Prediction Method for Energy Consumption of High-rise Buildings Based on Artificial Neural Network and Big Data Analysis

Wenbin Kuai*

ABSTRACT

In terms of the fact that the thermal load of high-rise buildings is affected by a series of influence factors, including outdoor meteorological environment, architectural characteristics, and building envelope, it is difficult to use the traditional mechanism to construct the prediction model because there are many difficult parameters and the reliability of the predicted result is low. Based on big data, the energy consumption of high-rise buildings is predicted by BP and RBF artificial neural network analysis methods because the artificial neural network does not rely on the model. The experimental result shows that the two models can well predict the energy consumption of high-rise buildings. What’s more, RBF artificial neural network is more stable than BP in prediction, so it is more suitable to predict the energy consumption of high-rise buildings.

Key Words: Artificial Neural Network, Energy Consumption of High-rise Buildings, Big Data, Prediction

Introduction

During the 11th Five-Year Plan period, energy conservation and emission reduction has been listed as an important task. During the 12th Five-Year Plan period, as China put forward green development to build an environment-friendly society, energy conservation and emission reduction has been promoted to a new height. In order to realize energy conservation and emission reduction effectively, we should not only actively develop clean energy (Gardner et al., 1998; Filho et al., 2006; Magrini et al., 2017; Sadaghiyani et al., 2018; Du et al., 2017; Bataineh and Taamneh, 2017; Carla and Giuseppe, 2017; Lodi et al., 2017; Wang et al., 2018), but conduct standardized management for use of energy (Miguélez et al., 2009). The energy consumption of high-rise buildings is high (Brahm et al., 2003). Therefore, if the mathematical model is used for accurate prediction and heating is provided according to actual needs, energy conservation and emission reduction will be effectively realized.

In recent years, scholars at home and abroad have conducted several prediction researches on thermal load of high-rise buildings, and established various models (Gorantla et al., 2018; Liu et al., 2018; Wang and Guo, 2017). For example, Kreider et al., (1991) and Bosch et al., (2009) introduced the neural network method in energy consumption prediction of air conditioning equipment. Bingdong et al., (Dong et al., 2005; Barabási et al., 2003) applied the support vector method to energy consumption prediction of buildings. Nielsen (Nielsen et al., 2006) used the grey box theory in the analysis of energy consumption of buildings in a certain region. However, these researches mainly perform static prediction based on outdoor environmental temperature (Gokmentayfur, 2002;
Abarghouei et al., 2013; Gen et al., 2012), but haven’t achieved systematic real-time monitoring (Whitney et al., 1996; Yetis et al., 2010; Hellmann et al., 2014). In view of the above problems, by taking a high-rise office building in northern China as the research object, this study puts forward the energy consumption prediction method of high-rise buildings based on artificial neural network, which can predict the time-point thermal load by inputting the outdoor meteorological data of present or future time point.

Artificial neural network

Artificial neural network method

In the artificial neural network method, the input and output sample data are input into the artificial neural network model, then the model grasps the hidden law among the input data by learning and training, and the new input sample is input to obtain the predicted data. The advantage of this model lies in relatively simple model that can deal with nonlinear problems with self-learning and adaptive capability, and strong applicability. However, this method also has obvious disadvantage. It is created by simulating the neural signal transmission principle of human brain and lacks theoretical guidance, so it often uses trial-and-error based on experience when determining the parameters of the model.

Artificial neural network model

The artificial neural network model is to simplify and simulate the human brain from the microcosmic structure and function with the ability of learning, associating, and memorizing. The neural network consists of a large number of neurons and nodes that are connected by connection signal. The change of the weight of connection signal makes the neural network have certain adaptive and memory capabilities.

The neuron model, a multi-input and single-output model, is the basic unit of neural network. Figure 1 shows a neuron model of an n-dimensional input, and its activation function and primary function are represented by \( f(\cdot) \) and \( u(\cdot) \) respectively. The primary function \( u(\cdot) \) is a multi-input function. The influence degree of the input on the neuron is expressed by the weight \( W_k \), where \( W_k=(w_{k1}, w_{k2}, \ldots, w_{kn}) \).

**BP and RBF neural network models**

**BP neural network model**

By making use of the opposite propagation direction of the signal and error, BP neural network makes the signal propagate in the forward direction and the error propagate in the back direction. The error reduces through layer-by-layer simulation and iteration so that the information is propagated more accurately. The input signal is processed by the neuron of the input layer and the hidden layer. If the processing result is ideal, the signal propagates forward. Otherwise, the signal propagates backward and returns according to the original path until the result is satisfying, as shown in Figure 2.

![Figure 1](image1.png)

**Figure 1.** The model of single neuron

![Figure 2](image2.png)

**Figure 2.** Training progress of backward propagation network

The processing process is actually a process of obtaining a minimum value. \( k \) represents the number of iterations, and the modifier formula of the weight and threshold is shown in formula (1):

\[
 x(k+1) = x(k) - a g(k) 
\]

(1)

Where, \( x(k) \) is the weight and threshold value vector between layers for the \( k_{th} \) iteration; \( a \) is a constant, indicating the learning rate; \( g(k) \) is the gradient vector of output error versus weight

Backward propagation of error

Forward propagation of information
and threshold value for the $k_{th}$ iteration; $E(k)$ is the total error function for the $k_{th}$ iteration, as shown in formula (2):

$$E(k) = E[e^2(k)] = \frac{1}{n^2} \sum_{j=1}^{n} \sum_{i=1}^{j} [e^2_j - a^2_j(K)]^2$$  

(2)

Where, $n$ is the input sample; $S^2$ is the number of neurons at the second layer; $w$ is the connection weight, and $b$ is the threshold value, as shown in formula (3):

$$a^2_j(K) = f^2 \left\{ \sum_{j=1}^{S^2} [w^2_{ij}(k)a^2_j(k) + b^2_j(k)] \right\}$$  

(3)

### RBF neural network model

The network structure of RBF is shown in Figure 3, where $x_1, x_2, x_3, x_4$ represents input data that has no change at the input layer after being input into the neural network. The hidden layer makes a simple linear change to the input data, and outputs it after linear weighting.

![Figure 3. The structure of RBF](image)

The hidden layer can be represented by formula (4):

$$F(x) = \sum_{i=1}^{N} w_i \psi(\|x - c_i\|)$$  

(4)

Where, $c$ is the center of the primary function, $PP$ is the norm and $w_i$ is weight. $\psi(\|x - c_i\|)$ is a set of primary functions usually in several forms as follows:

$$\psi(x - c_i) = e^{-\frac{\|x - c_i\|^2}{2\sigma_i^2}}$$  

(5)

$$\psi(x - c_i) = (x^2 + c_i^2)^{\frac{1}{2}}$$  

(6)

$$K(X) = e^{-x^2 \cos(1.75x)}$$  

(7)

Thus, the output function of RBF is:

$$y^q_q(x_q) = \sum_{i=1}^{n} w^q_i \psi^q_i(x_q) + b^q_i$$  

(8)

Where, $w_i$ is the of the weight of $i_{th}$ neuron of the hidden layer and the $q_{th}$ neuron of the output layer. The threshold value of $q$ is represented by $b_i$.

RBF neural network is usually trained by adjusting the parameters of hidden nodes to minimize the objective function. The objective error function of RBF can be expressed by formula (9):

$$E = \frac{1}{2} \sum_{j=1}^{N} e^2_j = \frac{1}{2} \sum_{j=1}^{N} [y_j - \sum_{i=1}^{S^2} w_i \psi_i(x_j)]^2$$  

(9)

When $E$ is the minimum, the training algorithm of $c_i$, $\sigma_i$ and $w_i$ is:

$$\nabla c_i = \frac{2w_i}{\sigma_i} \psi(x_i)(x - c_i)$$  

(10)

$$\nabla \sigma_i = \frac{2w_i}{\sigma_i} \psi(x_i) \|x - c_i\|^2$$  

(11)

$$\nabla w_i = \frac{\psi(x_i)}{\sum_{i=1}^{N} w_i \psi(x_j)}$$  

(12)

Then the following correction formulas are obtained:

$$c_i(n+1) = c_i(n) - \eta \frac{2w_i}{\sigma_i} \sum_{j=1}^{N} e_j \psi_i(x_j)(x_j - c_i)$$  

(13)

$$\sigma_i(n+1) = \sigma_i(n) - \eta \frac{w_i}{\sigma_i} \sum_{j=1}^{N} e_j \psi_i(x_j) \|x_j - c_i\|^2$$  

(14)

$$w_i(n+1) = w_i(n) - \frac{\eta}{2} \sum_{j=1}^{N} e_j \psi_i(x_j)$$  

(15)

$\psi_i(x_j)$ represents the input of the hidden node $i$ to $x_j$, $\eta_1$, $\eta_2$, and $\eta_3$ respectively represents the learning rate.

By using this algorithm, the primary function neural network can automatically update the center of the processing unit at the hidden layer and improve the performance of the radial direction and network while prolonging the training time and increasing the complexity of the network.
Energy consumption analysis of buildings
Different buildings have different energy consumption for their different building materials and purposes. This study selects a high-rise office building with a heating area of 4,000 square meters for energy consumption analysis.

Influence factors of energy consumption
The influence factors of energy consumption of buildings mainly include climate condition and time. Among climatic factors, temperature and humidity are the main factors affecting energy consumption. In the process of analysis and prediction, outdoor temperature, wind speed and sunshine are measured as input data. The time factor refers to the a small cycle in 24 hours and a middle cycle in a week of energy consumption caused by the way people work and rest. In addition, the influence factors affecting energy consumption also include opening window for ventilation and other random behaviors of independent users.

Prediction error
In the actual prediction process, there will be some errors between the predicted value and the actual value of the model due to the influence and limitation of various factors, including environment and human cognitive level. Generally, that a short-term prediction error of energy consumption is within 3% is acceptable. The mean square error is used as the index to evaluate error, as shown in formula (16):

\[ P_{MSE} = \frac{1}{N} \sum_{i=1}^{N} (L_i - \overline{L}_i)^2 \]  

(16)

Where N represents the number of data, \( L_i \) is the data value of \( i \)th data, and \( \overline{L}_i \) is the \( i \)th predicted value.

Artificial neural network training
Outdoor wind speed, sunshine, temperature and indoor temperature are taken as input data. In order to prevent individual data from overflowing during calculation, normalization processing is first carried out. Both BP and RBF are three-layer neural networks. The effective data of four days in December is input into BP and RBF neural networks for training. The learning rate of the two neural networks is 0.01, and the target value is 0.001. The comparison of training result and the actual load is shown in Figure 4.

![Figure 4. Curve of actual value and training value](image)

It can be seen from the figure that the thermal load obtained by the two neural network models is close to the actual value, and the coincidence degree is high, and RBF is closer to the actual value. The mean square error of BP and RBF neural networks is 1.56 and 0.38 respectively, and the average relative error is 0.080 and 0.0017 respectively (see Figure 5). Therefore, the accuracy of RBF model is higher.

BP artificial neural network iterates for 14 times while RBF iterates for 250 times. Thus, the training speed of BP artificial neural network is faster than that of RBF artificial neural network.

![Figure 5. The relative error curve](image)

![Figure 6. BP and RBF algorithm to optimize the weight of error change curve](image)
Prediction of BP artificial neural network
The data of the next four days in December is input into the trained BP model. The number of neurons at the hidden layer is 290, and the target value is 0.001. The predicted energy consumption and the actual energy consumption output by the BP neural network are shown in Figure 7. It can be seen from the figure that the basic trend of the predicted value and the actual value is the same, which can better predict the heating power. In particular, at night when the weather is stable, a good tracking prediction can be obtained.

In the prediction process, the BP model just iterates for five times to satisfy the error requirement, as shown in Figure 8. The absolute error curve is shown in Figure 9. The average absolute error is 0.85 w/m$^2$ and the mean square error is 15.8.

![Figure 7. BP prediction curve](image)

![Figure 8. BP algorithm to optimize the weight of error change curve](image)

![Figure 9. Absolute error curve of BP prediction](image)

Prediction of RBF artificial neural network
RBF artificial neural network is used to predict with the expansion constant being 0.32 and the target value being 0.005. The data of the next four days in December is input into RBF artificial neural network for prediction, as shown in Figure 10.

It can be seen from the figure that RBF neural network can predict the fluctuation law of sample value in wave crest and wave trough. In order to meet the requirement of prediction accuracy, it iterates for 24 times. The average absolute error is 0.80w/m$^2$ and the mean square error is 14.8, as shown in Figure 11 and Figure 12 respectively.

To sum up, BP and RBF artificial neural network models are adopted to predict the energy consumption of a high-rise building in northern China. It is found that the prediction method is feasible and effective, and the results are good. In addition, the prediction accuracy of RBF artificial neural network model is higher than that of BP artificial neural network model.

![Figure 10. RBF prediction curve](image)

![Figure 11. RBF algorithm to optimize the weight of error change curve](image)

![Figure 12. RBF absolute error curve](image)
Conclusions
The energy consumption of high-rise buildings in winter is influenced by many meteorological conditions and random factors, so the traditional prediction model cannot predict it accurately. Artificial neural network simulates the processing process of information by human brain neurons, and forms error backward propagation and radial basis neural network. BP and RBF artificial neural networks are used to establish two kinds of prediction models for high-rise buildings. The results show that:

(1) Both algorithms can predict the heating load very well with relatively high prediction accuracy. The BP model just iterates for five times to satisfy the error requirement. The mean absolute error is 0.85w/m² and the mean square error is 15.8. RBF neural network can predict the fluctuation law of sample value in wave crest and wave trough by iterating for 24 times. Its average absolute error is 0.80w/m², and the mean square error is 14.8.

(2) From the comparison of the output result of the two prediction models, it is found that prediction accuracy of RBF artificial neural network model is higher than that of BP artificial neural network model.

Acknowledgements
Key Projects of Natural Science Research of West Anhui University in 2018: Study on Intelligent Urban Planning Based on Large Data Type and Its Application – A Case Study of Hexi New Town in Liu’an City (No.: WXZR201813); Provincial Quality Engineering Project in 2017: Teaching Reform and Practice of Architectural Design Courses in Local Application-oriented Universities from the Perspective of Innovation and Entrepreneurship (No.: 2017jyxm0375).

References

Sadaghiyani OK, Boubakran MS, Hassanazadeh A. Energy and exergy analysis of parabolic trough collectors,