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Research Article

Convolutional Neural Network Based Energy Consumption Management Model for the Full Life Cycle of Buildings and Information System Design

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With the continuous improvement in China's economy, the construction industry has developed and rampantly progressed. Besides the wastage of resources and energy, the development has caused serious pollution to the environment. This makes the construction industry a high energy-consuming and highly polluting industry. There is a pressing need to reduce the wastage of resources and to adequately manage consumption of energy throughout the life cycle of buildings. This paper explores an effective method of building life cycle energy management by appropriately utilizing information system and the emerging deep learning technology. To achieve energy saving in buildings, a feasible model is proposed for predicting, analyzing, and building energy consumption based on neural networks. By analyzing the massive data stored in the building information system, the operation of each subsystem in the building is guided and regulated to achieve energy deployment and build energy optimization. Focusing the key meters, the average generalization ability of the proposed model (R-Squared = 1.9, MSE = 1.02) is better than the other contemporarily used models, LightGBM, LSTM, and SVR. Moreover, the method can effectively predict the energy consumption of the whole life cycle of the building and has higher prediction accuracy. The method proposed has great significance in research related with improving building energy performance and designing decision support tool.

1. Introduction

In recent years, with strong advocacy and active promotion of the Ministry of Housing and Construction and local building energy efficiency authorities, constructions of large public buildings are increasing adamantly [1–3]. Buildings are the major energy consumers, and many buildings in China are high energy-consuming buildings, which impose a heavy energy burden on society [4–6]. The annual energy consumption of public and civil buildings is also increasing with the passage of time. According to a recent research [7], the energy consumed by buildings accounts for 40% of the whole energy consumption, causing a major chunk of atmospheric emissions (40%) and greenhouse gas emission (33%).

However, building energy management is a systematic project, and the actual energy consumption after the building is put into operation may be reduced. By extending building energy management to multiple stages, such as project, design, construction and operation, and covering the whole life cycle of the building, can achieve the goal of controlling and saving energy. The goal is put into practice through the promotion of energy-saving indicators and technical measures at each stage. Effective management of energy consumption during the whole life cycle of a building is just getting started in China. The information on energy consumption during each construction phase is distributed among different departments for apt compliance. However, the collection of relevant data and the standards of information system construction are yet to be established.

At present, people mainly focus on the improvement and optimization of energy consumption during building use, including energy consumption in heating, air conditioning, lighting, household appliances, and cooking utensils. In fact, each stage of the building life cycle, from design to construction completion, delivery, and use until demolition, is constantly consuming energy. Moreover, with the continuous emergence of new materials, technologies, and techniques, the proportion of energy consumed in the building materials and construction process is relatively higher. Therefore, it is not enough to consider only the energy consumption in the operation phase of a building but the energy consumption in the whole life cycle of a building should be systematically considered. According to the life cycle theory of buildings, the life cycle of a building includes five stages: the preparation stage of building materials, the building construction stage, the building use stage, the building demolition stage, and the disposal stage of used building materials, see Figure 1.

Systems engineering is a dedicated domain which deals with materials, construction techniques, and other factors of construction. Systems engineering requires a system perspective, focuses on the interconnectedness, interaction, and mutual constraints between the whole and its parts, and between the whole and the outside [8–12]. The openness, relevance, and dynamics of building systems determine that energy saving in building systems must consider the whole process from energy and resource acquisition to transmission and distribution. For example, double-glazed windows are better insulated than ordinary wood windows and doors, but double-glazed windows consume more energy in the production process than the production of ordinary wood windows and doors. Therefore, when choosing building solutions, the energy consumption of the whole life cycle should be considered from a system perspective.

Building information system is a digital technology to simulate the real information of the building by constructing digital information system through information technology. The information description is to clearly and intuitively obtain the energy consumption in different seasons and to provide guidance for building construction and environmental protection. The information system provides guidance for building construction and environmental protection, thus controlling energy and resource waste and saving construction costs, which is important for the sustainable development of the construction industry [13]. Moreover, the technology may be used to dynamically reflect building information in real-time. The application of building information system for the whole life cycle of building focuses on the continuity of information. The whole life cycle of building contains four stages such as planning and design, construction, operation, and maintenance, and it is very important to keep the continuity and connection of the four stages [14]. The building information system contains a lot of data and information related to building performance, so the building information system software needs to export the relevant data first and then import them into the building information system database for integration and analysis after conversion. Following that, the indicators are integrated and adjusted to control energy requirements of the building. The data and parameters related to energy consumption are imported into the comprehensive database of the building information system to form quantitative index parameters [15–17].

In 2012, in the deep learning (DL) technology, convolutional neural network (CNN) emerged in the field of image recognition that attracted the attention of research scholars all over the world. The CNN technology has a wide range of applications in the field of computer vision, natural language processing, and other research fields. Compared with ordinary neural network technology, CNN has powerful data feature extraction ability with convolutional layers and has better generalization ability. The model proposed in this paper for the whole-life energy consumption management is based on CNN. The aim behind the research study is to provide preliminary findings and relevant technology preparation for further research and practice in the field of construction. To realize the whole-life energy consumption management of buildings, firstly, it is necessary to determine the monitoring target, i.e., to split the comprehensive control target of the whole-life energy consumption of buildings into several implementable, measurable, and controllable indicators, to choose a suitable management stage, and then to refine and decompose each of the indicators. Secondly, it is necessary to determine the implementation path, integrate requirements of energy consumption, and design a suitable energy consumption management process.

In this paper, we sort out the logical relationships among the monitoring objects, implementation paths, and expected results of energy consumption in the whole life cycle. A model for energy consumption management for the whole life cycle of buildings is proposed to provide guidance for the development of information systems. The model construction schematic is shown in Figure 2.

2. Related Work

Building construction is a compound process encompassing various phases and plans [18]. Energy consumption control requirements in the preproject stage and indexes in the project planning stage are used as the baselines for the design stage. The data linkage with the building energy consumption control requirements is established during the project planning phase. Moreover, analysis about investment, sales, social benefit analysis, risk, project investment, and financing are also performed in the planning phase. In the design phase, dedicated software technology, comprehensive database, and system model are used to improve the efficiency of related building energy consumption, green building, and other analysis tools and also to reduce the huge workload during the whole process. Moreover, the building information system is used to achieve dynamic output of building energy analysis such as electromechanics, architecture, Heating, Ventilation, and Air Conditioning (HVAC), and curtain wall and to provide a basis for parametric design. Quantitative indicators in the information system like system indicators, equipment parameters, and operation parameters are helpful to integrate and adjust the energy consumption of a building [19–24].

The construction phase is an important stage where design of the building energy management is meticulously brought into actuality. Integration and adjustment may be performed in the comprehensive database of the building

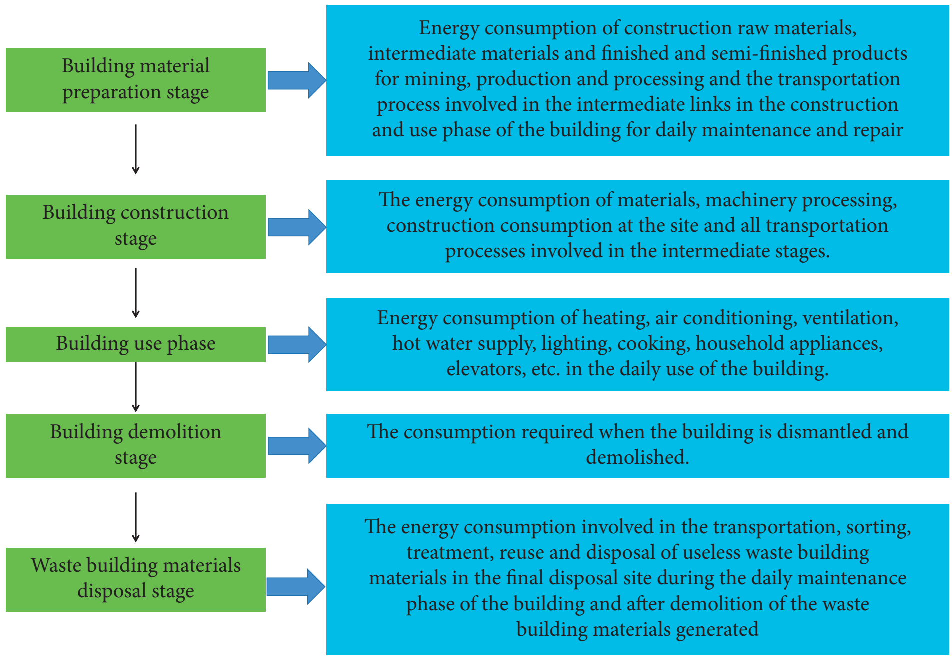

Figure 1: Energy consumption in all phases of the building life cycle.

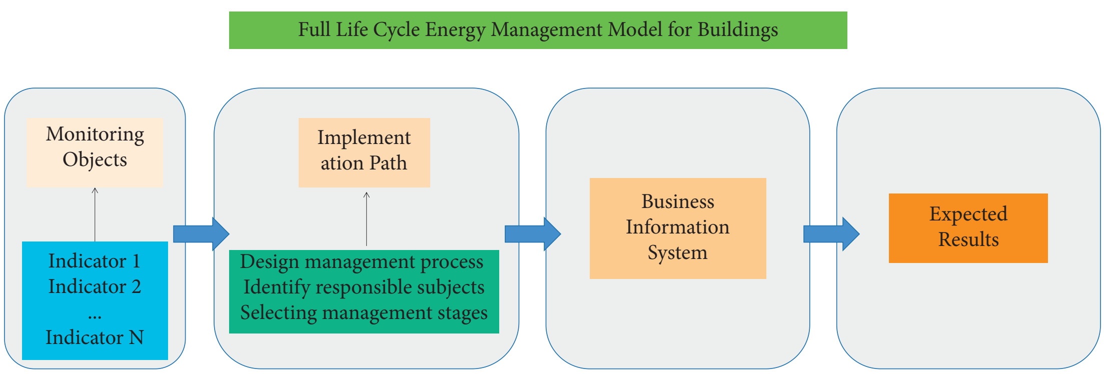

Figure 2: Schematic of the building life cycle energy management models.

information system. However, special attention is paid to include the comparison of equipment parameters binding indexes with actual procurement according to the comparison, actual installation, piping, and construction drawings. At the same time, since a project may undergo relevant changes due to uncontrollable factors such as equipment manufacturers, construction environment, and building layout, the energy consumption and control parameters are kept adjustable [25–28]. The key inputs (or constraints) in the construction phase include various parameters of electromechanical equipment (performance, equipment life, and index), installation location, supplier information, operation monitoring and control index, the correlation of electromechanical systems (piping diagram, logic of the cooling, heat source system and air conditioning system), variable air volume (VAV) system, and area space layout.

The operation phase is the phase to test the results of building energy management and to adjust and optimize building energy management in conjunction with other information about building operation. On the basis of real-time collection of dynamic data information such as human flow, environment, and operation of facilities and equipment, it integrates real-time data and historical data of various types of energy consumption in the building, extracts relevant information from the building information system model. Data simulation and analysis techniques may be used to carry out simulation estimation of operational energy consumption under various conditions. After the building operation is stabilized (generally two heating and cooling cycles), the building energy management system collects dynamic data such as the optimal performance curve of equipment operation, the optimal life curve of equipment operation, and the monitoring data of the operating equipment [26].

With the development of information technology, a huge amount of complicated information is flooded around all the time. However, the information that human beings can receive is limited, and researchers have discovered that the human visual system has a huge visual information processing capacity with a limited field of view [27–29]. Mimicking the human visual system, researchers have developed the idea of attentional mechanisms. The core idea of the attention mechanism is to obtain the importance of each feature map by certain means and devote more computational resources of the neural network to more important tasks and use the results of the tasks to guide the update of weights of the feature maps so that the corresponding tasks can be completed efficiently and quickly [30].

Convolutional neural network (CNN) is a widely used model in deep learning, which is an important part of target detection algorithm and plays the role of feature extractor in target detection algorithm mainly completing the feature extraction task and outputting the feature map containing rich feature information, which lays the foundation for the subsequent classification and regression tasks in target detection. In 2012, the AlexNet network was proposed to focus research in the field of computer vision on convolutional neural networks and deep learning. With the emergence of various advanced frameworks in 2014, improved AlexNet and ZFNet were introduced [31–33]. In the same year, RepVGG, which consists of only 3×3 convolutions with ReLU activation functions further enhances the feature extraction performance of the VGG network through a simple branchless structure [34–36]. To realize the deployment of CNN models in miniaturized mobile and embedded platforms, scholars have also conducted in-depth research on how to reduce the number of CNN model parameters and the complexity of CNN structures. Among them, SqueezeNet utilizes many 1×1 convolutional kernels to replace 3×3 convolutional kernels while reducing the number of channels of 3×3 convolutional kernels to reduce the number of parameters.

3. Methods

Machine learning models work as a black box discovering the relation between various features of building and generate outputs about the energy performance. In this paper, the supervised ML approach used adequate data about building to predict targets for unseen samples.

3.1. Model Architecture. As any ML model works on data, initially, the historical number of buildings and meteorological data are collected to have a dataset for the model training. The algorithm is used to identify the building run cycles as the time steps of the model. Finally, the hybrid model is trained based on the convolutional neural network algorithm. The optimal hyperparameters of the hybrid model are found using the grid search algorithm. The structure of the proposed model is shown in Figure 3.

3.2. Big Data Information System. With the continuous development and wide application of big data technology, the platform architecture of big data is extending. The architecture is divided into two basic types: (1) master-slave and (2) P2P. The former storage architecture is developed by Google and represented by GFS and BigTable. The main representative of master-slave is Hadoop. The later storage architecture is developed by Amazon whereas its main representative is Dynamo. The Hadoop master-slave architecture is mainly reflected in the architecture design of HDFS (Hadoop Distributed File System).

3.3. Feature Embedding. Word embedding refers to a kind of word representation where words with similar meaning have a similar representation. Word embedding is normally used in natural language processing. The embedding layer maps sparse word vectors to a low-dimensional and compact feature space. The vectors in this feature space can be used to measure the similarity between features by computing their relative distance. Since the feature space is a feature compression of the original vector space, its dimensionality is much smaller than that of the original vector space. Hence, the complexity of distance calculation can be greatly reduced. Moreover, the undesirable effects of expanded feature vectors are avoided.

In the N-dimensional word vector space VERX, the relationship between its features can be expressed in terms of conditional probabilities as

$$p(v_1, v_2, \cdots, v_n \mid v_i) = \prod_{j \neq i}^{N} p(v_j \mid v_i), \tag{1}$$

where $v_i$is the target feature and v_j is the other features in the feature space. In the neural network, $p(v_j \mid v_i)$ can be expressed as

$$p(v_j \mid v_i) = \frac{\exp s_j}{\sum_{j'=1}^{M} \exp\ s_{j'}}, \tag{2}$$

where H is the hidden layer, M is the dimension of the original N-dimensional feature mapping to the feature space S, s_j is the j-th component of the weight W of the hidden layer H to the feature mapping space S, and h and W is the weight of the original feature input to the hidden layer H. Therefore, given the target feature v_i, the loss function of the network can be obtained as

$$\begin{aligned} L &= -\sum_{i=1}^{N} \ln\ p(v_1, v_2, \cdots, v_N \mid v_i) \\ &= -\ln\ \prod \frac{\exp s_j}{\sum_{j'=1}^{M} \exp\ s_{j'}} \\ &= -\sum_{j=1}^{N} s_j + N \ln \sum_{j'=1}^{M} \exp_{j'}. \end{aligned} \tag{3}$$

As clear from the equation, after the word embedding layer, the relevance of the classification features can be fully extracted, and the new features are embedded in a layer of network. This reduces the dimensionality of the input data, and the layer may be used for solving the problem of feature discretization. There are categorical features in building metainformation, such as features related with the use and location of buildings. Though the features have obvious effects on the energy consumption of the building, they do not exist in numerical form. If the categorical features are

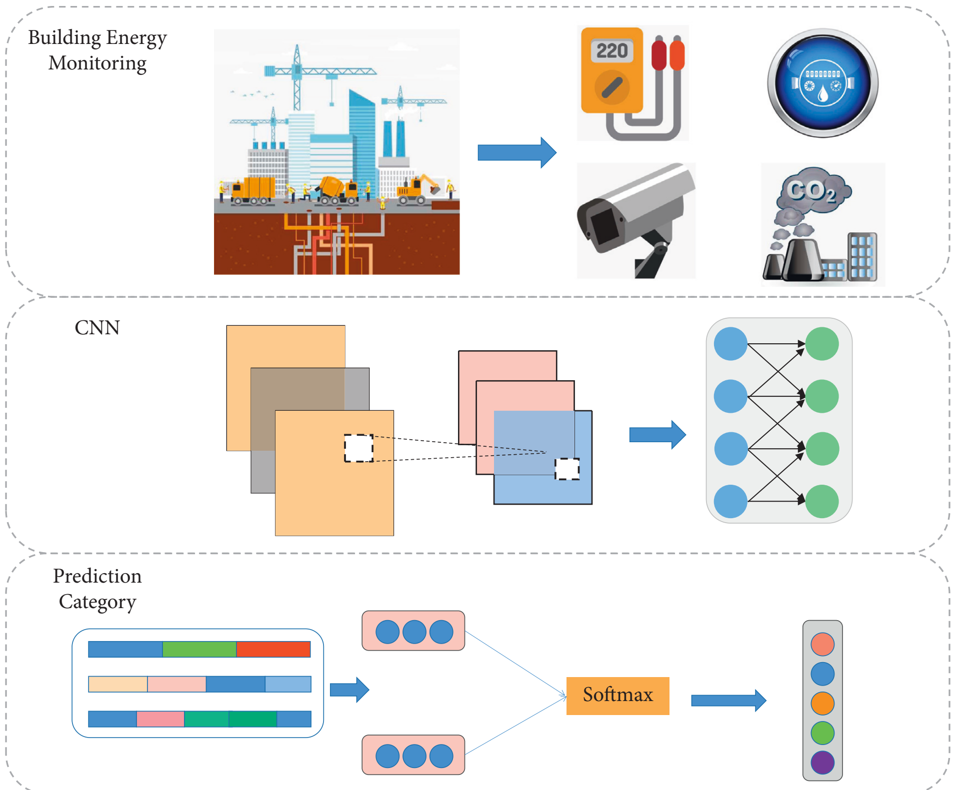

Figure 3: Structure of the proposed model.

coded with the unique thermal coding, it will lead to too large data dimensionality. For this reason, the fusion neural network established in this study introduces an embedding layer, which is used to compute the embedding of discrete classification signals, thus mapping the discrete classification features to a continuous word embedding space enabling the fusion of discrete features with numerical features. At the same time, the word embedding layer reduces the data dimensionality and reduces the training time of the network.

3.4. Convolutional Layer. The convolutional neural network is selected to perform regression on the data. Convolution is a mathematical operation in which the process is to take a tensor, matrix, or vector and pass it through the convolution operation of a convolution kernel to obtain a tensor of smaller dimension containing feature information. Deep convolutional neural networks based on two-dimensional convolutional kernels have made significant breakthroughs in image recognition in recent years. However, the two-dimensional convolution kernel operates on two dimensions of image data, namely, length and width. Considering that the dimension of time-series data is only one-dimensional, this study selects one-dimensional convolution to extract time-series features from the data. The one-dimensional convolution kernel convolves the time-series data on the time series.

By inputting the input of the network into k branches, the input of each cardinal, where R represents the number of branches after split in each cardinal, k represents the k-th cardinal, and U represents the input of each branch after split. The output of each cardinal module, V, represents the output of cardinal with channel weights, $a(c)$ is the weight calculated by SoftMax, and G represents the weight of each split. The final k outputs are stitched after the cardinal module combine the information of the k cardinal outputs and the stitched outputs are element-wise summation with the original inputs to obtain the final output.

$$
\begin{aligned}
\hat{U}^k &= \sum_{i=R(k-1)+1}^{Rk} U_i, \\
V_c^k &= \sum_{i=1}^{R} a_i^k(c) U_{R(k-1)+i}, \\
a_i^k(c) &= \begin{cases} \dfrac{\exp\left(G_i^c\left(s^k\right)\right)}{\sum_{j=1}^{R} G_j^c\left(s^k\right)}, & R > 1, \\[2ex] \dfrac{1}{1+\exp\left(-G_i^c\left(s^k\right)\right)}, & R = 1, \end{cases} \\
V &= \mathrm{Concat}\left\{V^1, V^2, \cdots, V^k\right\}.
\end{aligned} \tag{4}
$$

3.5. Model Training. As a first step, preprocessing of various types of data involved in building energy consumption is performed. Particularly data dissimilar in scales are preprocessed to avoid computational cost. There are various types of data such as pressure, temperature, voltage, current, and flow. Abnormalities of various forms may occur in the data due to many reasons, including change in the environment. Therefore, it is needed to normalize data so that it is not affected by various types of magnitudes. In this paper, the maximum-minimum normalization method is used to reduce abnormalities in data.

$$x_{nom} = \frac{x - A_{\min}}{A_{\max} - A_{\min}}. \tag{5}$$

The mean absolute percentage error (MAPE) is used as the evaluation criterion for the outcome error as follows.

$$MAPE = \sum_{i=1}^{N} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \frac{100}{N}, \tag{6}$$

where N is the total number of prediction experiments, y_i is the true value, $\hat{y}_i$ is the predicted value. The smaller the value of MAPE, the smaller the difference between the predicted value and the true value.

4. Experiments and Results

To design a suitable energy consumption management process, it is necessary to integrate requirements of energy consumption, after preprocessing and appropriate analysis of enough volume of data. Therefore, the CNN-based model proposed in this paper is trained by a dataset of 800,000 samples.

4.1. Experimental Setup. The experimental configuration environment is Ubuntu 18.04LTS with 32G RAM, Intel Corei7-7700 CPU and Nvidia GTX-1070Ti GPU, and Keras deep learning framework and TensorFlow as Backend. The data used in this study come from the internal nonpublic data of a Chinese construction company, and the historical data of different buildings in different places for one year are collected. The main information contained in the data include meter (electricity meter, cooling meter, steam meter, and heat meter) readings, building metainformation (e.g., usage, commissioning time, number of floors, building location) and meteorological information (e.g., air temperature, cloud cover, dew point temperature, air pressure, and wind speed). Correspondingly, there are test datasets in the data that have the same structure as the training dataset. For the training data selection, the original data, after the missing value processing, have 11714696 items, containing 27 temporal features and 3 classification features. This study divided the data into training set and test set according to the ratio of 4 : 1; however, in the process of training the model, the author found that the training speed of SVR and LSTM on large datasets was too slow; therefore, for the above two models, this study only selected 800,000 of these samples as the dataset for training the model and also divided the training set and test set according to the ratio of 4 : 1. In this study, the early stopping strategy is used to stop the training to prevent overfitting of the models. Also, k-fold cross-validation is used for all algorithms, and the k-value is set to 6, and the results are averaged over six times. The model parameters were set as shown in Table 1.

Table 1: The model parameters setting.

Predictive models	Parameter name	Parameters
CNN	Number of hidden layer neurons	100
	Dropout	0.2
	Learning rate	0.001
	Optimization algorithm	Adam

The training process performance enhancement and loss convergence are shown in Figures 4 and 5.

4.2. Experimental Results and Analysis. To evaluate the prediction performance of the proposed models, LightGBM, CatBoost, support vector machine regression, and long short-term memory (LSTM) network were selected as the cross-sectional comparison models. LightGBM and CatBoost algorithms are both improvements of the gradient boosted decision tree (GBDT) algorithm. Compared to the GBDT algorithm, which slices features at each level, the LightGBM algorithm slices features directly at the leaf nodes of the tree and introduces histogram optimization without sorting each feature, resulting in a significant speedup compared to the GBDT algorithm. Both the integrated learning algorithms are widely used in the field of data mining. Meanwhile, in order to verify that the one-dimensional convolutional neural network (Conv1D) has the performance of extracting temporal features in temporal order, a long- and short-term memory network is selected for comparison.

From the results in Figures 6, 7, and 8, the model proposed in this study possesses high performance in terms of accuracy and model interpretation, which is only slightly lower than the LightGBM algorithm and better than other integrated learning algorithms and neural networks. The model in this study consumes more time in convergence, which is caused by the search of hyperparameters for more iterations of training. Compared with the LSTM model, the LIGHTGBM model has higher prediction accuracy, and compared with SVR and GA algorithms, TSA has better merit-seeking ability and convergence in optimizing the LSTM model, indicating that the TSA algorithm is suitable for parameter optimization of the LSTM model. Compared with the three single neural network models LSTM, LIGHTGBM, and LSTM, the LIGHTGBM-LSTM model has better prediction accuracy and robustness and has stronger generalization ability. This indicates that the hybrid prediction model proposed makes full use of the advantages of different neural networks and has better prediction performance. As the model meets the practical engineering needs, it provides effective data support for the power system of buildings.

In order to verify the generalization ability of the model, regression prediction is performed for each of the other three measures in the paper, and the LightGBM algorithm is used to compare with the model proposed in this study. In the LightGBM algorithm, the parameters are set in the same way as those for the meter prediction. For the parameters of the model in this study, the parameters of the electricity

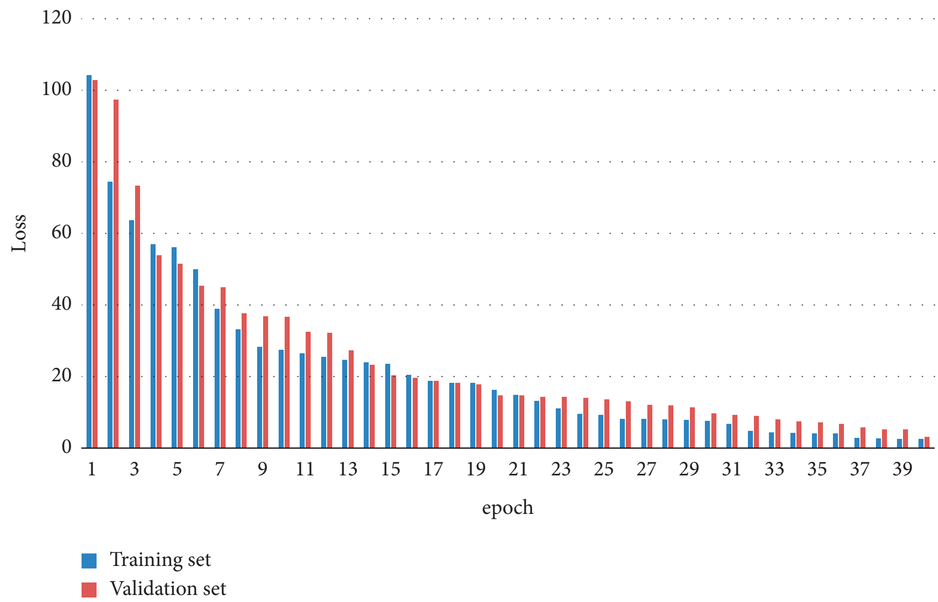

Figure 4: Schematic diagram of training process performance improvement.

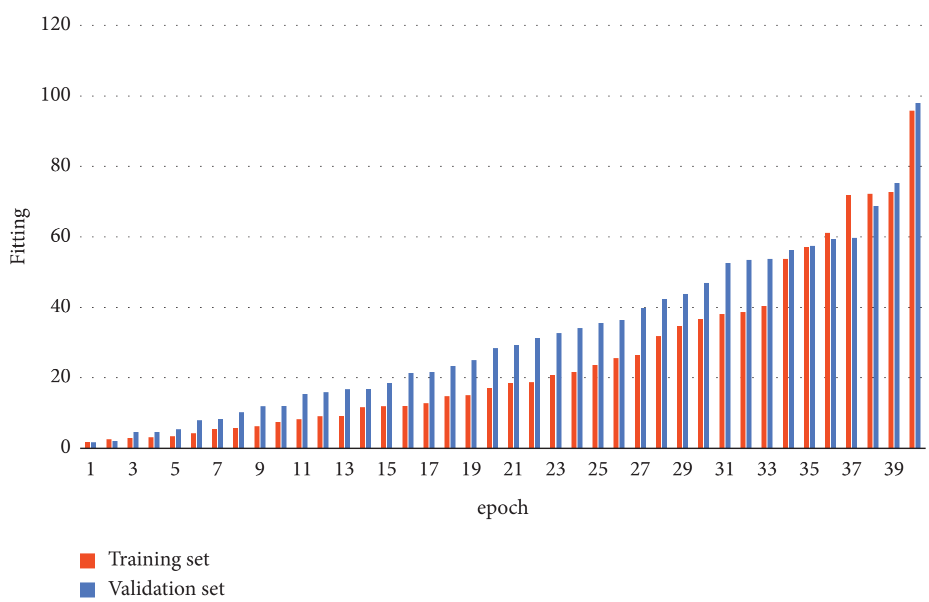

Figure 5: The training process loss convergence schematic.

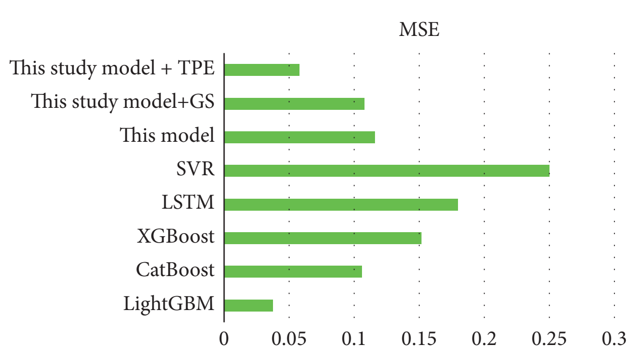

Figure 6: MSE comparison results.

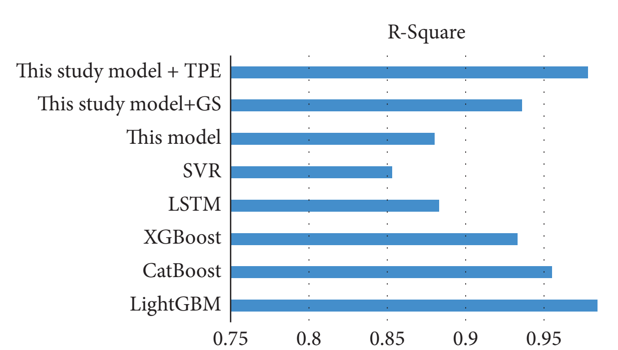

Figure 7: *R*-square comparison results.

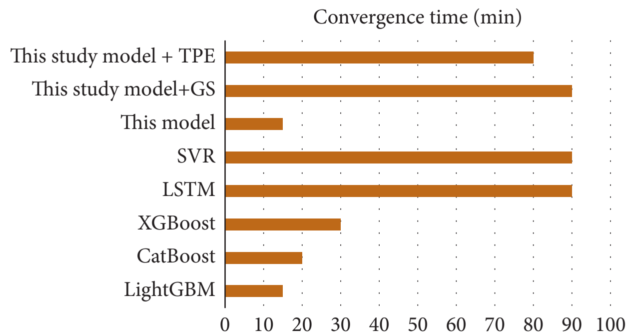

Figure 8: Convergence time comparison results.

Table 2: *R*-square validation of model generalization capability.

Meters	MSE	
	LightGBM	Proposed model
Cooling meters	0.2467	0.216
Steam meters	0.6171	0.606
Heat meters	0.5800	0.600

Table 3: Model generalization capability MSE validation.

Meters	*R*-square	
	LightGBM	Proposed model
Cooling meters	0.859	0.878
Steam meters	0.833	0.840
Heat meters	0.828	0.825

consumption prediction model were still used as the basis for parameter setting, and the TPE algorithm was not used for the superparameter search. The experimental results are shown in Tables 2 and 3. As seen in Tables 2 and 3, the performance of the model proposed in this study is close to or even better than that of the LightGBM algorithm.

It can be seen that the model proposed in this study has good generalization ability and is not only suitable for prediction of building electricity consumption but also can get good results when predicting energy consumption such as building cooling and heat.

5. Conclusion

With this research work, the building information system based on convolutional neural network is proposed to analyze building energy consumption of the four cycles-planning, design, construction, and operation-cum-maintenance. The key elements of building construction with the findings observed are summarized. Information integrity, significance, and correlation of the building information system are discussed. In the proposed model, regardless of the quantitative data and correlation rules, features are passed through the comprehensive database of the building information system after digitization and quantification. The building information system can simulate and predict the operation energy consumption in the visualized parameter environment and provide guidance for energy consumption management in the initial operation stage of different buildings. In short, the application of building information system is clearly and intuitively analyzed in terms of the building energy consumption of the whole building cycle and provides a basis for the development of scientific energy consumption management schemes. The efficient generalization ability of the proposed model suits it well in the designing of decision support tools and to improve building energy performance. With the advent of Big Data and Internet of Things, advance sensors and energy meters are required in buildings. In future, the method will be enhanced to support the futuristic sensors and meters so as to meet the requirements of the upcoming data processing systems.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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