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Research Article

Prediction of Building Energy Consumption Based on BP Neural Network

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In order to solve the energy consumption hypothesis of large buildings, the energy consumption hypothesis based on the BP neural network is proposed. First, to study the system of statistical index of building energy consumption and the system of statistical reporting of energy consumption of civil construction. In addition, to establish reliable consumer authority control to ensure the security and management of the database. Second, based on an analysis of the mechanism by which the BP neural network operates, this article optimizes it and describes the structure of the neural network, which includes the number of network layers, the number of neurons in each layer, and the number of latent neuron layers. hidden neuron layers and hidden neurons. The maximum value method is used to normalize the input sample data; finally, the learning and training process of neural network is determined. Based on BP neural network theory, the energy consumption statistics platform and prediction system are established by using Delphi 6.0. These include functional modules such as basic building information management, building energy consumption information management, building energy consumption summary, energy presampling information management, and building energy consumption forecast; the collection of building energy consumption data is mainly completed by intelligent energy consumption monitoring sensor network system. Finally, the city's building energy consumption information system conducts construction energy audits and analyzes the potential for energy savings. The results show that the hypothesis model determined by the BP neural network algorithm has an average error of 10.6% in predicting the construction energy consumption data, which is better than Matlab's predicted result and the mean error is 12.6%. From this, it can be seen that the BP neural network algorithm can provide better predictions of building energy consumption.

1. Introduction

Energy is the capital of human existence. As the world economy continues to grow, energy issues are becoming more acute in various countries, and energy conservation is a constant topic of discussion around the world. As one of the three largest consumers of social energy, energy consumption in the construction sector accounts for about one-third of society's total energy consumption and is expected to grow steadily. As China's economy grows and urbanization progresses, energy consumption is increasing day by day, and China's energy consumption is a very important part of the world [1]. Relevant data show that energy consumption in the construction sector still accounts for about 1/5 of total social energy consumption, which is significantly lower than in 30-40% of developed countries, but per capita heat consumption does not matter per building area. Energy consumption in construction is one of the most important strategies for the sustainable development of society, as energy consumption in the construction sector is a heavy burden limiting long-term rapid economic growth [2]. As an important index to judge whether the building has low energy consumption, whether the building energy consumption data is objective and comprehensive is very important to the realization of its energy-saving design. Therefore, to achieve real building energy conservation, we need to start from the actual energy consumption data, not simply pursue how many energy-saving technologies are used, but need to speak with data and scientifically evaluate building energy consumption. The main part of building energy consumption is the use of building energy, such as building heating, ventilation, air conditioning, lighting, household appliances, transportation, energy, cooking, water supply, drainage, and hot water supply. use. At present, China's construction energy consumption accounts for about a quarter of society's total energy consumption. iar reduction. Building energy efficiency is a difficult task, saving 1.1,100 million tons of standard coal energy and reducing emissions. Although China has adopted energy-saving design standards for residential and public buildings, and the energy-efficient work of new buildings has achieved remarkable results, the potential for high-energy construction remains huge [3, 4].

In addition to the influence of its own thermal parameters, the energy consumption level of buildings is closely related to the performance of equipment, operation mode, management level, and energy-saving quality of managers and users. The results of energy consumption statistics give us only a general understanding, and we need to audit the building energy consumption. Energy audit is a process of finding energy efficiency and energy-saving potential through building energy consumption statistics. Some studies have shown that building energy audit without cost or low cost can achieve 6%~30% energy-saving effect. Countries have been successful in establishing a database of energy consumption in construction and have successfully promoted the development of energy efficiency in construction, so China is conducting research to establish a database of energy consumption statistics and establishing energy consumption databases, an effective tool for sorting and analyzing building energy consumption. plays an important role. The building energy audit survey opens up the possibility of building energy savings, which lays the foundation for the implementation of building energy consumption quotas and the establishment of an energy consumption monitoring platform. Estimates of energy consumption of existing buildings can be used for comparative analysis and optimization of building energy consumption schemes for energy-efficient renovations, and can also be used in the design stage to guide whether the actual energy consumption of buildings can achieve the expected purpose after completion, which has important practical significance [5, 6]. Figure 1 shows a zero energy consumption building. This paper proposes a hypothesis of energy consumption in buildings based on the BP neural network. Based on the analysis of the mechanism of action of the BP neural network, optimize it and determine the number of network layers, the number of neurons in each layer, the number of latent neuron layers, and the structure of the neural network. hidden neuron layers and hidden neurons. the maximum value method is used to normalize the input sample data; finally, the learning and training process of neural network is determined. Based on BP neural network theory, using Delphi 6.0 establishes energy consumption statistics platform and prediction system. These include functional modules such as basic building information management, building energy consumption information management, building energy consumption summary, energy presampling information management, and building energy consumption forecast. Finally, the effectiveness of the information system in improving data processing speed, assisting building energy audit, and predicting building energy consumption by BP neural network algorithm is verified by experiments.

2. Related Works

The formulation of energy-saving policies and regulations lacks relevant data guidance; therefore, it is important to find effective models and methods to predict energy consumption. So far, researchers have proposed many effective methods; commonly used are regression analysis, wavelet analysis, and neural network [7]. Yu, W. and others in order to "systematically identify the realities of the process of building energy consumption, creating a heating environment, and saving energy," a study was conducted covering the northern heating zone and various buildings in the middle and lower parts. The Yangtze River aims to understand the relationship between the city's heating environment and building energy efficiency, and to improve energy consumption and building energy-saving policies and plans. This study provides data on energy consumption per unit area of the surveyed city, which provides a solid basis for the development of building energy-saving regulations and policies, and is the first large-scale study of building energy consumption [8]. Wang, Y. and others studied how to use artificial neural network to simulate complex building information system and realize the prediction of energy consumption [9]. Zou, X. and others used artificial neural network instead of time series method, combined artificial neural network and evolutionary algorithm to predict power consumption, and achieved good results [10]. Zhang, Y. and others used artificial neural network to analyze and train the lighting energy consumption of an office building for three consecutive months, and used the trained network to predict the lighting energy consumption of the building [11]. Tao, F. and others combined genetic algorithm and neural network algorithm to construct the prediction model of iron and steel enterprises. It is concluded that the composite model is better than the pure BP network in prediction accuracy and training speed [12]. Wang, W. and others proposed a method of building energy consumption prediction using improved gray model. Based on the traditional gray prediction, this method performs triangular transformation on the existing building energy consumption data [13]. Referring to the meteorological parameters of a city, Liu, C. Y. and others predicted the hourly cooling load of an office building for six consecutive months by using artificial neural network, and the results are very close to those calculated by dynamic simulation method [14]. Xu, H. and others constructed the domestic energy consumption prediction system of civil buildings in Chongqing by using the gray neural network system model, and obtained good results [15]. Deng, Z. and others investigated the current situation of building energy consumption of a large and medium-sized shopping mall, analyzed the characteristics and composition of energy consumption, compared it with the energy consumption of other regions, and analyzed and

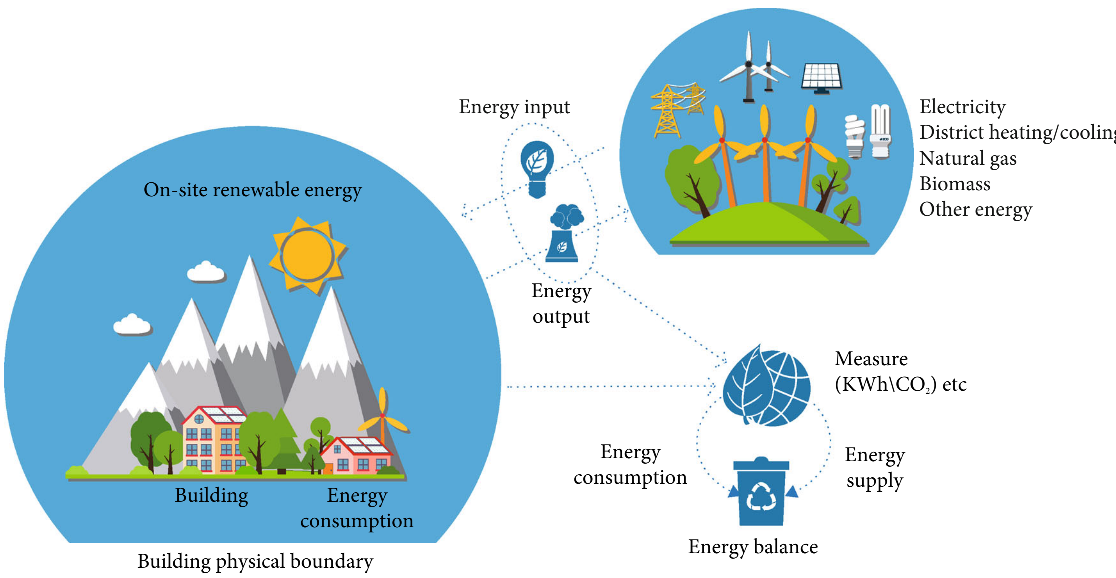

Figure 1: Zero energy consumption building.

evaluated the building energy consumption of shopping mall based on the survey data [16]. Zhang, L. and others building energy consumption database was established, using a spreadsheet to store basic building data and energy consumption data, and MATLAB's own toolbox to predict the energy consumption of buildings and units per building. There are clear differences in the accuracy of the predictions in the energy consumption parameters [17].

3. Research Methods

3.1. Building Energy Consumption Prediction Model

3.1.1. BP Neural Network. Artificial neuron simply and abstractly describes the information transmission process of biological neurons. It is the smallest unit for neural network to control and process information [18]. Many artificial neurons with simple functions are associated through the topological structure to form a neural network. The signal transmission between them realizes the information processing of the neural network, and the repeated correction and adjustment of the connection weight completes the training and learning process of the neural network [19]. Figure 2 shows the simple structure of an artificial neuron model.

It can be seen from Figure 2 that $x_1, x_2, \cdots, x_n$ corresponds to multiple input signals of artificial neurons, but there is only one output signal Y, so the corresponding relationship between $x_1, x_2, \cdots, x_n$ and y can be shown by formula (1):

$$\begin{cases} I = \sum_{j=1}^{n} w_j x_j + \theta \\ y = f(I) \end{cases}. \tag{1}$$

The signal transmission of artificial neurons is simulated by the input signal $x_j (j = 1, 2, \cdots, n)$, the synaptic weight w_j representing the connection strength between neurons, the internal threshold of WJ, the transfer function $f(x)$ simulating the transfer characteristics of biological neurons, and the output signal y. We can customize the transfer function as our desired function, such as log and e^x square root. We can also choose common transfer functions, such as linear transfer function, threshold function, and hyperbolic tangent function. Sometimes, for convenience of expression, $-\theta$ in equation (1) is also regarded as the weight of input x_0. x_0 is equal to 1. The sum of this style (1) can be expressed as equation (2):

$$I = \sum_{j=0}^{n} w_j x_j, \tag{2}$$

where $w_0 = -\theta, x_0 = 1$.

The BP neural network is currently the most widely used neural network, and the transmission function of BP neurons is a nonlinear function. By inserting a known training sample, the first layer calculates the output of each neuron backwards, then the last layer calculates the weight and threshold forward by entering the established network structure, the previous iteration weight, and the threshold. Thus changing the weight and threshold. This is repeated until it merges [20, 21]. The traditional BP algorithm is based on a gradient reduction method, and the merger rate is usually slow. The basic reasons are: the error surface is very flat or steep in the weight space, and the adjustment of the weight will be very small or large, resulting in little or excessive error adjustment effect; the adjustment of the weight of the gradient algorithm may point away from the wrong direction of the gradient algorithm. The main idea of back propagation network (BP network for short) is to transmit the signal forward and the error backward, so as to continuously adjust the weight and threshold of each layer of the network

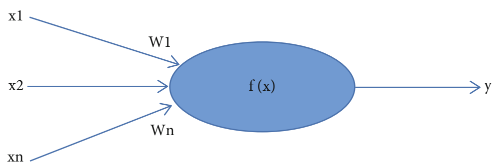

Figure 2: Neuron structure model.

[22]. BP network has the ability of global approximation, and the hidden layer is set so that it can arbitrarily approximate complex nonlinear problems. The BP neural network training process uses gradient search to reduce error step by step, and the transfer function selects a continuous derivative Sigmoid function as shown in Equation (3).

$$f(x) = \frac{1}{1 + \exp(-x)}. \quad (3)$$

If the characteristics of the identified model change in a positive and negative interval, the transfer function of the network can choose hyperbolic function, that is, symmetrical Sigmoid function, see equation (4):

$$f(x) = \text{than}(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)}. \quad (4)$$

3.1.2. BP Neural Network Prediction of Building Energy Consumption. There is a fine nonlinear relationship between energy consumption data and energy consumption impact factor information, which is difficult to be described intuitively and clearly. The neural network algorithm is able to find the hidden relationship between the parameters by studying and training the sample data without knowing in advance the relationship between the sample inputs and outputs, thus determining the mapping between the sample inputs and outputs.

The input vector of the network is equation (5):

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{18} \\ X_{21} & X_{22} & \cdots & X_{28} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \vdots & X_{n8} \end{bmatrix}. \quad (5)$$

The output vector of the network is equation (6):

$$Y[y_1, y_2, \cdots y_n]^T \quad (6)$$

Among them, X_{ij} represents each influence factor of building energy consumption, $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, 8$, a line represents a sample, and N represents the number of input samples.

A large number of studies show that in the process of network training, as long as there is a hidden layer, the network can approximate a function arbitrarily. In order to make the network structure as simple and compact as possible, the proposed building energy consumption forecasting model in this document is defined as a three-layer network structure with only one hidden layer. Therefore, the network topology of the building energy consumption training model is shown in Figure 3.

BP network model can be used not only for classification but also for linear approximation. When performing classification processing, the transfer function of the output layer generally selects binary type, such as Sigmoid function. The prediction of building energy consumption is to use the network model to approximately simulate the relationship between energy consumption influence factors and energy consumption values, which belongs to linear approximation. Therefore, the output layer transfer function chooses the linear function. In this paper, the Sigmoid function is selected as an intermediate layer transfer function, and the training strategy is a gradient reduction method [23].

The determination of the number of neurons in the hidden layer is a very important and difficult problem. So far, no scientific method has been found in theory. It is often determined by step-by-step experiments using empirical formulas. If the number of selected hidden layer nodes is too small, network prediction errors will increase, training time will increase, and it will not be possible to accurately represent the corresponding relationship between network inputs and outputs; if the number of hidden layer nodes is too large. There are many factors that affect the number of latent neurons, such as the number of neurons in the input layer, the number of neurons in the output layer, the nature of the data sample, the nature of the transmission functions, and the complexity of the problem to be solved. In this paper, formula (7) is used to select the optimal number of neurons in the latent layer by step-by-step trial and error.

$$b < \sqrt{(m + n)} + a. \quad (7)$$

Of these, a is the constant in the interval [0,10], m is the number of neurons in the input layer, the number of neurons in the output layer, and b is the number of neurons in the latent layer. In this paper,$m = 8$,$n = 1$, and see Table 1 for the results of trial and error.

The above trial and error results represent different network prediction errors caused by the number of neurons in the hidden layer being controlled within the range of [3, 13]. From the data in Table 1, it can be seen that the relative error rate of network prediction will show a trend of first decreasing and then increasing with the increase of the number of neurons in a general range of the number of neurons in the hidden layer. Therefore, the number of neurons in the hidden layer of this paper is determined to be 8 [24].

When selecting the learning rate η of the network, we should consider the stability of the training process. If the selected η is too small, the network training time will be prolonged, the convergence speed will be too slow, and η is too large. In the process of weight adjustment, the change of network connection weight will be too large. Sometimes, the weight may exceed the set error minimum and the algorithm will not converge. Therefore, in order to ensure the stability

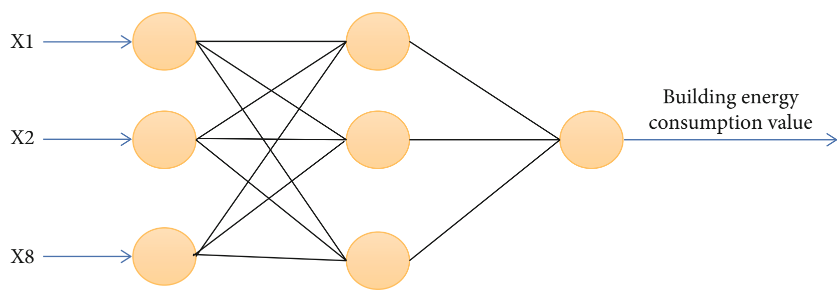

Figure 3: Schematic diagram of building energy consumption network model.

Table 1: The trial and error results that the number of neurons in the hidden layer is controlled within the range of [3, 13].

Number of neurons	Error%	Number of neurons	Error%
3	13.66	8	12.74
4	14.65	9	14.36
5	16.06	10	14.15
6	12.88	11	15.57
7	11.18	12	16.03
8	9.25	—	—

of the system, a smaller value is generally selected as the learning rate, which is usually controlled within the interval of [0.01,0.7]. η selected in this paper is 0.1. There is no rule to follow and no rule to determine the error value of the network. It can be set randomly and determined through continuous testing. In this paper, the maximum training time of the network is 1500, and the network training error target is 0.001. Figure 4 shows the network design training process defined by the building energy consumption sample data.

The following method is used for normalization. In order to avoid the occurrence of 0, a constant a is added to ensure the data volume of the input sample (Equation (8)).

$$y = (x - \min x + a)/(\max x - \min x + a). \tag{8}$$

Using the outputs of each node in the latent layer and the output of each nerve node in the output layer, Equations (9) and (10) are:

$$O_j = f\left(\sum_{i=1}^{n} \omega_{ij} x_i + \theta_j\right), \tag{9}$$

$$Y_k = f\left(\sum_{j=1}^{l} O_j \sigma_{jk} + d_k\right). \tag{10}$$

Using hidden layer error and output layer error, equation (11) is:

$$\delta_j = f'\left(\sum_{i=1}^{n} \omega_{ij} x_i + \theta_j\right) \cdot \sum_k \delta_k \omega_{jk} 及 \delta_k = (H_k - Y_k) \cdot f'\left(\sum_{j=1}^{l} O_j \omega_{jk} + d_k\right). \tag{11}$$

Always adjust the weight. If the global error of network training E is less than the initial minimum error target or the number of learning periods exceeds the initial maximum set R, the algorithm will stop and the algorithm will end [21].

3.2. Building Energy Consumption Statistics and Prediction System

3.2.1. Overall Objective of the System. The hierarchy of building energy consumption is shown in Figure 5:

The energy consumption of the envelope structure has been completed at the design stage. The energy consumption of the envelope structure will not change much after the construction is completed [25, 26]. The power consumption of the equipment will be determined by equipment parameters and equipment maintenance. During the operation of the equipment. Power consumption, system power consumption means the power consumption determined by the system error correction, automatic control, control system design and adjustment, control power consumption normal operation and maintenance. on buildings and consumer energy consumption behavior. Effective management and ways to implement energy consumption, which are determined by improving energy efficiency and improving energy efficiency. The system is divided into six functional modules, as follows:

(1) Comprehensive operation of basic building information, which can be searched according to one or more keywords in building number, building name, building age, and area, so as to carry out accurate retrieval and fuzzy retrieval; you can also enter, modify, and delete data

(2) Comprehensive retrieval of building energy consumption prediction sample data, retrieval according to building number, and data entry, modification, and deletion

(3) Dynamic statistics of building energy consumption data, dynamic statistics of building energy consumption information according to keywords such as month, year, region, and energy type, and produce real-time results. The data results are displayed in various histogram forms

(4) The comprehensive management of the sample data of building energy consumption prediction includes data entry, modification, and division according to

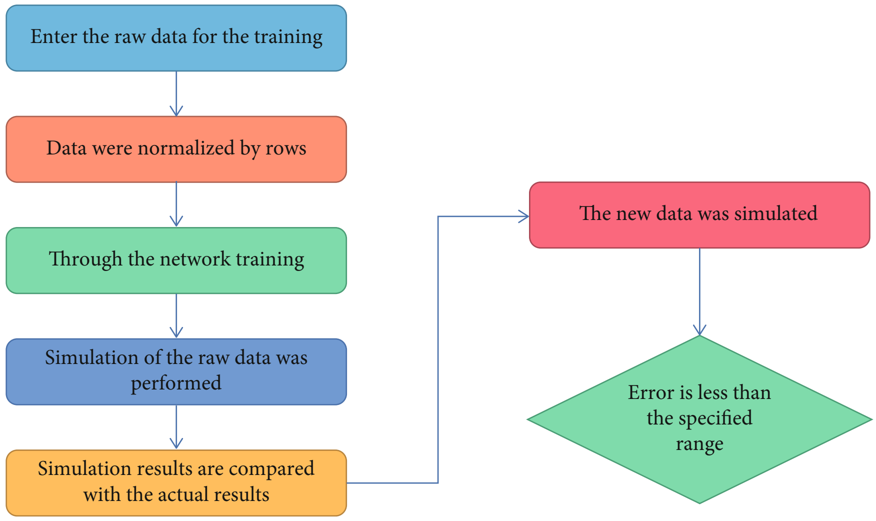

Figure 4: BP neural network flow chart.

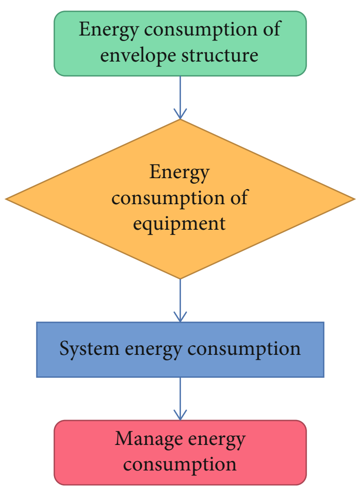

Figure 5: Hierarchy of building energy consumption.

the keyword retrieval. If necessary, it can be imported into the basic information data sheet of building energy consumption

(5) The prediction of future building energy consumption adopts the neural network algorithm. Through the existing energy consumption data in the database, the network can learn and train, find the general law to predict the future energy consumption trend, and provide basis and guidance for the analysis of energy-saving potential

(6) User management, the system creates users according to needs and saves them in the database. Every time a user logs in, they will be authenticated through the database; otherwise, they will not be able to enter the system. The system can dynamically manage user permissions

By using statistical software for historical energy consumption of buildings, it is possible to analyze the energy consumption of buildings in a timely manner, understand the situation of future energy consumption, and develop construction energy saving by forecasting future energy consumption.

3.2.2. Design Principles of Prediction System. This system is used by energy consumption statisticians to perform statistical analysis of data and perform energy consumption forecasts after receiving information in order to implement construction energy-saving work and guide energy consumption decisions in the next stage.

(1) *Accuracy*: the system ensures the accuracy and accuracy of data entry, statistics, and calculation and test results, and provides correct reference materials for relevant personnel

(2) *Reliability*: the system must execute specified functions and instructions without failure within a certain time and under certain conditions. Therefore, the system has been tested for a long time to ensure reliability

(3) *Security*: the information obtained from energy consumption statistics is related to the privacy of residents, companies, and enterprises. In addition, these data must provide an important basis for future scientific decision-making. The system must adopt effective security and confidentiality measures to control the access rights of data information, so as to ensure that the data will not be leaked and tampered with

(4) *Expandability*: the system function module should be expandable. With the change of demand, the system function can be expanded accordingly. The framework of building energy consumption statistical prediction system established in this paper is shown in Figure 6

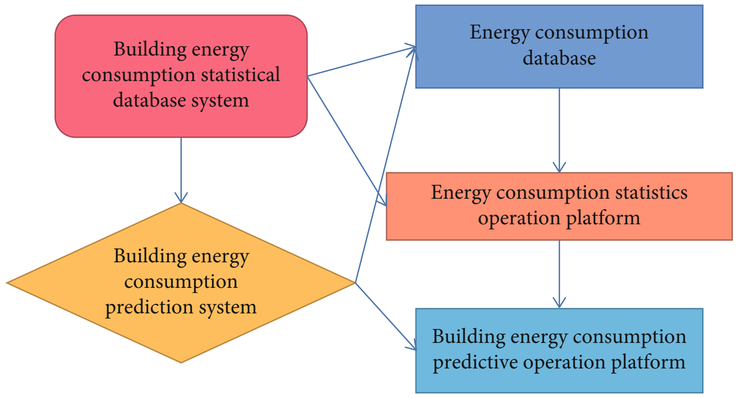

Figure 6: Schematic diagram of building energy consumption system framework.

Table 2: The expected input of forecast 1 adopts the sample data of the annual power consumption index of air conditioners and the forecast error.

	1	2	3	4	5	6	7	8	9
Average heat transfer coefficient of wall	1.51	1.51	1.51	1.54	1.55	1.51	1.51	1.51	1.62
Average thermal inertia index of wall	3.23	3.23	3.21	3.21	3.21	3.23	3.23	3.23	3.27
Roof heat transfer coefficient	0.65	0.65	0.7	0.65	0.65	0.65	0.65	0.65	0.63
Solar radiation absorption coefficient of exterior wall	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.64
Window shading coefficient	0.6	0.66	0.7	0.7	0.68	0.66	0.7	0.7	0.45
Comprehensive shading coefficient	0.7	0.68	0.7	0.7	0.68	0.68	0.67	0.7	0.46
Annual power consumption index of air conditioner	58.34	58.4	57.82	65.5	58.1	58.4	63.37	64.83	59.22
Estimate	58.05	58.80	58.14	63.60	58.30	58.81	64.81	64.67	57.15
Error (%)	0.70	0.36	0.28	3.03	0.01	0.38	0.68	1.41	3.10

Table 3: Using MATLAB to predict the second sample, the annual building energy consumption per unit area, and the predicted value.

	1	2	3	4	5	6	7	8	9
Average heat transfer coefficient of wall	1.51	1.51	1.51	1.53	1.55	1.51	1.51	1.51	1.62
Average thermal inertia index of wall	3.23	3.23	3.23	3.21	3.21	3.23	3.23	3.23	3.17
Roof heat transfer coefficient	0.65	0.65	0.70	0.65	0.65	0.65	0.65	0.65	0.63
Solar radiation absorption coefficient of exterior wall	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.64
Window shading coefficient	0.6	0.68	0.7	0.7	0.68	0.68	0.7	0.7	0.5
Comprehensive shading coefficient	0.7	0.68	0.7	0.7	0.68	0.68	0.67	0.7	0.0.46
Annual energy consumption per unit building area	8.45	11.30	11.32	11.62	8.51	6.67	10.80	9.58	10.73
Estimate	7.82	9.7	10.60	11.11	9.47	9.65	10.64	11.04	4.81

3.3. Metrics for Evaluating the Regression Model

3.3.1. Mean Squared Error. Mean square error (MSE) is defined as formula (11):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \in[0,+\infty). \tag{12}$$

3.3.2. Root Mean Square Error. Root mean square error (RMSE) is a typical indicator of the regression model, used to indicate how much error the model will produce in the prediction, with higher weight for larger errors, as shown in formula (13):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \in[0,+\infty), \tag{13}$$

where y is the actual value and $\hat{y}$ is the predicted value; the smaller the RMSE, the better.

4. Result Discussion

4.1. Prediction and Analysis Using MATLAB. The first mock exam is carried out in Matlab (the prediction model of

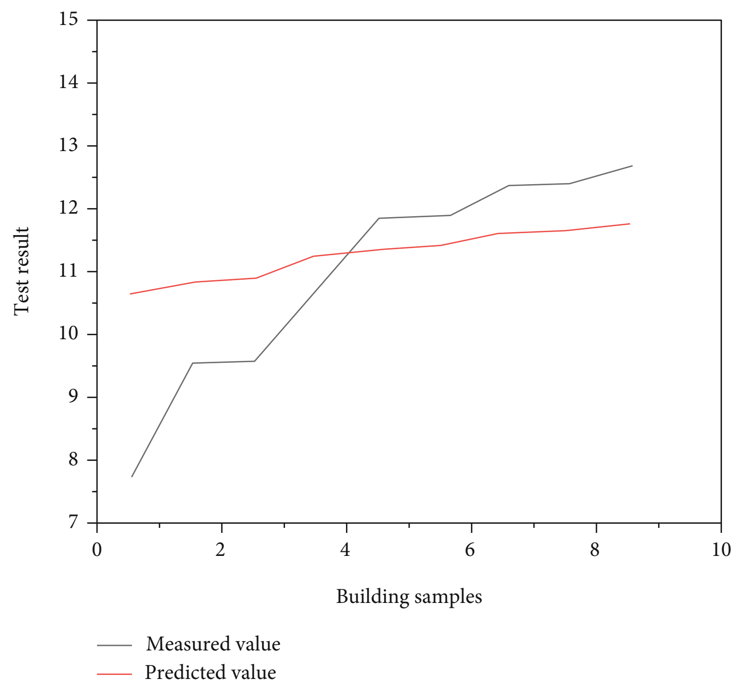

Figure 7: Broken line diagram of predicted value and measured value.

Matlab's self-contained neural network toolbox adopts BP neural network algorithm). The transmission function of neurons in the latent layer of the BP neural network and neurons in the output layer uses the tansig function and the logsig function. The training method adopts "momentum gradient descent back propagation algorithm," which has undergone inverse training), and the network structure and number of hidden neurons are determined. The first one is to use the consumption index of air conditioning year to be expected. The model is obtained by DeST simulation. This model adopts a standard model of residential energy consumption in the standard of energy-efficient design of apartment buildings with hot summers and warm winters, and uses the default values for other parameters. The expected input of prediction 2 adopts the measured value. The sample data and error values of each prediction are shown in Tables 2 and 3.

According to the table, the average error of prediction I is 1.70%. The closer the building parameter value is to the average value of all building parameters, the smaller the prediction error is. Also, if the number of neurons in the latent layer is 5, the error is minimal. The difference between predictions 2 and predictions 1 is based on envelope structural parameters that predict the actual energy consumption of a building. Due to the difficulty of obtaining accurate data on building energy consumption, the forecast includes 9 building samples. There are many human factors that affect energy consumption in predicting real energy consumption, which makes it difficult to predict, so it is necessary to improve the representation of the sample, increase the sample data, and cover it. Try to cover the entire variation range of each parameter. Prediction 2 is a preliminary study that predicts the actual energy consumption of a building based on building cladding parameters. When the number of neurons is 6, the prediction error is minimal.

Comparing the simulated value prediction with the actual value prediction, it is found that the error of predicting the annual energy consumption per unit building area is greater than that of the simulated value prediction, that is, the error of prediction 2 is greater than that of prediction 1. The prediction error of the number 6 of neurons in the optimal hidden layer of prediction 2 is 13.77%, and the prediction error of the prediction value 5 of the number of neurons in the optimal hidden layer of prediction 1 is 1.70%.

4.2. Building Energy Audit, Energy-Saving Potential Analysis, and Energy Consumption Forecast. The building samples in the prediction are 9 buildings, which are predicted by the prediction system in this paper. The prediction method is to use the data of the first eight buildings as the training samples to predict the ninth building, then add the data of the ninth building to the training sample set to replace the eighth building and predict the eighth building, then add the data of the eighth building into the sample set to replace the seventh building, and predict by analogy to obtain the sample and predicted value data table. Arrange the measured value and predicted value in the order from small to large, and then make a broken line diagram, as shown in Figure 7.

The following results can be obtained by analyzing the results:

(1) The test results are all within the range of the maximum and minimum values of the actual values

(2) The average error of the prediction results is 10.6%. According to the broken line chart of predicted value

and measured value, it can be found that the trend of predicted value and measured value is consistent. Although the error is relatively large, the predicted value reflects the change law of energy consumption index

(3) The variation range of the predicted value is obviously smaller than the measured value. In fact, it also proves from the opposite side that under the parameter bar of the sample data, the results of the measured value must be affected by other factors

(4) The magnitude of the error is inversely proportional to the mean of the expected values and is proportional to the difference between the maximum and minimum values of the expected values. The error is significantly higher than in the previous section. To explain this phenomenon, the error index W is defined here, which is determined by the difference between the maximum and minimum values of the desired value and the mean value. The value of the desired value. The formula is as follows (14):

$$W = (\max_{\text{desired value}} - \min_{\text{desired value}})/\text{ave}_{\text{desired value}}. \quad (14)$$

From the above, it can be seen that the higher the error index, the greater the error of the assumed value obtained, so the error of Assumption 3 is much greater than Assumption 1.

5. Conclusion

Energy consumption in the construction sector has always been high, and energy consumption in the construction sector is expected to increase rapidly due to the continuous development of the construction sector and the need to improve people's living conditions. It has become very important to work actively in the energy sector to save energy. It is important to analyze the energy consumption of existing buildings, dig, and create a model of energy consumption forecasts for new buildings to guide the energy consumption forecasts of new buildings during the architectural design phase. In this paper, a building energy consumption database is created by analyzing the building energy consumption statistical reporting system, the energy consumption statistical process, and the building energy consumption forecast index. The actual collection of building energy consumption data is generally completed by the intelligent energy consumption monitoring sensor network system, which can be entered into the database in real time. System prediction software uses neural network algorithms, i.e., neural network algorithms have achieved good results in many aspects of prediction. Using the hypothesis model established by the BP neural network algorithm, the mean error obtained from the hypotheses of the energy consumption data of a particular building is 10.6%, which is better than Matlab's predicted result, and the mean error is 12.6%. It can be seen that the BP neural network algorithm can achieve better results. It is a good result to predict the construction energy consumption. Firstly, the building energy consumption statistical index system and the civil building energy consumption statistical report system are researched, and a database is established based on SQL server 2000, including three major parts: building basic information, building energy consumption information, and building forecasting sample data. Secondly, on the basis of analyzing the working mechanism of BP neural network, this paper optimizes it and determines the neural network structure, including the number of network layers, the number of neurons in each layer, the number of hidden neuron layers, and the number of hidden neurons; the value method normalizes the input sample data and finally determines the learning and training process of the neural network. Finally, based on the statistical data of energy consumption in a city and the building energy consumption data in a city, the system conducts building energy audit and energy-saving potential analysis, and verifies that the information system can improve data processing speed and assist building energy audit and BP neural network algorithm to predict building energy consumption. This paper looks forward to:

(1) The advent of a software requires detailed and scientific testing by professionals. After the completion of the system, due to the limitation of conditions, the test work cannot be done in detail and comprehensively, and it needs to be improved continuously during the use process

(2) At present, the statistical investigation of building energy consumption has just started, and the use of energy consumption data is still in the exploratory stage. With the deepening of the research, the requirements for the functions of the building energy consumption statistical information management system will also increase. System functions need to be further improved.

(3) When BP neural network is used for prediction, if there are enough sample data, and the more comprehensive and accurate the data, the more accurate the prediction result will be. When verifying the prediction part of the system, there is a certain deviation in the prediction accuracy due to too little sample data. In future research, attention should be paid to obtaining better sample data

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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