end{pmatrix} \quad (10)$$

Where n is the number of sparrows, and d is the dimension of the variables. And the value of each row ($f([x_{n,1}, x_{n,2}, \dots, x_{n,d}])$) in F_X represents the fitness value of the individual.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \times \exp\left(\frac{-i}{\alpha \times iter_{max}}\right), & \text{if } R_2 < ST \\ X_{i,j}^t + Q \times L, & \text{if } R_2 \geq ST \end{cases} \quad (11)$$

Where t represents the current iteration. j represents the code of dimension ($j=1, 2, \dots, d$). i represents the code of sparrows ($i=1, 2, \dots, n$). $X_{i,j}^t$ represents the position of the j th dimension of the i th sparrow at iteration t . $iter_{max}$ represents a constant with the largest number of iterations. α represents a random number between 0 and 1. R_2 represents the alarm value (range: 0–1). ST represents the safety threshold (range: 0.5–1). Q represents a random number that obeys a normal distribution. L represents a $(1 \times d)$ matrix and every element is 1. When $R_2 < ST$, it means that the producer enters the wide search mode where there are no predators around; while when $R_2 \geq ST$, it means some sparrows have discovered the predators and all sparrows need to enter safe areas.

$$X_{i,j}^{t+1} = \begin{cases} Q \times \exp\left(\frac{X_{worst}^t - X_{i,j}^t}{i^2}\right), & \text{if } i > \frac{n}{2} \\ X_p^{t+1} + |X_{i,j}^t - X_p^{t+1}| \times A^+ \times L, & \text{otherwise} \end{cases} \quad (12)$$

$$A^+ = A^T(AA^T)^{-1} \quad (13)$$

Where X_p represents the best position currently occupied by the producer. X_{worst} represents the current global worst position. A represents a $(1 \times d)$ matrix and the elements in the matrix are randomly assigned as 1 or -1. A^+ represents the matrix A after the operation rule of equation (13). In addition, the i th sparrow with a poor adaptation value may be starved.

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^t + \beta \times |X_{i,j}^t - X_{best}^t|, & \text{if } f_i > f_g \\ X_{i,j}^t + K \times \left(\frac{|X_{i,j}^t - X_{worst}^t|}{(f_i - f_w) + \epsilon}\right), & \text{if } f_i = f_g \end{cases} \quad (14)$$

Where β represents the step control parameter (a random normally distributed value with mean 0 and variance 1). K represents a random number (range: -1–1). f_g and f_w represent the global best and worst fitness values for the current state respectively. ϵ represents a very small constant to avoid the equation being meaningless if the divisor is 0. $f_i > f_g$ means that sparrow i is at the edge of the population. X_{best}^t represents the position of the population center where is safe around it. While $f_i = f_g$ means that the sparrow in the middle of the population is aware of the danger and needs to move closer to the other sparrows.

The number of sparrow populations is set to 10 and the maximum iteration is set to 20. ST is set to 70%, the proportion of producers is set to 40%, and the proportion of sparrows aware of the danger is set to 20% [79–80].

2.3.3 Squeeze-and-Excitation attention mechanism

The Squeeze-and-Excitation (SE) block is a structural unit that focuses on the channel dimension and introduces a channel attention mechanism. This mechanism enhances or suppresses the respective channels based on the task at hand and assigns the importance weights to each feature channel, thereby

leading to the extraction of valuable features while disregarding irrelevant ones. This process typically comprises three distinct steps. The detailed process is shown in Figure 3.

First, in Step 1 (Squeeze), the features are compressed in spatial dimensions while the number of feature channels remains constant. Specifically, the module produces global pooling, converting each two-dimensional feature channel into a real number (U_k) using the equation (15), where M and N represent the spatial dimensions.

$$U_k = \frac{\sum_{m=1}^M \sum_{n=1}^N u_{m,n}}{M \times N}, m, n = 1, 2, \dots \quad (15)$$

Second, in Step 2 (Excitation), this module contains two fully connected layers, a Sigmoid activation function layer, and a ReLU activation function layer. S is the output of the Sigmoid activation function. *Sigmoid* and *ReLU* represent the two activation functions respectively. The parameters W_1 and W_2 represent these two fully connected layers. This step results in a lifting and then a reduction in the dimensionality of the features, as shown in equation (16).

$$S = \text{Sigmoid} [W_2 \times \text{ReLU}(W_1 \times U)] \quad (16)$$

Finally, in Step 3 (Reweight), the input features are weighted channel-by-channel to complete the weight reassignment of the original features.

In the SE attention module, the sigmoid function is employed as the activation function, while the neurons of SE are set to 128 according to recent studies ^[99–104] (It will be set to 128 or 256 generally). Researchers proposed that a higher dimensionality would permit more refined attention but augment model complexity and computational requirements. For balancing these factors, 128 may be deemed a suitable compromise, offering sufficient granularity while keeping the computational demands within manageable limits ^[104]. Moreover, the SE module is usually appended as a fully connected layer subsequent to the convolutional layer, hence constituting a single-layer structure without hidden layers.

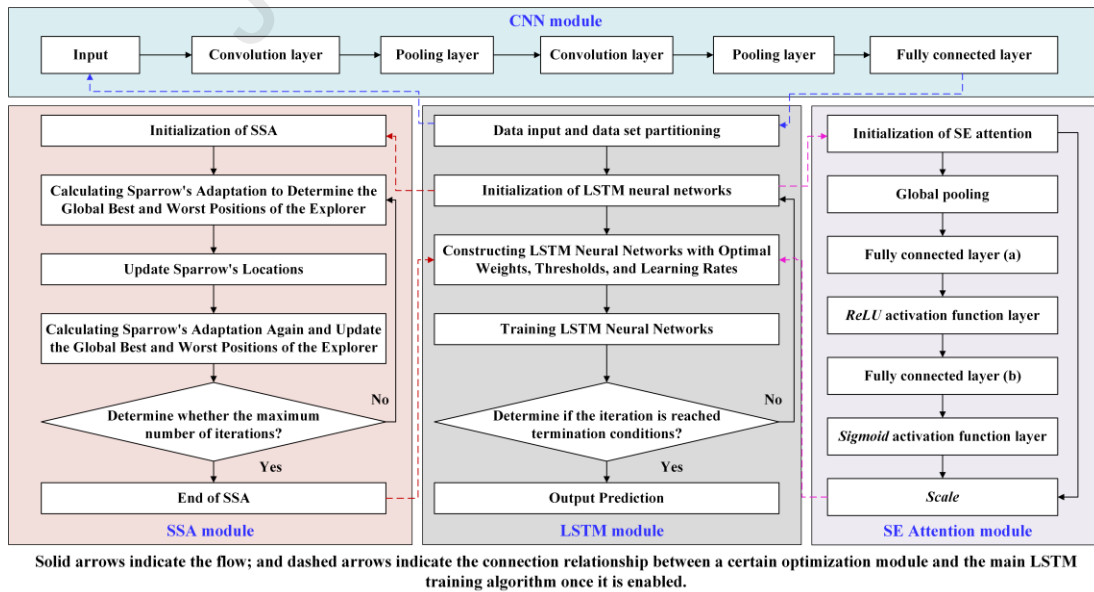


Figure 3 The process of CNN, SSA, SE attention, and LSTM modules

2.4 Evaluation Indicators

The performance of the proposed method is evaluated using five indices: the coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient-of-variation of root mean square error (CV-RMSE), computed using equations (17–21).

$$R^2 (E_a, E_b) = 1 - \frac{\sum_{c=1}^n (E_{a,c} - E_{b,c})^2}{\sum_{c=1}^n (E_{b,c} - \bar{E})^2} \quad (17)$$

$$MAE (E_a, E_b) = \frac{\sum_{c=1}^n |E_{a,c} - E_{b,c}|}{n} \quad (18)$$

$$MAPE (E_a, E_b) = \frac{\sum_{c=1}^n |E_{a,c} - E_{b,c}| \times 100\%}{E_{b,c}} \quad (19)$$

$$RMSE (E_a, E_b) = \sqrt{\frac{\sum_{c=1}^n (E_{a,c} - E_{b,c})^2}{n}} \quad (20)$$

$$CV - RMSE (E_a, E_b) = \frac{RMSE (E_a, E_b)}{\bar{E}_b} \quad (21)$$

Where E_a , and E_b is the prediction and actual energy consumption, kWh. In addition, to measure the improvement, PI is defined. PI_{RMSE} , $PI_{CV-RMSE}$, PI_{MAE} , and PI_{MAPE} is shown in equation (22), while PI_R is shown in equation (23). In the two equations, the positive values indicate performance improvement while negative values mean performance degradation.

$$PI_{RMSE, \text{ or } MAPE, \text{ or } MAE, \text{ or } CV-RMSE} = \frac{M_b - M_a}{M_a} \times 100\% \quad (22)$$

$$PI_{R^2} = \frac{M_a - M_b}{M_b} \times 100\% \quad (23)$$

Where M_b and M_a represent the evaluation index values pre-development and post-development. For example, when comparing LSTM and LSTM-SSA, M_b represents the performance of LSTM while M_a represents the performance of LSTM-SSA.

In addition, assessing the implementation time was crucial. It encompasses the whole algorithm realization duration, from initial data import to the completion of evaluation index outputs, including the whole training and validation process. The unit of measurement is second (s). In this study, the time consumption was recorded using the timing program provided by MATLAB. The program was executed on a specific computer (Lenovo, Tianyi 510 pro, CPU: i7-13700), maintaining consistent operator and other influencing factors such as hyperparameter selection.

2.5 Input system and training algorithm with optimization selection

The step-flow chart illustrating all the steps is shown in Figure 3. The naming convention is as follows.

Traditional input system: Hour of one day, period of one year, historical energy consumption (an hour ago), indoor air temperature, outdoor air temperature, and indoor CO₂ concentration (or the number of occupants).

Improved input system: Probability of occupant behaviors, and all inputs in the traditional system.

Simplified input system: Probability of occupant behaviors and outdoor air temperature. This system is taken due to the consideration of time and some environmental parameters in solving the probability of different occupant behaviors. This study attempts to discuss whether there is a possibility that parameters that have already been used in solving for certain inputs do not have to be used again as input parameters on their own. If this simplified input system is feasible, it appears that the computational efficiency of the prediction algorithm can be significantly improved due to a substantial reduction in the number of inputs; while if this simplified input system proves unfeasible, it would demonstrate that the proposed occupant behavior probabilities are not yet self-sufficient, and need to rely on the traditional inputs.

Original algorithm: LSTM.

Existing upgraded algorithms (a) and (b): LSTM-SSA, and CNN-LSTM.

Improved upgraded algorithm: CNN-LSTM-Attention.

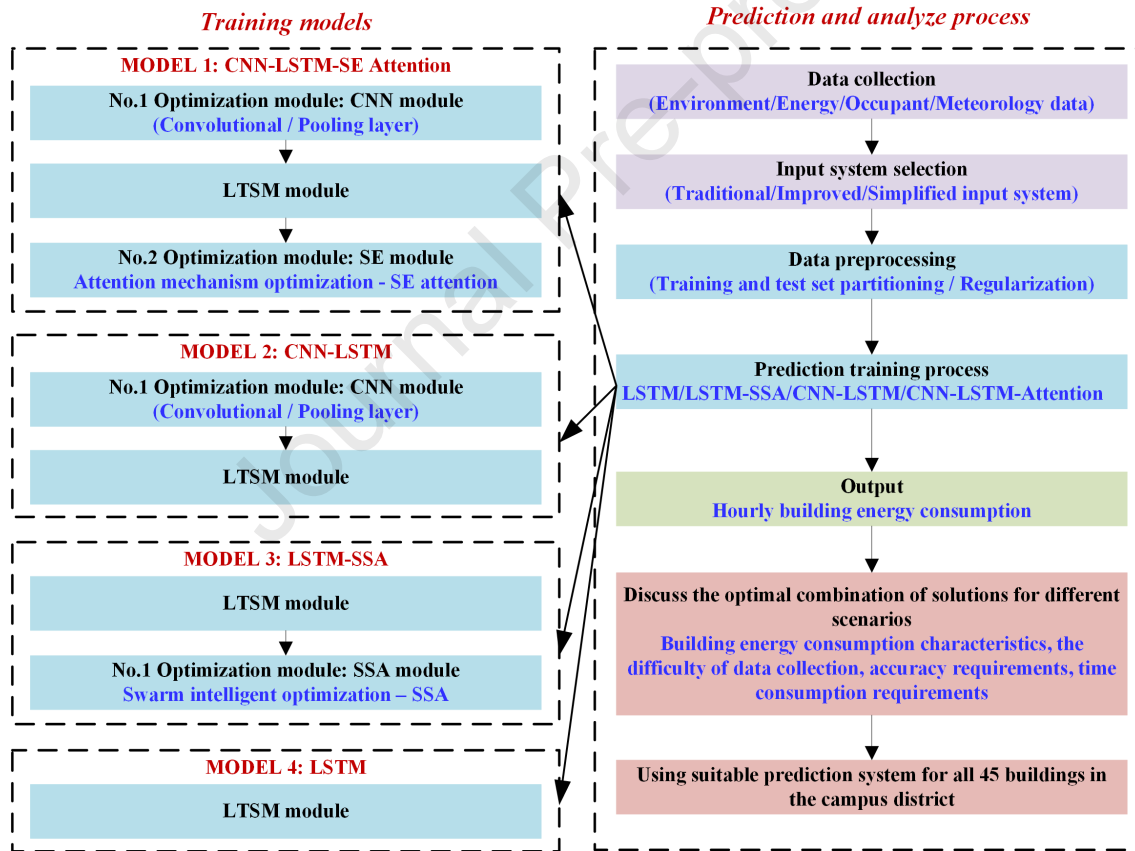


Figure 4 The step flow chart of the proposed energy consumption prediction system in seven sample buildings and all forty-five buildings in the university community

In some proposed algorithmic models, the SSA and SE attention modules will be used to optimize key hyperparameters including weights, thresholds, and learning rates. As for other hyperparameters such as the number of convolutional layers, number of LSTM layers, and activation functions, this study will select appropriate hyperparameter settings based on relevant references and practical situations, as

shown in Section 2.3.1–2.3.3. The CNN module will be used to extract complex features among multiple sensor variables collected for building energy consumption forecasting and to capture complex irregular trends. In the CNN-LSTM structure (including CNN-LSTM-Attention structure), the upper layer consists of CNN. This CNN layer can receive various variables that affect electric energy consumption such as historical energy consumption data. In addition, other features such as date, time, occupant behaviors, and occupancy can also be modeled as meta information in the CNN layer ^[105].

3 Results and discussion

3.1 Results and discussion of ROEBP in seven sample buildings

3.1.1 AC-related behavior probability models

Table 2 presents the AC-related probability models with their corresponding control strategies and modes, as proposed in Section 2.2. Simulation experiment results are presented in Appendix A. Moreover, more detailed information on AC-related behavior probability models can be referenced in previous studies ^[61, 97].

In Table 2, x_1 represents indoor air temperature, whereas f and g represent mapping relationships modeled using Logistic and Cubic functions, respectively. Moreover, the hours of one day can be divided into three categories: working hours, transition hours, and nighttime as shown in Figure 2. It is worth noting that time division does not directly affect the design of the control strategies and modes, but serves solely to enhance modeling accuracy.

operating

Table 2 Practical time for opening and closing the buildings and practical strategies for AC usage

Building (Operating time)	Time division	Strategies and modes for AC usage	Probability models
A, B (All 24 h)	09:00–22:00 in cooling season	The ACs can be activated, deactivated, and regulated at any moment by all occupants freely depending on their thermal sensation.	$P = f(x_1)$
	23:00–07:00 the following day in cooling season		
	07:00–09:00 and 22:00–23:00 in cooling season		
	09:00–22:00 in heating season		
	23:00–07:00 the following day in heating season		
	07:00–09:00 and 22:00–23:00 in heating season		$P = g(x_1)$
	All time in transition season		
C (07:00–23:00)	09:00–22:00 in cooling season	The ACs can be activated, deactivated, and regulated at any moment by all occupants freely depending on their thermal sensation.	$P = f(x_1)$
	23:00–07:00 the following day in cooling season		
	07:00–09:00 and 22:00–23:00 in cooling season		
	All time in heating and transitionseason	No use.	$P=0$
D (7:30–22:30)	08:00–22:00 in cooling season	All ACs will be kept activated by administrators.	$P = 1$
	23:00–07:00 the following day in cooling season	All ACs will be kept deactivated by administrators.	$P = 0$
	07:00–08:00 and 22:00–23:00 in cooling season	All ACs will be turned on at 7:30 and off at 22:30.	$P = 0.5$
	All time in heating and transitionseason	No use.	$P = 0$
E	08:00–22:00 in cooling season	All ACs will be kept activated by administrators.	$P = 1$

(7:30–22:30)	23:00–07:00 the following day in cooling season	All ACs will be kept deactivated by administrators.	$P = 0$
	07:00–08:00 and 22:00–23:00 in cooling season	All ACs will be turned on at 7:30 and off at 22:30.	$P = 0.5$
	08:00–22:00 in heating season	All ACs will be kept activated by administrators.	$P = 1$
	23:00–07:00 the following day in heating season	All ACs will be kept deactivated by administrators.	$P = 0$
	07:00–08:00 and 22:00–23:00 in heating season	All ACs will be turned on at 7:30 and off at 22:30.	$P = 0.5$
	All time in transition season	No use.	$P = 0$
F, G (7:30–22:30)	All time in the whole year	No use.	$P = 0$

3.1.2 Lighting-related behavior probability models

Table 3 presents the lighting-related probability models with their corresponding control strategies and modes, as also proposed in Section 2.2. Simulation experiment results are presented in Appendix A and Figure 6.

In Table 3, x_2 represents solar radiation intensity, whereas g represents a mapping relationship that is modeled using a Logistic function. It is essential to note that, in Buildings C, F, and G, lights usually remain active during operating hours, even in the absence of occupants, as indicated in Figures 5(a)–(c). A similar phenomenon has been observed in previous studies [81–85], with some studies reporting that lighting-control strategies frequently involve activating all lights when the first occupant enters and deactivating them when the last occupant leaves without considering illumination [65, 86–87]. Consequently, although this practice is wasteful and unreasonable, this study considered that $P=1$ in such cases in these buildings following the facts.



Figures 5(a)–(c) The phenomenon of lights kept on even though no occupants in different buildings (These figures are from Buildings C, F, and G)

Table 3 Practical time for opening and closing the buildings and practical strategies for lighting usage

Building (Operating time)	Time division	Strategies for lighting usage	Probability models
A, B (All 24 h)	23:00–07:00 the following day	All lights will be turned on or off freely.	$P = h(x_2)$
	18:00–23:00	All lights will be kept on by occupants.	$P=1$
	07:00–18:00	All lights will be turned on or off freely.	$P = h(x_2)$
C (7:00–23:00)	23:00–07:00 the following day	All lights will be kept off. (administrators will check the state at about 23:00)	$P = 0$
	07:00–23:00	All lights will be kept on by occupants.	$P = 1$
D, E	08:00–22:00	All lights will be kept on by administrators.	$P = 1$

F, G	(7:30–22:30)	23:00–07:00 the following day	All lights will be kept off by administrators.	$P = 0$
		07:00–08:00 and 22:00–23:00	All lights will be turned on at 7:30 and off at 22:30.	$P = 0.5$
		08:00–22:00	All lights will be kept on by occupants.	$P = 1$
	(7:30–22:30)	23:00–07:00 the following day	All lights will be kept off by administrators. (administrators will check the state at about 23:00)	$P = 0$
		07:00–08:00 and 22:00–23:00	All lights will be turned on at 7:30 and off at 22:30.	$P = 0.5$

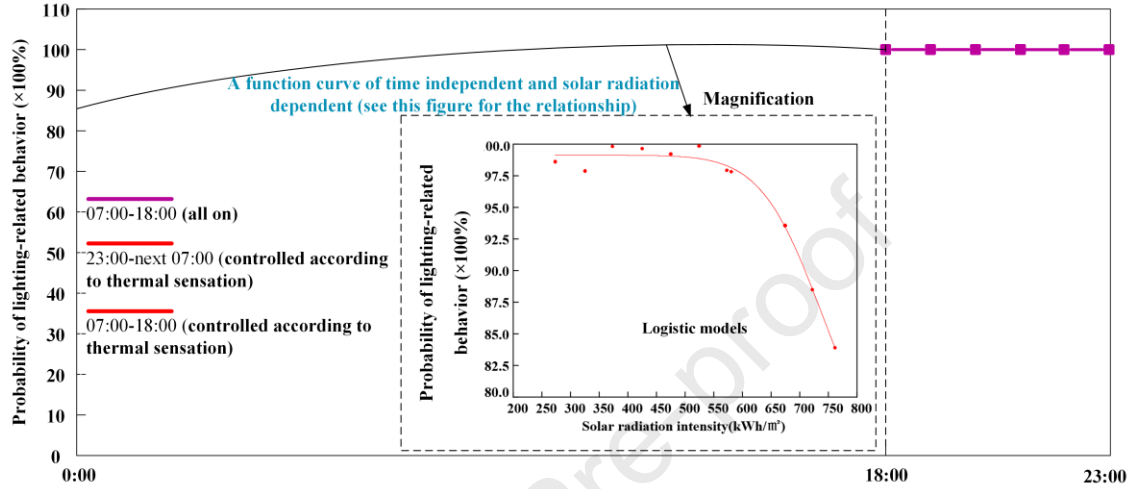


Figure 6(a) Lighting-related behavior probability models in Building A

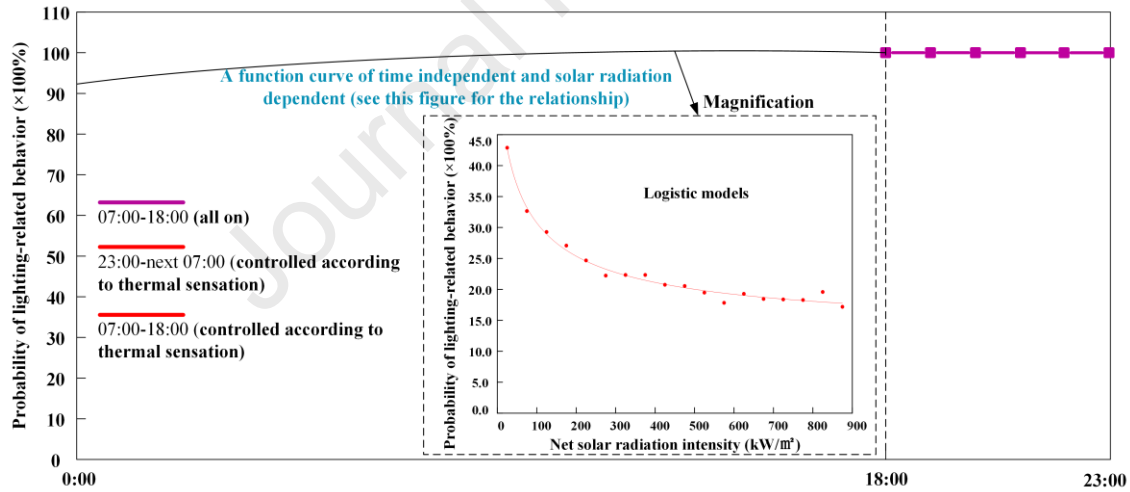


Figure 6(b) Lighting-related behavior probability models in Building B

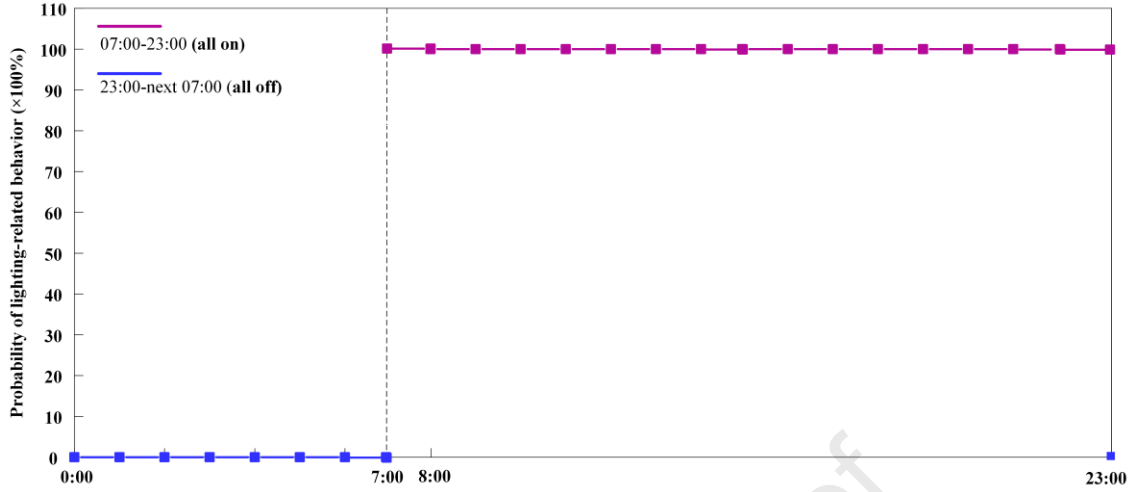


Figure 6(c) Lighting-related behavior probability models in Building C

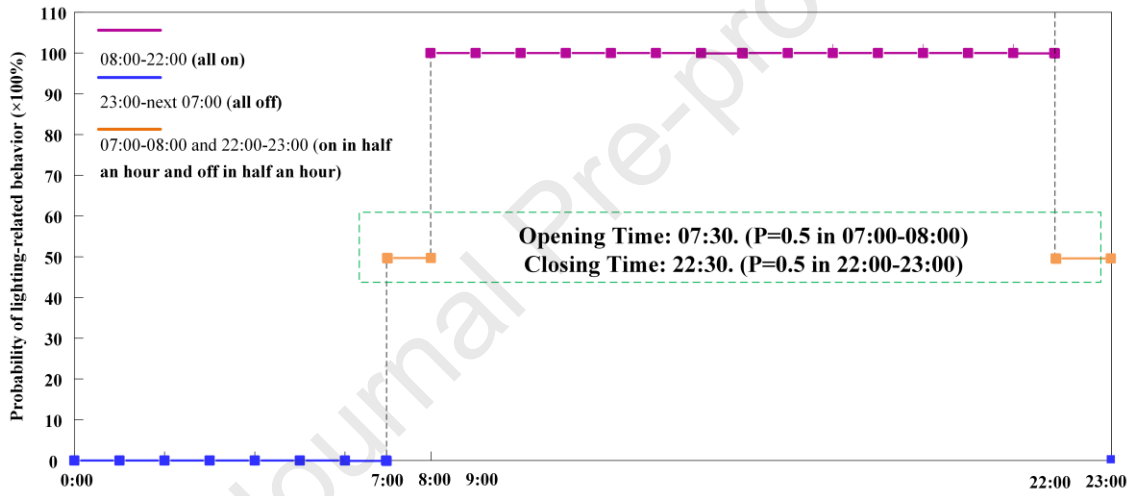


Figure 6(d) Lighting-related behavior probability models in Buildings D-G

Figure 6 Lighting-related behavior probability models in Buildings A-G

3.1.3 Socket-related behavior probability models

Table 4 present the socket-related probability models with their corresponding control strategies and modes in Section 2.2. Simulation experiment results are presented in Appendix A. Moreover, more detailed information on socket-related behavior probability models can be referenced in previous studies [96].

In Table 4, x_3 represents CO_2 concentration and a represents a constant reflecting the use at night (23:00–07:00) of a few pieces of equipment such as emergency equipment and anti-theft monitoring, whereas t represents a mapping relationship that is modeled using a Logistic function. Moreover, during winter vacation, Buildings D and E will remain closed, and as a result, the probability is 0 during this period. Buildings F and G have different socket-control strategies because of different course schedules during various terms, leading to a complex time division of periods. The time division is shown in Figure 2.

Table 4 Practical time for opening and closing the buildings and practical strategies for socket usage

Building (Operating time)	Time division	Strategies for socket usage	Probability models
A, B (All 24 h)	All time	All sockets will be controlled and used freely	$P = t(x_3)$
C (7:00–23:00)	23:00–07:00 the following day	Except for a few pieces of equipment such as emergency equipment, all other sockets will not be used	$P = a$
	07:00–23:00	All sockets will be controlled and used freely	$P = t(x_3)$
	All time in winter vacation	All sockets will not be used	$P=0$
D, E (7:30–22:30)	23:00–07:00 the following day in other periods	Except for a few pieces of equipment such as emergency equipment, all other sockets will not be used	$P = a$
	07:00–23:00 in other periods	All sockets will be controlled and used freely	$P = t(x_3)$
	07:00–23:00 in summer term	All sockets will be controlled and used freely	$P = t(x_3)$
	07:00–23:00 in spring term	All sockets will be controlled and used freely	$P = t(x_3)$
	07:00–23:00 in autumn term	All sockets will be controlled and used freely	$P = t(x_3)$
F, G (7:30–22:30)	23:00–07:00 the following day in all periods except winter vacation	Except for a few pieces of equipment such as emergency equipment, all other sockets will not be used	$P = a$
	All time in winter vacation	All sockets will not be used	$P=0$

3.2 Results and discussion of building energy consumption prediction in seven sample buildings

3.2.1 Overall analyses of different combinations of inputs and algorithms

In Section 2.5, three kinds of input systems and four algorithms will be tested in these seven sample buildings. All prediction results with different inputs and algorithms can be found in Table C-2 of Appendix B. The schematic of the results is shown in Figure 7, where MAPE, $1/R^2$, time, and CV-RMSE are normalized using the Max-Min normalization method^[90–91] for comprehensive comparison in different scenarios. These values tend towards 0 to indicate better performance and towards 1 to denote poorer performance.

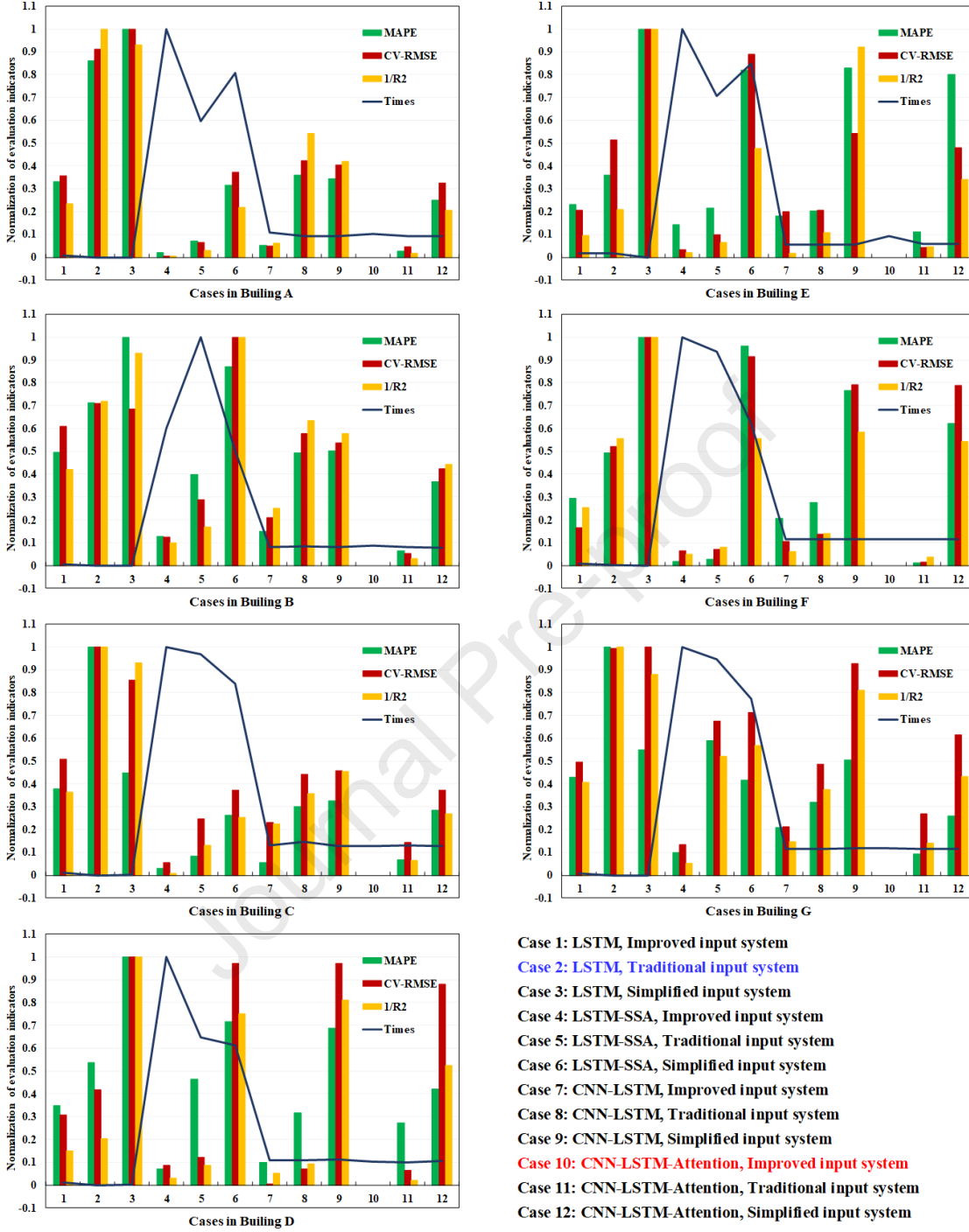


Figure 7 Normalization of evaluation indicators in Buildings A–G

According to Figure 7 and the prediction results in Table C-2 in Appendix B, SSA, CNN, and Attention modules have all significantly improved the prediction performance of LSTM. Notably, the proposed innovative prediction system (Case 10) reduced MAPE by 2.49%–72.62% (average: 36.32%) and CV-RMSE by 0.38%–63.63% (average: 31.20%) while increasing R^2 by 0.20%–73.20% (average: 13.56%). Meanwhile, the time consumption only rose by 25.722s–167.014s (average: 118.354s)

compared to the least time-consuming method. Therefore, it can be argued that the proposed prediction method brings maximum performance improvement while consuming very little extra time, and the additional time consumption is small compared to this prediction time scale (1 hour, 3600s). The performance improvement range of the proposed innovative prediction system (Case 10) compared to other prediction methods (Cases 1–9 and 11–12) is shown in Figure 8.

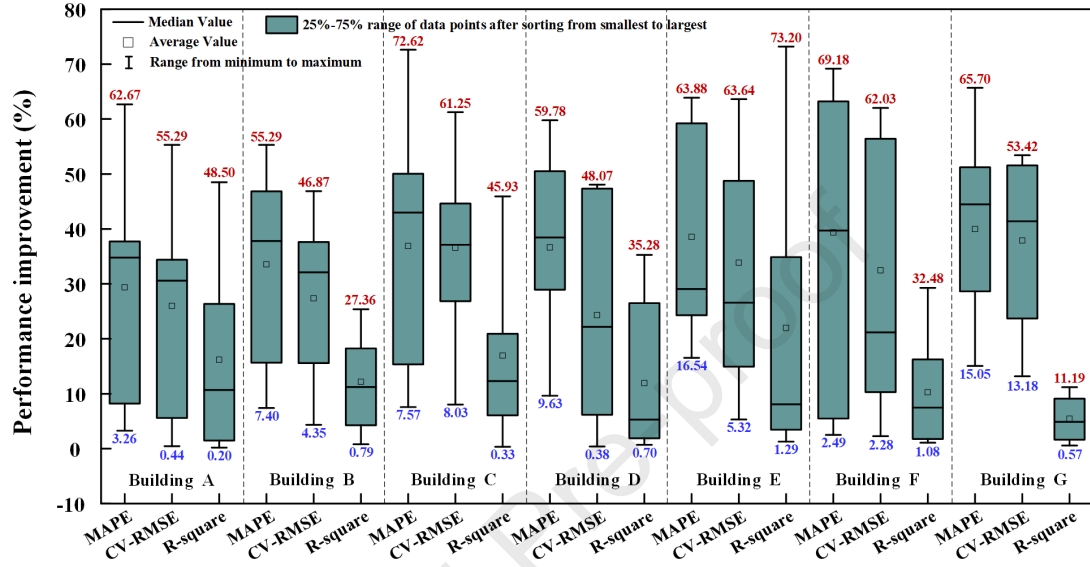


Figure 8 Performance improvement from the innovative prediction system (Case 10) compared to other prediction methods (Cases 1–9 and 11–12)

To summarize, the proposed improved method shows substantial accuracy improvements while consuming less extra time compared to the most traditional methods (LSTM and traditional inputs), and it shows accuracy improvements in each case while consuming less time compared to the other methods with optimization (using LSTM-SSA or CNN-LSTM).

3.2.2 Performance improvement from improving input system or algorithms

To discuss the performance improvement resulting from solely improving the input system and solely improving the algorithm, this study keeps inputs the same when discussing improvements from improving algorithms, and vice versa.

(1) Improving the input system without improving algorithms can enhance prediction performance comprehensively, with all metrics showing improvement in all conditions (i.e., different algorithms and buildings), as shown in Figure 9. However, the improvement efficacy varied for different algorithms and buildings. The observed ranges encompass a 1.59%–45.17% (average: 19.54%) reduction in MAPE, a 0.39%–42.17% (average: 17.97%) reduction in MAE, a 1.80%–37.25% (average: 15.59%) reduction in RMSE, a 0.68%–35.06% (average: 14.98%) reduction in CV-RMSE, and a 0.70%–33.33% (average: 6.11%) increase in R^2 . The average increase in additional time consumption was 71.662s.

(2) Improving the algorithms without improving the input system (that is using CNN-LSTM-

Attention) can also enhance prediction performance comprehensively, with all metrics showing improvement in all conditions, as shown in Figure 10. It reduced 33.36% in MAPE, 30.41% in MAE, 27.34% in RMSE, 27.58% in CV-RMSE, and 14.62% increase in R^2 on average, while the additional time consumption required was relatively low with an average increase of 98.17s, compared to LSTM. Moreover, once compared to LSTM-SSA, LSTM, and CNN-LSTM simultaneously, CNN-LSTM-Attention reduced 24.04% MAPE, 18.92% CV-RMSE, and increased 9.10% R^2 on average.

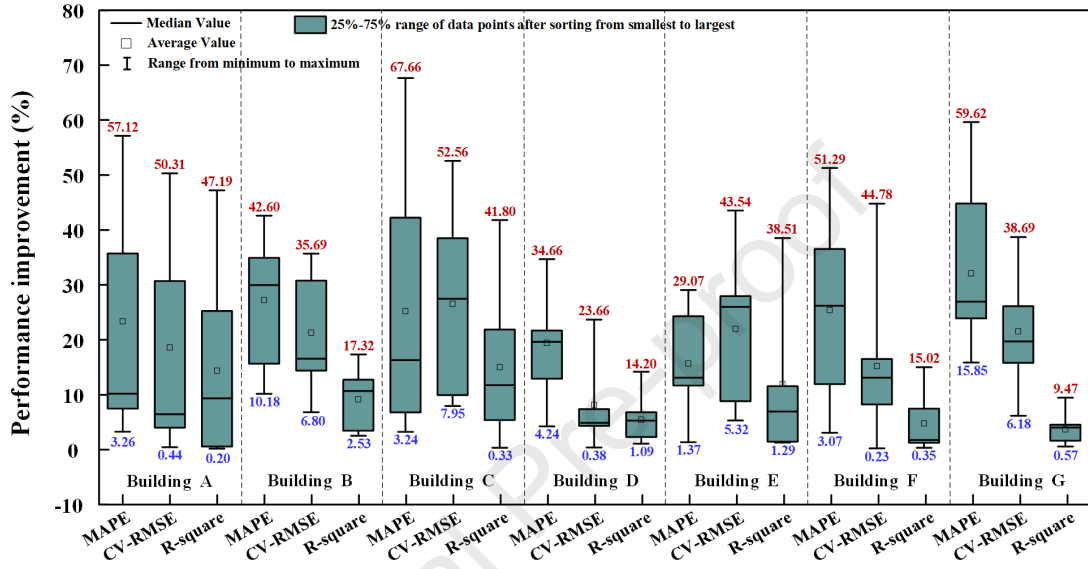


Figure 9 Performance improvement from improving inputs without improving algorithms

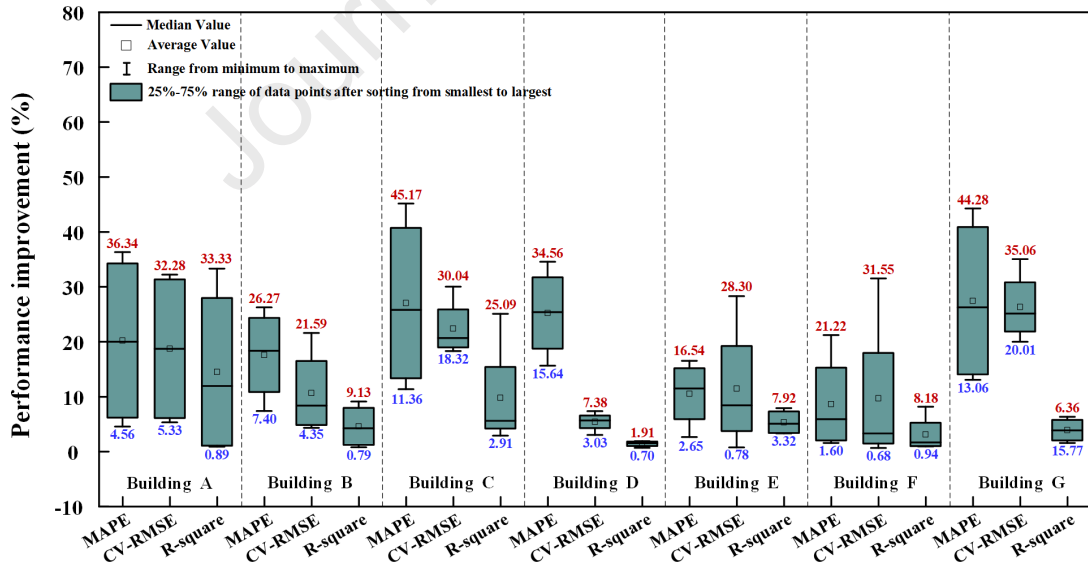


Figure 10 Performance improvement from improving algorithms without improving inputs

(3) In all cases, improving both the input and the algorithm simultaneously always resulted in a more significant performance improvement than using only one improvement. For buildings with more complex energy behavior and fluctuating energy consumption (Buildings A, B, C, and G), either

improving the inputs or the algorithm alone proves to be highly effective, although simultaneous improvement proves to be better. In contrast, buildings with simple energy-use behavior and weak energy consumption fluctuations (Buildings D, E, and F) necessitate and benefit from improving both inputs and algorithms. Moreover, if only one improvement is allowed, using CNN-LSTM-Attention for algorithm improvement demonstrates slightly greater efficacy than improving inputs alone.

3.2.3 Energy consumption prediction system selection priority

This study ranked MAPE, MAE, RMSE, CV-RMSE, and R^2 for different cases (The smaller the ranking the better the performance), and the results are shown in Appendix C. For a comprehensive comparison, the average ranks of prediction performance are presented in Table 6, derived from the equally weighted rankings of MAPE, MAE, RMSE, CV-RMSE, and R^2 . According to some existing review studies, these five parameters, commonly used in energy consumption prediction studies, address different aspects such as average accuracy, fitting effect, and degree of dispersion. Therefore, the above five parameters will be considered simultaneously and be given equal weight in this step.

Table 6 The average ranks (Rank 1–12) of prediction performance in different buildings

Algorithm	Input system	Building A	Building B	Building C	Building D	Building E	Building F	Building G
LSTM	Improved	8	7	10	7	6	7	7
LSTM	Traditional	11	10	12	8	8	8	12
LSTM	Simplified	12	11	11	12	12	12	11
LSTM-SSA	Improved	2	3	2	4	2	3	2
LSTM-SSA	Traditional	5	5	5	6	5	5	9
LSTM-SSA	Simplified	7	12	6	10	11	11	8
CNN-LSTM	Improved	4	4	4	2	3	4	4
CNN-LSTM	Traditional	10	9	8	5	6	6	5
CNN-LSTM	Simplified	9	8	9	11	10	10	10
CNN-LSTM-Attention	Improved	1	1	1	1	1	1	1
CNN-LSTM-Attention	Traditional	3	2	3	3	4	2	3
CNN-LSTM-Attention	Simplified	6	6	7	9	9	9	6

Drawing upon the conclusions from Sections 3.2.1–3.2.2, and considering prediction performance, time requirements, data collection challenges, and building types, this study attempts to propose several selection guidelines for appropriate input systems and training algorithms.

(1) When building energy consumption and behavior exhibit complex and drastic fluctuations, the improved input system is recommended.

(2) When monitoring energy-use behavior is difficult or other challenges to calculating the ROEBP models exist, the traditional input system is recommended.

(3) When using the simplified input system, an optimization algorithm becomes essential to mitigate unacceptably high errors.

(4) CNN-LSTM-Attention is better in most cases as it significantly balances prediction accuracy

and time consumption.

(5) LSTM-SSA can significantly enhance performance, particularly in buildings with complex and drastic energy consumption and behavior fluctuations, despite requiring more time consumption than other algorithms.

(6) CNN-LSTM is relatively weaker in terms of performance improvement but requires less time than LSTM-SSA and is less contingent on building features.

To summarize these guidelines, this study presents a selection tree diagram in Figure 11. Green text indicates the recommended input system based on building energy characteristics and data collection conditions, while black text indicates the appropriate algorithm based on prediction performance and time consumption requirements. And the recommended input system and algorithm under given conditions are shown in red and blue text, respectively. Connections by 'and' indicate that all conditions must be satisfied, whereas those by 'or' indicate that any of the conditions may be satisfied. The greater than symbol ('>') indicates the priority level.

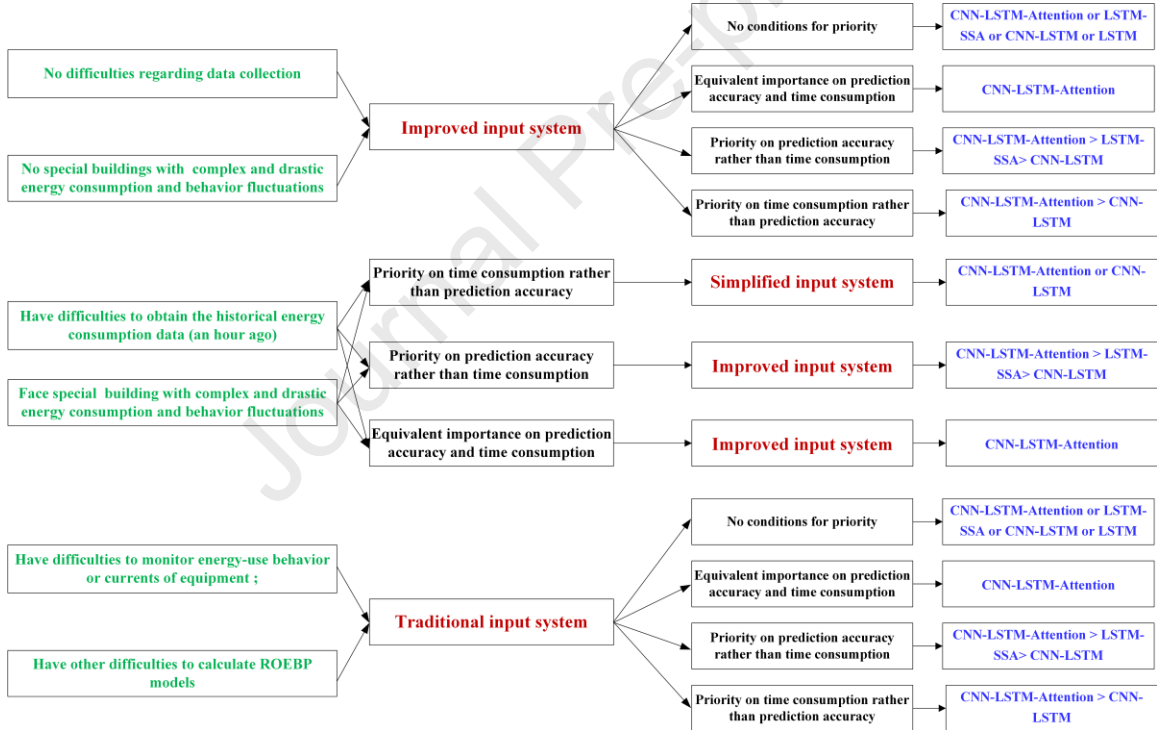


Figure 11 The selection tree diagram of various combinations of input systems and algorithms

3.3 Prediction performance comparison of the CNN-LSTM-Attention with other advanced machine learning algorithms

According to the references cited in the Introduction, some other advanced machine learning algorithms have been employed in building energy consumption prediction [31–39]. Referring to the utilization rate [39], this section will examine SVM, RF, and XGBoost as benchmarking models for validating the performance of the proposed CNN-LSTM-Attention. In RF, the number of decision trees

is set to 100, the maximum depth is set to 30 (to control the growth of the tree to prevent overfitting), and the minimum number of leaf node samples is set to 5^[106–107]. In XGBoost, XGBoost uses a classification and regression tree (CART) model as the base classifier, with the maximum number of iterations being set to 100, a learning rate of 0.1, a subsample of 0.8, and a maximum depth of 5^[108]. In SVM, the penalty factor c is set to 1.0 and the kernel function is chosen as a radial basis function^[109].

The results are shown in Table C-3 in Appendix B. The schematic of the results is shown in Figure 12 where MAPE, $1/R^2$, time, and CV-RMSE are also normalized by the Max-Min normalization method^[90–91] for comparison in different scenarios.

Key conclusions drawn are as follows:

(1) The CNN-LSTM-Attention algorithm still shows the highest performance.

(2) Some advanced machine learning algorithms (SVM, RF, and XGBoost) have inconsistent performance and are all weaker than CNN-LSTM-Attention. For example, RF performs sub-optimally in Building C but relatively well in Building G. It is hypothesized that the reason for this is that these algorithms are highly influenced by the input features and energy consumption, particularly in RF.

(3) In a small number of cases, it has been observed that using improved inputs may instead degrade prediction performance compared to using traditional inputs. These cases occur in SVM, RF, and XGBoost. The reason for this may be that the LSTM can read the temporal information better, and the CNN can extract feature information directly from the input. Therefore, LSTM and CNN may be more suitable for the improved input system (adding timing-dependent probability parameters to the traditional input system), while SVM, RF, and XGBoost may be not suitable.

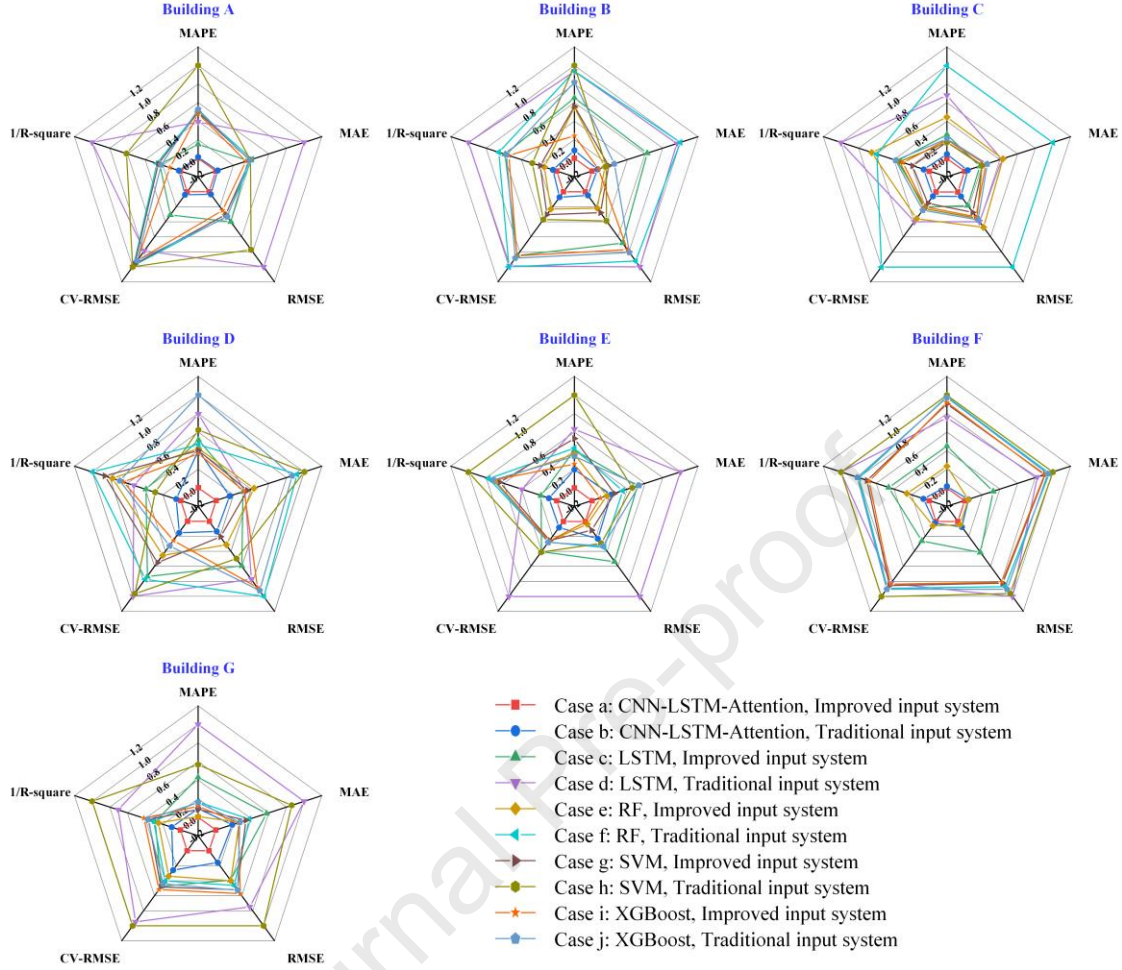


Figure 12 Comparison of prediction results using CNN-LSTM-SE, SVM, RF, and XGBoost in seven sample buildings

3.4 Results and discussion of building energy consumption prediction in all forty-five buildings

According to Figure 13, this study selected the suitable system for forecasting the building energy consumption in all forty-five buildings within the university community. The primary criterion for algorithm selection prioritizes prediction accuracy, but excessive time consumption needs to be avoided. Meanwhile, the selection of the input system prioritizes the use of the improved input system as long as sufficient data is available.

The results are shown in Table C-4 in Appendix B, and the visualization is shown in Figure 13. The MAPE range is 0.88%–21.98% (average: 12.35%); the CV-RMSE range is 0.0132–0.2782 (average: 0.1707); and the R^2 range is 0.8092–0.9748 (average: 0.8941). Since the absence of a recognized standard for data-driven building energy consumption prediction accuracy and considering the diverse prediction difficulties and accuracy requirements across different building types, this study adopts the relevant requirements for building energy consumption simulation accuracy as a reference standard. Notably, these standards propose a MAPE of less than 20% for monthly energy consumption prediction and a MAPE of less than 10% for annual energy consumption prediction ^[82]. In contrast, the method

proposed method in this study allows the vast majority of buildings to achieve a predicted MAPE of less than 20% for hourly energy consumption, with an average MAPE of 12.35%. These results show the superiority and practicality of the proposed energy consumption prediction model.

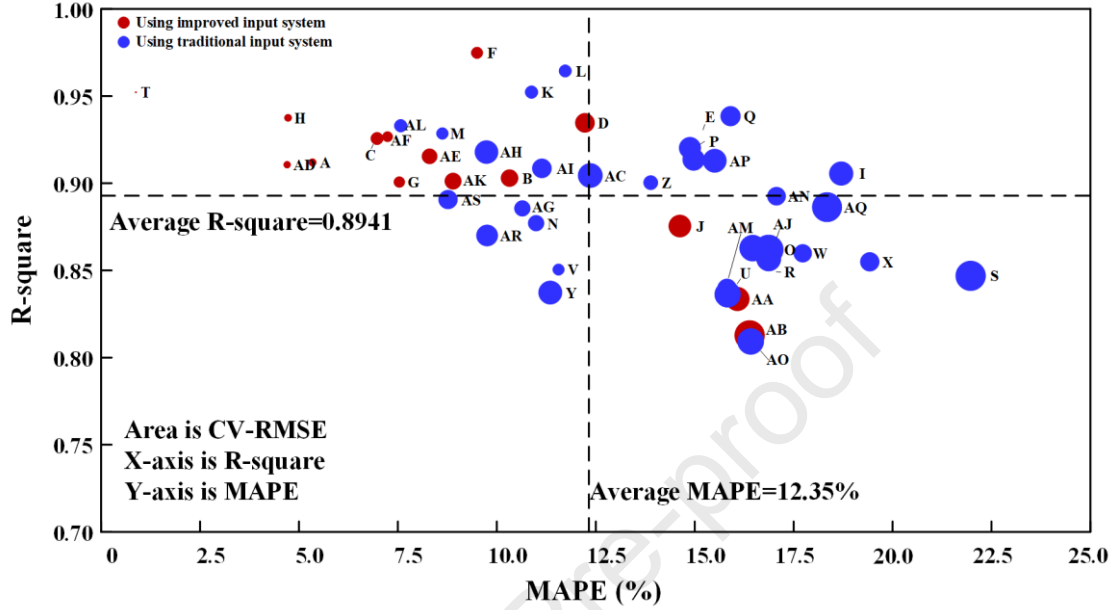


Figure 13 Prediction results in all forty-five buildings in the university community (The building codes are shown in Appendix B-1)

4 Limits

In the context of ROEBP modeling, AC and lighting-related behavior models have garnered consensus, while the modeling of socket-related behavior especially random socket-related behaviors still requires further development. This gap can be attributed to the fact that indoor air temperature and illumination are the primary drivers of AC and lighting-related behaviors respectively, whereas indoor CO₂ concentration only indirectly reflects the probability of socket-related behaviors through its correlation with the number of occupants. Moreover, this indirect relationship also depends on the stability of the occupants, which may be compromised in the face of frequent changes in occupant behavior patterns or occupant population. Furthermore, certain sockets are interconnected with lighting and split ACs, particularly in single-person offices or residences. Thus, it is crucial to address the pressing need for the continued development of socket-related behavior models to enhance the applicability of the ROCBP model. Recent studies suggest that combining stochastic Markov models with CO₂-based statistical models may further refine the probabilistic model of socket-related behaviors.

5 Conclusion

This study proposes an enhanced building energy consumption prediction system integrating novel occupant behavior models and using many optimization modules including SSA, CNN, and SE attention.

(1) As for the overall prediction system: the enhanced prediction system with the improved input system and CNN-LSTM-Attention achieves the best balance between time consumption and prediction

performance. In the seven sample buildings, it reduced MAPE by 2.49%–72.62% (average: 36.32%) and CV-RMSE by 0.38%–63.63% (average: 31.20%) with increasing R^2 by 0.20%–73.20% (average: 13.56%). Meanwhile, it only increased time consumption by 25.722s–167.014s (average: 118.354s) compared to the least time-consuming method. Extending the proposed methodology to all forty-five buildings, the MAPE range is 0.88%–21.98% (average: 12.35%), and the CV-RMSE range is 0.0132–0.2782 (average: 0.1707), highlighting the superiority and practicality of the proposed energy consumption prediction method compared to some existing methods.

(2) For the improved input system: this study introduces a novel occupant energy-use behavior probability into the input system for better reflecting real-time energy-human-environment interactions and subsequently enhancing the prediction performance. Using the improved input system reduced MAPE by 19.54%, CV-RMSE by 14.98%, and increased R^2 by 6.11% on average compared to the traditional input system using the same training algorithms in the same buildings. Moreover, the improvements exerted more substantial effects, especially when using more simplified algorithms or in buildings with complex energy consumption and behavior fluctuations.

(3) For the proposed algorithms: this study employs the CNN process and SE attention mechanisms to optimize the data processing and hyperparameter selection. Using CNN-LSTM-Attention reduced MAPE by 24.04%, CV-RMSE by 18.92%, and increased R^2 by 9.10% on average compared to LSTM-SSA, LSTM, and CNN-LSTM simultaneously when using the same input systems in the same buildings. Moreover, some advanced machine learning algorithms (SVM, RF, and XGBoost) have been also verified and the performance of these algorithms is weaker than CNN-LSTM-Attention. Notably, while CNN-LSTM demonstrated marginally inferior performance improvements compared to LSTM-SSA, it needed less time consumption. Furthermore, these algorithms exhibit more pronounced enhancements for the traditional input system, followed by the improved input system, and have the lowest improvement for the simplified input system.

(4) For the prediction system selection priority: the selection of a suitable input system should align with the building energy characteristics and challenges related to data collection. For input selection, when in buildings with complex and fluctuating energy consumption and behavior, the improved input system is recommended. On the other hand, if it is difficult to calculate the ROEBP models, the traditional input system is advisable. For algorithms, considering the balance between time consumption and prediction precision, CNN-LSTM-Attention is the recommended choice.

Author Statement

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Acknowledgment

The work described in this paper was supported by the National Natural Science Foundation of China (Grant No. 52078096), the Fundamental Research Funds for the Central Universities (Grant No. DUT20JC47), 2023 Dalian University of Technology-Cardiff University Cooperation and Exchange Foundation Project, 2023 International Exchange Foundation Project of "Co-Creation of Excellence Program" from Dalian University of Technology (Grant: DUTIO-ZG-202307), and the Key Project of DUT for International Students Studying and Researching in China: Innovation and Practice of Talent Cultivation Model in the Field of Smart Buildings for the "Belt and Road" Initiative (Grant No. 1103-82120001).

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Appendix A The equations of ROEBP models

Building A

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = \begin{cases} 9.54 + \frac{7.84}{1 + \left(\frac{x}{25.24}\right)^{65.61}}, & 9:00 - 22:00 \text{ in heating season} \\ 9.31 + \frac{8.11}{1 + \left(\frac{x}{24.50}\right)^{115.81}}, & 23:00 - 07:00 \text{ in heating season} \\ 9.21 + \frac{8.34}{1 + \left(\frac{x}{24.89}\right)^{87.81}}, & 7:00 - 9:00 \text{ and } 22:00 - 23:00 \text{ in heating season} \\ -1111.97 + 137.44x - 5.51x^2 + 0.07x^3, & \text{in transition season} \\ 298155.16 + \frac{-298133.66}{1 + \left(\frac{x}{48.66}\right)^{27.87}}, & 9:00 - 22:00 \text{ in cooling season} \\ 2028.53 + \frac{-2023.01}{1 + \left(\frac{x}{60.69}\right)^{9.47}}, & 23:00 - 07:00 \text{ in cooling season} \\ 42188.97 + \frac{-42180.30}{1 + \left(\frac{x}{60.69}\right)^{13.59}}, & 7:00 - 9:00 \text{ and } 22:00 - 23:00 \text{ in cooling season} \end{cases}$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, & 23:00 - \text{next } 7:00 \\ 100, & 18:00 - 23:00 \\ 141.58 + \frac{53.74}{1 + \left(\frac{x}{747.52}\right)^{12.91}}, & 07:00 - 18:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = 62.368 + \frac{-22.909}{1 + \left(\frac{x}{417.46156}\right)^{43.95645}}$$

Building B

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = \begin{cases} -1047.80 + \frac{1186.01}{1 + \left(\frac{x}{269.98}\right)^{0.83}}, & 9:00 - 21:00 \text{ in heating season} \\ -11787.09 + \frac{11836.07}{1 + \left(\frac{x}{1492.77}\right)^{1.30}}, & 7:00 - 9:00 \text{ and } 21:00 - 23:00 \text{ in heating season} \\ 2.52 + \frac{6.02}{1 + \left(\frac{x}{17.49}\right)^{17.49}}, & 23:00 - 07:00 \text{ in heating season} \\ 296.16 - 26.53x + 0.60x^2, & \text{in transition season} \\ 4515.70 + \frac{-4529.05}{1 + \left(\frac{x}{122.29}\right)^{3.28}}, & 9:00 - 21:00 \text{ in cooling season} \\ 9637.17 + \frac{-9635.35}{1 + \left(\frac{x}{70.06}\right)^{7.32}}, & 7:00 - 9:00 \text{ and } 21:00 - 23:00 \text{ in cooling season} \\ 2148.46 + \frac{-2146.70}{1 + \left(\frac{x}{62.41}\right)^{9.29}}, & 23:00 - 07:00 \text{ in cooling season} \end{cases}$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 21:00 - \text{next } 7:00 \\ 100, 18:00 - 21:00 \\ 12.63 + \frac{47.30}{1 + \left(\frac{x}{53.02}\right)^{0.75}}, 07:00 - 18:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = 46.58 + \frac{-30.48}{1 + \left(\frac{x}{420.16}\right)^{11.23}}$$

Building C

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = \begin{cases} 64.99 + \frac{-102.38}{1 + \left(\frac{x}{21.46}\right)^{11.96}}, 7:00 - 9:00 \text{ and } 21:00 - 23:00 \text{ in cooling season} \\ 74.05 + \frac{-6510.29}{1 + \left(\frac{x}{13.58}\right)^{13.02}}, 9:00 - 21:00 \text{ in cooling season} \\ 0, 23:00 - \text{next } 7:00 \text{ in cooling season and all hours in heating season} \end{cases}$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 7:00 - 23:00 \\ 100, 23:00 - \text{next } 7:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = 68.09 + \frac{-20.90}{1 + \left(\frac{x}{415.63}\right)^{10.34}}$$

Building D

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 8:00 \text{ in cooling season, and all hours in heating season} \\ 100, 9:00 - 22:00 \text{ in cooling season} \\ 50, 8:00 - 9:00, \text{ and } 22:00 - 23:00 \text{ in cooling season} \end{cases}$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 8:00 \\ 100, 9:00 - 22:00 \\ 50, 8:00 - 9:00, \text{ and } 22:00 - 23:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, \text{ All hours in winter vacation} \\ 20, 23:00 - \text{next } 7:00 \text{ in other days} \\ 92.11 + \frac{-45.22}{1 + \left(\frac{x}{464.83}\right)^{19.49}}, 7:00 - 23:00 \text{ in other days} \end{cases}$$

Building E

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 8:00 \text{ in cooling season, and all hours in heating season} \\ 100, 9:00 - 22:00 \text{ in cooling season} \\ 50, 8:00 - 9:00, \text{ and } 22:00 - 23:00 \text{ in cooling season} \end{cases}$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 8:00 \\ 100, 9:00 - 22:00 \\ 50, 8:00-9:00, \text{ and } 22:00-23:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, \text{ All hours in winter vacation} \\ 20, 23:00 - \text{next } 7:00 \text{ in other days} \\ 92.11 + \frac{-45.22}{1 + \left(\frac{x}{464.83}\right)^{19.49}}, 7:00-23:00 \text{ in other days} \end{cases}$$

Building F

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = 0$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 7:00 \\ 100, 8:00 - 22:00 \\ 50, 7:00-8:00, \text{ and } 22:00-23:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, \text{ All hours in winter vacation} \\ 5, 23:00 - \text{next } 7:00 \text{ in the whole year except winter vacation} \\ 46.17 + \frac{-9.65}{1 + \left(\frac{x}{462.97}\right)^{7.00}}, 7:00-23:00 \text{ in summer vacation} \\ 24729.73 + \frac{-24680.76}{1 + \left(\frac{x}{261036.17}\right)^{1.39}}, 7:00-23:00 \text{ in spring term} \\ 44.07 + \frac{-4.06}{1 + \left(\frac{x}{1111.29}\right)^{12.30}}, 7:00-23:00 \text{ in autumn term} \end{cases}$$

Building G

(1) AC-related behavior model (x is indoor air temperature):

$$P_{(T_1-T_2)}\% = 0$$

(2) Lighting-related behavior model (x is solar radiation intensity):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, 23:00 - 7:00 \\ 100, 8:00 - 22:00 \\ 50, 7:00-8:00, \text{ and } 22:00-23:00 \end{cases}$$

(3) Socket-related behavior model (x is CO₂ concentration):

$$P_{(T_1-T_2)}\% = \begin{cases} 0, \text{ All hours in winter vacation} \\ 12, 23:00 - \text{next } 7:00 \text{ in the whole year except winter vacation} \\ 48.89 + \frac{-17.90}{1 + \left(\frac{x}{450.10}\right)^{28.50}}, 7:00-23:00 \text{ in summer vacation} \\ 77.92 + \frac{-34.25}{1 + \left(\frac{x}{42.25}\right)^{1.98}}, 7:00-23:00 \text{ in spring term} \\ 79.58 + \frac{-40.14}{1 + \left(\frac{x}{498.05}\right)^{4.50}}, 7:00-23:00 \text{ in autumn term} \end{cases}$$

Appendix B Results and other information on all buildings

Table B-1(a) Information on all forty-five buildings in the campus district

No.	Code	Type	Name
1	A	Research laboratories and offices	Faculty of Environment and Biology-No.2 Building
2	B	office	Faculty of Economics and Management
3	C	Research laboratories and offices	Faculty of Electronic Information and Electrical Engineering
4	D	Library	Bochuan Library
5	E	Library	Lingxi Library
6	F	Education building	No.1 Teaching Building
7	G	Education building	No. 2 Comprehensive Teaching Building
8	H	Research laboratories and offices	Faculty of Marine Engineering
9	I	Laboratory	Shipbuilding Laboratory
10	J	Hotel	Science and Technology Park Building
11	K	Education building	Graduate Student Teaching Building
12	L	Education building	No. 1 Comprehensive Teaching Building
13	M	Dormitory	No.1 Dormitory
14	N	Dormitory	No.2 Dormitory
15	O	Dormitory	No.3 Dormitory
16	P	Dormitory	No.4 Dormitory
17	Q	Dormitory	No.5 Dormitory
18	R	Dormitory	No.6 Dormitory
19	S	Dormitory	No.7 Dormitory
20	T	Data center building	Network and Informatization Center
21	U	Research laboratories and offices	Department of Polymer Materials
22	V	Research laboratories and offices	Department of Catalytic Chemistry and Engineering
23	W	Research laboratories and offices	Department of Chemical Processing
24	X	Research laboratories and offices	Department of Chemical Engineering
25	Y	Research laboratories and offices	Department of Fine Chemicals
26	Z	Research laboratories and offices	Chemical Analysis and Testing Center
27	AA	Research laboratories and offices	Department of Pharmacy
28	AB	Research laboratories and offices	Department of Chemical Machinery and Safety
29	AC	Research laboratories and offices	Faculty of Environment and Biology-No.1 Building
30	AD	Research laboratories and offices	Faculty of Energy and Power
31	AE	Research laboratories and offices	Faculty of Construction Engineering-No.1 Building
32	AF	Research laboratories and offices	Faculty of Construction Engineering-No.2 Building
33	AG	Research laboratories and offices	Faculty of Delivery Engineering and Mechanics
34	AH	office	Faculty of Architecture and Art
35	AI	office	Faculty of Philosophy
36	AJ	office	Faculty of Humanities and Foreign Languages
37	AK	office	Campus History Exhibition Center
38	AL	office	University Administration office Building
39	AM	Laboratory	Laboratory of High Velocity Water Flow
40	AN	Laboratory	Laboratory of Ocean Dynamics
41	AO	Laboratory	Laboratory of Aerospace
42	AP	Laboratory	Laboratory of Internal Combustion Engine
43	AQ	Laboratory	Laboratory of Automotive
44	AR	Laboratory	Laboratory of Materials Modification By Laser, Ion and Electron-No.1 Building
45	AS	Laboratory	Laboratory of Materials Modification By Laser, Ion and Electron-No.2 Building

Table B-1(b) Information of all forty-five buildings in the campus district

No.	Code	Area (m ²)	Number of floors above ground	Number of floors below ground	Year of construction	Energy items
1	A	32291	7	1	2015	Sockets, lighting, ACs
2	B	35998	6	1	2015	Sockets, lighting, ACs
3	C	36500	19	2	2005	Sockets, lighting, ACs
4	D	20415	5	0	1999	Sockets, lighting, ACs
5	E	29933	6	0	2010	Sockets, lighting, ACs
6	F	9084	4	0	1952	Sockets, lighting
7	G	17540	7	0	2009	Sockets, lighting
8	H	4689	4	0	1980	Sockets, lighting, ACs
9	I	389.5	1	0	2013	Sockets, lighting, ACs

10	J	5818	19	0	2013	Sockets, lighting, ACs
11	K	11676	9	0	2005	Sockets, lighting, ACs
12	L	27700	7	0	2002	Sockets, lighting
13	M	8600	9	0	2011	Sockets, lighting
14	N	7238	9	0	2011	Sockets, lighting
15	O	12636	12	0	2011	Sockets, lighting
16	P	11574	12	0	2011	Sockets, lighting
17	Q	12843	12	0	2011	Sockets, lighting
18	R	11870	14	0	2014	Sockets, lighting
19	S	7630	9	0	2014	Sockets, lighting
20	T	2277	1	0	2013	Sockets, lighting, ACs
21	U	4990	5	0	2010	Sockets, lighting, ACs
22	V	5624	5	0	2010	Sockets, lighting, ACs
23	W	4355	5	0	2010	Sockets, lighting, ACs
24	X	4566	5	0	2010	Sockets, lighting, ACs
25	Y	8777	5	0	2010	Sockets, lighting, ACs
26	Z	5288	5	0	2010	Sockets, lighting, ACs
27	AA	3757	5	0	2010	Sockets, lighting, ACs
28	AB	4022	5	0	2010	Sockets, lighting, ACs
29	AC	10106	6	0	2013	Sockets, lighting, ACs
30	AD	25000	10	0	2012	Sockets, lighting, ACs
31	AE	11000	7	0	2005	Sockets, lighting, ACs
32	AF	9533	5	1	2009	Sockets, lighting, ACs
33	AG	11795	7	0	2002	Sockets, lighting, ACs
34	AH	8862	5	0	2013	Sockets, lighting, ACs
35	AI	5188	5	0	2020	Sockets, lighting, ACs
36	AJ	5822	6	0	2013	Sockets, lighting, ACs
37	AK	2280	4	0	2020	Sockets, lighting, ACs
38	AL	16844	7	0	1963	Sockets, lighting, ACs
39	AM	749	1	0	1955	Sockets, lighting, ACs
40	AN	547	1	0	2013	Sockets, lighting, ACs
41	AO	3660	3	0	2013	Sockets, lighting, ACs
42	AP	3363	4	0	1987	Sockets, lighting, ACs
43	AQ	2050	1	0	2013	Sockets, lighting, ACs
44	AR	1937	5	0	2013	Sockets, lighting, ACs
45	AS	2118	5	0	2013	Sockets, lighting, ACs

Note: The construction year is the year in which the building was completed. In the case of a building that has undergone major alterations (for example, complete replacement of the envelope and complete replacement of equipment systems), the year refers to the year in which the major alterations were completed.

Table B-2 Prediction results of seven sample buildings

Building	Algorithm	Input system	MAPE	MAE	RMSE	CV-RMSE	R ²	Times (s)
Building A	LSTM	Improved input system	8.3113%	23.9276	30.6473	0.1001	0.8187	20.6340
Building A	LSTM	Traditional input system	13.0547%	37.7388	44.7319	0.1477	0.6141	10.5400
Building A	LSTM	Simplified input system	14.3117%	39.3742	48.4697	0.1554	0.6283	10.6700
Building A	LSTM-SSA	Improved input system	5.5224%	16.2201	21.3099	0.0698	0.9101	1272.7300
Building A	LSTM-SSA	Traditional input system	5.9905%	17.2180	22.7875	0.0750	0.8986	765.0010
Building A	LSTM-SSA	Simplified input system	8.1905%	23.5198	30.9345	0.1017	0.8239	1028.7590
Building A	CNN-LSTM	Improved input system	5.8200%	17.1471	22.2901	0.0736	0.8850	148.6470
Building A	CNN-LSTM	Traditional input system	8.5800%	24.7235	32.1005	0.1059	0.7217	127.3200
Building A	CNN-LSTM	Simplified input system	8.4400%	23.8944	31.5898	0.1043	0.7578	128.2880
Building A	CNN-LSTM-Attention	Improved input system	5.3424%	15.9886	21.2531	0.0695	0.9119	137.9760
Building A	CNN-LSTM-Attention	Traditional input system	5.5974%	16.4572	22.0380	0.0734	0.9038	126.9510
Building A	CNN-LSTM-Attention	Simplified input system	7.5786%	22.1827	29.2229	0.0976	0.8286	126.2910
Building B	LSTM	Improved input system	16.6421%	19.0252	26.6760	0.2429	0.8157	23.4950
Building B	LSTM	Traditional input system	19.4216%	22.3029	30.0366	0.2567	0.7636	11.6110
Building B	LSTM	Simplified input system	23.0916%	24.7516	32.6237	0.2531	0.7306	11.6320
Building B	LSTM-SSA	Improved input system	11.9417%	14.9499	22.1884	0.1753	0.8806	1174.1310
Building B	LSTM-SSA	Traditional input system	15.3948%	16.7206	23.1992	0.1979	0.8660	1947.7870
Building B	LSTM-SSA	Simplified input system	21.4541%	25.0363	33.9293	0.2972	0.7201	981.9360
Building B	CNN-LSTM	Improved input system	12.2400%	14.8498	22.6317	0.1870	0.8486	169.7140
Building B	CNN-LSTM	Traditional input system	16.6000%	20.3208	28.7131	0.2385	0.7776	170.4430

Building B	CNN-LSTM	Simplified input system	16.7300%	19.6613	28.1428	0.2325	0.7874	170.1860
Building B	CNN-LSTM-Attention	Improved input system	10.3236%	12.9343	19.4203	0.1579	0.9029	178.6250
Building B	CNN-LSTM-Attention	Traditional input system	11.1483%	13.5395	19.9231	0.1651	0.8958	167.5180
Building B	CNN-LSTM-Attention	Simplified input system	15.0271%	18.5580	27.0265	0.2167	0.8119	162.9420
Building C	LSTM	Improved input system	13.9647%	23.2500	33.8701	0.2111	0.7934	20.7330
Building C	LSTM	Traditional input system	25.4695%	40.2056	51.0875	0.3017	0.6342	10.5710
Building C	LSTM	Simplified input system	15.2523%	28.0065	43.5650	0.2747	0.6486	10.7710
Building C	LSTM-SSA	Improved input system	7.5459%	12.3550	21.4907	0.1271	0.9225	925.5630
Building C	LSTM-SSA	Traditional input system	8.5132%	14.6515	26.3649	0.1624	0.8726	897.4200
Building C	LSTM-SSA	Simplified input system	11.8261%	19.8473	30.2213	0.1858	0.8289	778.4780
Building C	CNN-LSTM	Improved input system	8.0000%	13.8646	25.9125	0.1598	0.8388	128.9250
Building C	CNN-LSTM	Traditional input system	12.5600%	20.5747	32.2478	0.1989	0.7950	145.1790
Building C	CNN-LSTM	Simplified input system	13.0100%	21.2071	33.2802	0.2018	0.7654	128.7430
Building C	CNN-LSTM-Attention	Improved input system	6.9745%	11.4375	19.4180	0.1169	0.9256	126.2660
Building C	CNN-LSTM-Attention	Traditional input system	8.2372%	13.8493	23.9970	0.1431	0.8994	129.0320
Building C	CNN-LSTM-Attention	Simplified input system	12.2321%	20.0607	31.5992	0.1858	0.8241	127.9980
Building D	LSTM	Improved input system	22.5602%	18.5482	28.8239	0.2597	0.8740	20.2870
Building D	LSTM	Traditional input system	26.7419%	18.9372	30.8541	0.2804	0.8590	10.4810
Building D	LSTM	Simplified input system	37.0040%	30.5076	45.3891	0.3892	0.6802	10.9490
Building D	LSTM-SSA	Improved input system	16.4706%	14.7002	24.0825	0.2182	0.9103	1015.3990
Building D	LSTM-SSA	Traditional input system	25.1693%	17.5852	25.9984	0.2250	0.8932	660.8050
Building D	LSTM-SSA	Simplified input system	30.7267%	25.9696	41.6827	0.3837	0.7274	625.0460
Building D	CNN-LSTM	Improved input system	17.0900%	14.5040	22.9192	0.2029	0.9032	120.0050
Building D	CNN-LSTM	Traditional input system	21.8700%	16.4086	24.3258	0.2154	0.8910	121.3230
Building D	CNN-LSTM	Simplified input system	30.0800%	26.8506	42.6706	0.3837	0.7158	122.5610
Building D	CNN-LSTM-Attention	Improved input system	14.8838%	13.1582	22.0074	0.2021	0.9202	114.9410
Building D	CNN-LSTM-Attention	Traditional input system	20.9425%	15.8625	23.5553	0.2140	0.9138	111.7740
Building D	CNN-LSTM-Attention	Simplified input system	24.1783%	23.3967	38.6362	0.3670	0.7768	115.1520
Building E	LSTM	Improved input system	17.2394%	42.3465	60.6623	0.2421	0.8740	18.0300
Building E	LSTM	Traditional input system	20.0019%	54.3048	75.2417	0.3377	0.8098	17.3150
Building E	LSTM	Simplified input system	33.8533%	77.6895	109.2992	0.4891	0.5396	11.8410
Building E	LSTM-SSA	Improved input system	15.3138%	34.2511	48.9922	0.1879	0.9212	349.5410
Building E	LSTM-SSA	Traditional input system	16.8610%	36.6046	53.5379	0.2091	0.8916	250.5090
Building E	LSTM-SSA	Simplified input system	29.9775%	74.7102	106.8128	0.4548	0.6930	298.5120
Building E	CNN-LSTM	Improved input system	16.1500%	32.8917	44.1385	0.2403	0.9227	30.1660
Building E	CNN-LSTM	Traditional input system	16.5900%	43.2948	54.4085	0.2422	0.8648	30.5830
Building E	CNN-LSTM	Simplified input system	30.1700%	66.3363	94.5274	0.3470	0.5583	30.9780
Building E	CNN-LSTM-Attention	Improved input system	12.2277%	29.6738	43.9002	0.1779	0.9346	43.0370
Building E	CNN-LSTM-Attention	Traditional input system	14.6515%	35.0178	51.0754	0.1907	0.9034	31.3720
Building E	CNN-LSTM-Attention	Simplified input system	29.5669%	64.2813	89.7577	0.3277	0.7474	31.6490
Building F	LSTM	Improved input system	12.5019%	10.9277	14.5018	0.1303	0.8380	21.1040
Building F	LSTM	Traditional input system	15.8691%	15.7223	20.6638	0.1903	0.7746	14.7820
Building F	LSTM	Simplified input system	24.4564%	23.7481	29.9046	0.2705	0.6966	11.3110
Building F	LSTM-SSA	Improved input system	7.8480%	8.4608	12.2205	0.1137	0.8881	1090.0030
Building F	LSTM-SSA	Traditional input system	7.9752%	8.4936	12.4451	0.1145	0.8798	1020.1240
Building F	LSTM-SSA	Simplified input system	23.8304%	22.4253	28.3438	0.2561	0.7746	683.5060
Building F	CNN-LSTM	Improved input system	11.0400%	8.7798	11.1600	0.1204	0.8850	135.1110
Building F	CNN-LSTM	Traditional input system	12.1800%	9.4810	11.6941	0.1259	0.8650	136.3500
Building F	CNN-LSTM	Simplified input system	20.5000%	19.7509	25.9589	0.2356	0.7693	136.2690
Building F	CNN-LSTM-Attention	Improved input system	7.5379%	7.7956	10.1843	0.1027	0.9006	136.0170
Building F	CNN-LSTM-Attention	Traditional input system	7.7306%	8.2232	10.9511	0.1051	0.8910	136.0170
Building F	CNN-LSTM-Attention	Simplified input system	18.0543%	19.0842	25.9131	0.2351	0.7773	134.4000
Building G	LSTM	Improved input system	17.3078%	4.4633	6.7307	0.1692	0.9324	20.8670
Building G	LSTM	Traditional input system	27.6931%	5.7790	9.1230	0.2306	0.8767	11.4940
Building G	LSTM	Simplified input system	19.4719%	5.7921	8.7799	0.2316	0.8875	11.7110
Building G	LSTM-SSA	Improved input system	11.2885%	3.0494	4.6114	0.1242	0.9693	1429.7580
Building G	LSTM-SSA	Traditional input system	20.2593%	5.2451	7.3485	0.1913	0.9211	1353.0380
Building G	LSTM-SSA	Simplified input system	17.1045%	4.9576	7.5142	0.1962	0.9165	1107.6310
Building G	CNN-LSTM	Improved input system	13.3100%	3.2671	5.0450	0.1343	0.9591	176.2160
Building G	CNN-LSTM	Traditional input system	15.3100%	4.1929	6.3072	0.1679	0.9355	176.6050
Building G	CNN-LSTM	Simplified input system	18.7000%	5.5743	8.3642	0.2226	0.8936	178.8450
Building G	CNN-LSTM-Attention	Improved input system	9.4996%	2.6849	4.0881	0.1079	0.9748	178.4110

Building G	CNN-LSTM-Attention	Traditional input system	11.1824%	3.2606	5.1478	0.1414	0.9597	175.1620
Building G	CNN-LSTM-Attention	Simplified input system	14.2318%	4.3539	6.9177	0.1841	0.9296	175.2780

Table B-3 Prediction results using CNN-LSTM-SE, SVM, RF, and XGBoost of seven sample buildings

No.	Building	Input	Algorithm	MAPE	MAE	RMSE	CV-RMSE	R ²	Time (s)
1	Building A	Improved	CNN-LSTM-Attention	5.3424%	15.9886	21.2531	0.0695	0.9119	137.976
2	Building A	Traditional	CNN-LSTM-Attention	5.5974%	16.4572	22.0380	0.0734	0.9038	126.951
3	Building A	Improved	LSTM	8.3113%	23.9276	30.6473	0.1001	0.8187	20.634
4	Building A	Traditional	LSTM	13.0547%	37.7388	44.7319	0.1477	0.61405	10.540
5	Building A	Improved	RF	15.1567%	24.4179	28.3662	0.1652	0.8131	3.179
6	Building A	Traditional	RF	15.3868%	24.9130	28.9373	0.1671	0.8076	2.741
7	Building A	Improved	SVM	15.0891%	24.4420	28.4082	0.1652	0.8127	5.648
8	Building A	Traditional	SVM	25.0588%	24.5379	39.3509	0.1688	0.7035	1.479
9	Building A	Improved	XGBoost	14.8231%	23.4193	27.0837	0.1604	0.8625	15.257
10	Building A	Traditional	XGBoost	15.7444%	24.2713	29.0791	0.1605	0.8249	10.911
11	Building B	Improved	CNN-LSTM-Attention	10.3236%	12.9343	19.4203	0.1579	0.9029	178.625
12	Building B	Traditional	CNN-LSTM-Attention	11.1483%	13.5395	19.9231	0.1651	0.8958	167.518
13	Building B	Improved	LSTM	16.6421%	19.0252	26.6760	0.2429	0.8157	23.495
14	Building B	Traditional	LSTM	19.4216%	22.3029	30.0366	0.2567	0.7636	11.611
15	Building B	Improved	RF	15.6333%	14.3553	21.7438	0.1809	0.8802	3.523
16	Building B	Traditional	RF	19.4508%	22.6929	29.2110	0.2581	0.8065	3.052
17	Building B	Improved	SVM	15.7616%	14.7752	22.3728	0.1883	0.8731	2.358
18	Building B	Traditional	SVM	20.0457%	14.5021	23.5363	0.1949	0.8596	2.012
19	Building B	Improved	XGBoost	12.6763%	13.6352	27.5953	0.2433	0.8215	11.152
20	Building B	Traditional	XGBoost	18.2814%	15.3999	28.0014	0.2464	0.8179	11.128
21	Building C	Improved	CNN-LSTM-Attention	6.9745%	11.4375	19.4180	0.1169	0.9256	126.266
22	Building C	Traditional	CNN-LSTM-Attention	8.2372%	13.8493	23.9970	0.1431	0.8994	129.032
23	Building C	Improved	LSTM	13.9647%	23.2500	33.8701	0.2111	0.7934	20.733
24	Building C	Traditional	LSTM	25.4695%	40.2056	51.0875	0.3017	0.6342	10.571
25	Building C	Improved	RF	19.0904%	41.0372	56.9856	0.2835	0.7125	2.706
26	Building C	Traditional	RF	34.1622%	79.5985	99.2844	0.5845	0.7272	2.459
27	Building C	Improved	SVM	11.7355%	25.3521	41.0124	0.1869	0.8511	1.766
28	Building C	Traditional	SVM	11.7215%	24.9375	47.3540	0.2198	0.8015	1.611
29	Building C	Improved	XGBoost	12.5239%	27.8102	45.8550	0.2094	0.8138	11.134
30	Building C	Traditional	XGBoost	12.7533%	28.9461	48.9760	0.2303	0.7876	11.093
31	Building D	Improved	CNN-LSTM-Attention	14.8838%	13.1582	22.0074	0.2021	0.9202	114.941
32	Building D	Traditional	CNN-LSTM-Attention	20.9425%	15.8625	23.5553	0.2140	0.9138	111.774
33	Building D	Improved	LSTM	22.5602%	18.5482	28.8239	0.2597	0.8740	20.287
34	Building D	Traditional	LSTM	26.7419%	18.9372	30.8541	0.2804	0.8590	10.481
35	Building D	Improved	RF	21.2028%	20.7814	25.6000	0.2376	0.8337	3.020
36	Building D	Traditional	RF	21.8399%	29.4276	33.4964	0.2626	0.8114	2.882
37	Building D	Improved	SVM	20.8728%	19.4252	24.3604	0.2452	0.8249	1.629
38	Building D	Traditional	SVM	24.1749%	30.9075	27.7107	0.2776	0.8858	1.566
39	Building D	Improved	XGBoost	20.3633%	18.8272	32.1355	0.2222	0.8464	11.225
40	Building D	Traditional	XGBoost	29.8056%	28.4526	32.6033	0.2278	0.8422	11.170
41	Building E	Improved	CNN-LSTM-Attention	12.2277%	29.6738	43.9002	0.1779	0.9346	43.037
42	Building E	Traditional	CNN-LSTM-Attention	14.6515%	35.0178	51.0754	0.1907	0.9034	31.372
43	Building E	Improved	LSTM	17.2394%	42.3465	60.6623	0.2421	0.8740	18.030
44	Building E	Traditional	LSTM	20.0019%	54.3048	75.2417	0.3377	0.8098	17.315
45	Building E	Improved	RF	16.7022%	33.7888	45.0022	0.2206	0.7351	2.303
46	Building E	Traditional	RF	17.4972%	38.2316	54.7615	0.2217	0.7190	2.102
47	Building E	Improved	SVM	18.7671%	35.9280	47.5205	0.2181	0.7466	1.987
48	Building E	Traditional	SVM	24.5021%	40.8894	53.0074	0.2432	0.6726	1.937
49	Building E	Improved	XGBoost	15.3875%	32.0170	44.1053	0.2193	0.7300	11.094
50	Building E	Traditional	XGBoost	16.4138%	42.8097	54.0724	0.2224	0.7295	11.019
51	Building F	Improved	CNN-LSTM-Attention	7.5379%	7.7956	10.1843	0.1027	0.9006	136.017
52	Building F	Traditional	CNN-LSTM-Attention	7.7306%	8.2232	10.9511	0.1051	0.8910	136.017
53	Building F	Improved	LSTM	12.5019%	10.9277	14.5018	0.1303	0.8380	21.104
54	Building F	Traditional	LSTM	15.8691%	15.7223	20.6638	0.1903	0.7746	14.782
55	Building F	Improved	RF	10.1062%	8.1934	10.6318	0.1087	0.8650	3.415
56	Building F	Traditional	RF	18.3576%	17.0459	19.2778	0.1973	0.7972	2.804
57	Building F	Improved	SVM	17.5087%	16.5866	18.7827	0.1933	0.8079	1.852

58	Building F	Traditional	SVM	18.5453%	17.4361	20.2409	0.2089	0.7748	1.707
59	Building F	Improved	XGBoost	17.6816%	16.5125	18.6455	0.1914	0.8107	11.184
60	Building F	Traditional	XGBoost	18.2668%	16.8823	19.6388	0.1985	0.7952	11.111
61	Building G	Improved	CNN-LSTM-Attention	9.4996%	2.6849	4.0881	0.1079	0.9748	178.411
62	Building G	Traditional	CNN-LSTM-Attention	11.1824%	3.2606	5.1478	0.1414	0.9597	175.162
63	Building G	Improved	LSTM	17.3078%	4.4633	6.7307	0.1692	0.9324	20.867
64	Building G	Traditional	LSTM	27.6931%	5.7790	9.1230	0.2306	0.8767	11.494
65	Building G	Improved	RF	9.6295%	3.5069	6.7759	0.15185	0.93779	3.399
66	Building G	Traditional	RF	12.4775%	3.8567	7.1959	0.1599	0.92984	3.188
67	Building G	Improved	SVM	11.0510%	3.739	7.585	0.17043	0.92205	2.275
68	Building G	Traditional	SVM	19.8065%	5.3443	10.823	0.23741	0.84129	2.194
69	Building G	Improved	XGBoost	11.6380%	3.4684	7.9364	0.17491	0.91466	11.212
70	Building G	Traditional	XGBoost	12.3502%	3.5267	7.6365	0.16512	0.92099	11.139

Table B-4 Prediction results of all forty-five buildings in the university community

No.	Code	Input	Algorithm	MAPE	MAE	RMSE	CV-RMSE	R ²	Time (s)
1	A	Improved	CNN-LSM-attention	5.34%	15.9886	21.2531	0.0695	0.9119	137.9760
2	B	Improved	CNN-LSM-attention	10.32%	12.9343	19.4203	0.1579	0.9029	178.6250
3	C	Improved	CNN-LSM-attention	6.97%	11.4375	19.4180	0.1169	0.9256	126.2660
4	D	Improved	CNN-LSM-attention	12.23%	29.6738	43.9002	0.1779	0.9346	43.0370
5	E	Improved	CNN-LSM-attention	14.88%	13.1582	22.0074	0.2021	0.9202	114.9410
6	F	Improved	CNN-LSM-attention	9.50%	2.6849	4.0881	0.1079	0.9748	178.4110
7	G	Improved	CNN-LSM-attention	7.54%	7.7956	10.1843	0.1027	0.9006	136.0170
8	H	Improved	CNN-LSM-attention	4.73%	0.9217	1.3539	0.0691	0.9375	104.8640
9	I	Traditional	CNN-LSM-attention	18.71%	1.1108	2.0916	0.2202	0.9056	109.7060
10	J	Improved	CNN-LSM-attention	14.63%	17.8817	28.7765	0.2057	0.8754	188.4130
11	K	Traditional	CNN-LSM-attention	10.88%	6.9524	9.8802	0.1185	0.9523	192.5590
12	L	Traditional	CNN-LSM-attention	11.73%	6.6463	9.2032	0.1168	0.9644	264.7410
13	M	Traditional	CNN-LSM-attention	8.63%	4.6473	6.0076	0.1094	0.9285	209.1040
14	N	Traditional	CNN-LSM-attention	10.99%	11.6702	15.5265	0.1460	0.8771	192.7760
15	O	Traditional	CNN-LSM-attention	16.87%	9.9031	15.3590	0.2742	0.8619	203.2610
16	P	Traditional	CNN-LSM-attention	14.97%	21.4188	32.5380	0.2037	0.9136	199.8600
17	Q	Traditional	CNN-LSM-attention	15.91%	19.3000	27.9711	0.1842	0.9384	216.9380
18	R	Traditional	CNN-LSM-attention	16.87%	14.8067	21.6743	0.2260	0.8566	198.4460
19	S	Traditional	CNN-LSM-attention	21.98%	6.7336	10.7973	0.2782	0.8469	198.1200
20	T	Improved	CNN-LSM-attention	0.88%	1.6429	2.4519	0.0132	0.9522	182.9560
21	U	Traditional	CNN-LSM-attention	15.82%	0.6549	0.9906	0.1794	0.8396	148.9560
22	V	Traditional	CNN-LSM-attention	11.56%	1.2556	1.9754	0.1070	0.8505	144.5550
23	W	Traditional	CNN-LSM-attention	17.73%	0.2388	0.3362	0.1679	0.8598	156.1990
24	X	Traditional	CNN-LSM-attention	19.43%	1.3905	2.6040	0.1761	0.8549	157.6590
25	Y	Traditional	CNN-LSM-attention	11.35%	1.2667	2.0733	0.2180	0.8373	158.0670
26	Z	Traditional	CNN-LSM-attention	13.89%	0.6433	0.9175	0.1323	0.9003	156.0380
27	AA	Traditional	CNN-LSM-attention	16.08%	1.1313	1.7980	0.2198	0.8336	151.1160
28	AB	Traditional	CNN-LSM-attention	16.39%	0.2561	0.4208	0.2767	0.8127	159.4540
29	AC	Traditional	CNN-LSM-attention	12.36%	2.7621	3.9709	0.2252	0.9044	167.7140
30	AD	Improved	CNN-LSM-attention	4.70%	12.2036	16.6358	0.0639	0.9106	199.3390
31	AE	Improved	CNN-LSM-attention	8.30%	11.1041	17.7721	0.1405	0.9154	163.8910
32	AF	Improved	CNN-LSM-attention	7.24%	8.7465	11.9988	0.0953	0.9267	182.1760
33	AG	Traditional	CNN-LSM-attention	10.65%	9.3648	13.9696	0.1463	0.8856	174.0940
34	AH	Traditional	CNN-LSM-attention	9.74%	2.4749	3.6182	0.2152	0.9179	172.3980
35	AI	Traditional	CNN-LSM-attention	11.14%	2.2743	3.6432	0.1772	0.9085	189.8470
36	AJ	Traditional	CNN-LSM-attention	16.47%	2.1017	3.0846	0.2444	0.8628	152.3990
37	AK	Improved	CNN-LSM-attention	8.89%	1.9731	3.2739	0.1533	0.9011	178.6630
38	AL	Traditional	CNN-LSM-attention	7.57%	1.6906	2.5919	0.1195	0.9330	169.0020
39	AM	Traditional	CNN-LSM-attention	15.83%	0.1675	0.2775	0.2414	0.8362	101.2410
40	AN	Traditional	CNN-LSM-attention	17.07%	2.6795	4.3846	0.1710	0.8926	168.1810
41	AO	Traditional	CNN-LSM-attention	16.42%	1.9373	3.1466	0.2443	0.8092	141.3400
42	AP	Traditional	CNN-LSM-attention	15.51%	1.6449	2.6863	0.2184	0.9129	171.7930
43	AQ	Traditional	CNN-LSM-attention	18.34%	2.5461	4.1465	0.2752	0.8863	180.2940
44	AR	Traditional	CNN-LSM-attention	9.75%	1.8951	3.6141	0.1970	0.8700	131.0080
45	AS	Traditional	CNN-LSM-attention	8.77%	1.4341	3.5493	0.1765	0.8906	146.5550

Appendix C Results and other information on all buildings

The rank is from 1 to 12 where Rank 1 means the greatest and Rank 12 means the worst.

Appendix C-1 The ranks for different prediction systems in different buildings with different indicators

Building	Algorithm	Input system	MAPE	MAE	RMSE	CV-RMSE	R ²
Building A	LSTM	Improved input system	8	9	7	7	8
Building A	LSTM	Traditional input system	11	11	11	11	12
Building A	LSTM	Simplified input system	12	12	12	12	11
Building A	LSTM-SSA	Improved input system	2	2	2	2	2
Building A	LSTM-SSA	Traditional input system	5	5	5	5	4
Building A	LSTM-SSA	Simplified input system	7	7	8	8	7
Building A	CNN-LSTM	Improved input system	4	4	4	4	5
Building A	CNN-LSTM	Traditional input system	10	10	10	10	10
Building A	CNN-LSTM	Simplified input system	9	8	9	9	9
Building A	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building A	CNN-LSTM-SE	Traditional input system	3	3	3	3	3
Building A	CNN-LSTM-SE	Simplified input system	6	6	6	6	6
Building B	LSTM	Improved input system	8	7	6	9	6
Building B	LSTM	Traditional input system	10	10	10	11	10
Building B	LSTM	Simplified input system	12	11	11	10	11
Building B	LSTM-SSA	Improved input system	3	4	3	3	3
Building B	LSTM-SSA	Traditional input system	6	5	5	5	4
Building B	LSTM-SSA	Simplified input system	11	12	12	12	12
Building B	CNN-LSTM	Improved input system	4	3	4	4	5
Building B	CNN-LSTM	Traditional input system	7	9	9	8	9
Building B	CNN-LSTM	Simplified input system	9	8	8	7	8
Building B	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building B	CNN-LSTM-SE	Traditional input system	2	2	2	2	2
Building B	CNN-LSTM-SE	Simplified input system	5	6	7	6	7
Building C	LSTM	Improved input system	10	10	10	10	9
Building C	LSTM	Traditional input system	12	12	12	12	12
Building C	LSTM	Simplified input system	11	11	11	11	11
Building C	LSTM-SSA	Improved input system	2	2	2	2	2
Building C	LSTM-SSA	Traditional input system	5	5	5	5	4
Building C	LSTM-SSA	Simplified input system	6	6	6	7	6
Building C	CNN-LSTM	Improved input system	3	4	4	4	5
Building C	CNN-LSTM	Traditional input system	8	8	8	8	8
Building C	CNN-LSTM	Simplified input system	9	9	9	9	10
Building C	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building C	CNN-LSTM-SE	Traditional input system	4	3	3	3	3
Building C	CNN-LSTM-SE	Simplified input system	7	7	7	6	7
Building D	LSTM	Improved input system	6	7	7	7	7
Building D	LSTM	Traditional input system	9	8	8	8	8
Building D	LSTM	Simplified input system	12	12	12	12	12
Building D	LSTM-SSA	Improved input system	2	3	4	5	3
Building D	LSTM-SSA	Traditional input system	8	6	6	6	5
Building D	LSTM-SSA	Simplified input system	11	10	10	10	10
Building D	CNN-LSTM	Improved input system	3	2	2	2	4
Building D	CNN-LSTM	Traditional input system	5	5	5	4	6
Building D	CNN-LSTM	Simplified input system	10	11	11	11	11
Building D	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building D	CNN-LSTM-SE	Traditional input system	4	4	3	3	2
Building D	CNN-LSTM-SE	Simplified input system	7	9	9	9	9

Building E	LSTM	Improved input system	7	6	7	6	6
Building E	LSTM	Traditional input system	8	8	8	9	8
Building E	LSTM	Simplified input system	12	12	12	12	12
Building E	LSTM-SSA	Improved input system	3	3	3	2	3
Building E	LSTM-SSA	Traditional input system	6	5	5	4	5
Building E	LSTM-SSA	Simplified input system	10	11	11	11	10
Building E	CNN-LSTM	Improved input system	4	2	2	5	2
Building E	CNN-LSTM	Traditional input system	5	7	6	7	7
Building E	CNN-LSTM	Simplified input system	11	10	10	10	11
Building E	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building E	CNN-LSTM-SE	Traditional input system	2	4	4	3	4
Building E	CNN-LSTM-SE	Simplified input system	9	9	9	8	9
Building F	LSTM	Improved input system	7	7	7	7	7
Building F	LSTM	Traditional input system	8	8	8	8	9
Building F	LSTM	Simplified input system	12	12	12	12	12
Building F	LSTM-SSA	Improved input system	3	3	5	3	3
Building F	LSTM-SSA	Traditional input system	4	4	6	4	5
Building F	LSTM-SSA	Simplified input system	11	11	11	11	10
Building F	CNN-LSTM	Improved input system	5	5	3	5	4
Building F	CNN-LSTM	Traditional input system	6	6	4	6	6
Building F	CNN-LSTM	Simplified input system	10	10	10	10	11
Building F	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building F	CNN-LSTM-SE	Traditional input system	2	2	2	2	2
Building F	CNN-LSTM-SE	Simplified input system	9	9	9	9	8
Building G	LSTM	Improved input system	8	7	6	6	6
Building G	LSTM	Traditional input system	12	11	12	11	12
Building G	LSTM	Simplified input system	10	12	11	12	11
Building G	LSTM-SSA	Improved input system	3	2	2	2	2
Building G	LSTM-SSA	Traditional input system	11	9	8	8	8
Building G	LSTM-SSA	Simplified input system	7	8	9	9	9
Building G	CNN-LSTM	Improved input system	4	4	3	3	4
Building G	CNN-LSTM	Traditional input system	6	5	5	5	5
Building G	CNN-LSTM	Simplified input system	9	10	10	10	10
Building G	CNN-LSTM-SE	Improved input system	1	1	1	1	1
Building G	CNN-LSTM-SE	Traditional input system	2	3	4	4	3
Building G	CNN-LSTM-SE	Simplified input system	5	6	7	7	7

Highlights

1. An enhanced energy consumption prediction including improving input and algorithm is proposed.
2. It introduces occupant energy-use behavior probability as inputs.
3. It introduces SSA, SE attention and CNN modules for improving training algorithms.
4. It discusses the performance comparison of proposed algorithms and other advanced algorithms.
5. Method for selecting the suitable inputs and algorithms in different buildings is presented.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: