Journal of Computers Vol. 28, No. 6, 2017, pp. 257-268
doi:10.3966/199115992017122806023

Study of an Algorithm to Predict Future Building Cooling Load With Neural Networks

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Received 24 July 2017; Revised 19 September 2017; Accepted 19 October 2017

Abstract. The accurate cooling load prediction of an air conditioning system is the basis for energy saving optimization. To solve the problems of low accuracy of prediction, and most load predictions focusing on short-time prediction that causes reducing the practical significance, the application of improved BP neural networks prediction model is presented in this paper. Training and testing data for prediction model have been generated from DeST (Designer's Simulation Toolkits) with climate data of Beijing. The generalization ability of the model has been strongest based on Bayesian regularization algorithm to train data. A case study shows that high accuracy is achieved by using the BPNN prediction model based on Bayesian regularization method with the prediction error of 1.18% in predicting the building load for longer time.

Keywords: air-conditioning system, Bayesian regularization algorithm, BP Neural Networks, load prediction

1 Introduction

The energy consumed by heating, ventilation, and air-conditioning (HVAC) systems accounts for about 50% of the total energy in commercial buildings [1]. And the contradiction of grid electricity supply is that the electricity supply is insufficient in daytime and superfluous in night [2]. Therefore, it is necessary to reduce HVAC energy consumption. Predicting the load in a building is essential for optimal control of HVAC systems.

As a non-stationary random process affected by lots of factors, building cooling load calculation through mathematical approach is too complex and time-consuming. Precise consumption prediction is a tough problem due to its complexity. Therefore different prediction algorithm and criteria of load prediction should be selected to different running condition of air conditioning system in the actual project. Otherwise you might not achieve the desired prediction effect. The prediction algorithms include Regression Analysis (RA), Time Series Analysis Method, Support vector machine (SVM), and artificial neural network (ANN). In recent years, a number of approaches to load prediction have been proposed and applied. Tian, Qian, Gu, Yang and Liu [3] developed ANN model for EVACS performances prediction which based on experimental data. De Grande [4] applied the time series method to load prediction. Xu, Li and Wang [5] predicted traffic volume based on the autoregressive integrated moving average (ARIMA) model. Chiaa, Leeb, Shafiabadya and Isaa [6] used SVMs to predict the hourly cooling load of an office building.

Though there are various prediction models mentioned above, few of them has performed well enough because each method can take just several or usually only one relevant factor into consideration. For example, the time series method often considers only short-term load prediction, and it will have large deviation when considering the long-term load prediction. Accurately predicting the building cooling load is a challenging work. Cooling load in the building is affected by many factors. For an accurate prediction model, it is important to understand which factors influence the load level most. Compared with other algorithms, the artificial neural network algorithm can avoid onerous model building process and complicated computing process. Back-propagation (BP) Neural network modeling is now recognized as a more accurate modeling method, because that it is able to capture the related linear and nonlinear relationship between the predicted variables with its influence factors.

As a nonlinear mapping tool for system modeling and prediction, the BP neural network has been successfully applied to a number of real-world input-output modeling problems. But the standard BP neural network algorithm has some defects. In this paper, BP neural network based on Bayesian regularization algorithm is applied to predict the building cooling load in HVAC system with data generated from DeST, an excellent building environment simulation software with its simulation accuracy been tested by many users. Training data for prediction model by Bayesian regularization algorithm have enhanced the generalization ability.

2 BP Neural Networks

Neural network has ability to approximate any function, including non-linear functions. Artificial neural networks are being applied in many fields of science and engineering. Despite their wide range of applications and flexibility, there is still no general framework or procedure through which the appropriate neural network for a specific task can be designed. The design of neural networks is still considerably dependent upon the designer's experience. Specially, after the BP algorithm was put forth, neural networks have found more successful applications in diverse fields such as modeling, time series analysis, pattern recognition, signal processing, and information extraction. The forecast system based on the neural networks is initially set up and the applied example is put forth in the light of the problem of weather forecast [7]. The BP neural network is usually constituted by an input layer, an output layer and a number of hidden layers. Each layer has some nodes, and each node is a neuron.

2.1 The Selection of Input Parameters

Meteorological parameters and indoor heat disturbance are the most important factors affecting the cooling load of completed buildings (For completed buildings, transfer coefficients of all building envelop are settled down). The random indoor heat dissipation and outdoor climate influences on building cooling load are considered in the load prediction model, thus they are chosen as the inputs of the model of the next hour as the output. Generally speaking, the more input parameters, the stronger nonlinear mapping ability of neural network and less prediction error. But this will make computer solving time greatly extend and make the control system become more complex. The most important is that a lot of influence factors cannot be got because they cannot be directly measured and recorded in the practical engineering application.

The principle of input parameter selection should avoid those little correlations between prediction and parameter, and at the same time keep those a lot of correlation between prediction and parameters. In this paper, input parameters of prediction model are selected by using Principal Component Analysis (PCA) method which accords to the research of the related literature and actual data. Parameters selected after data analysis are including: outdoor temperature, outdoor relative humidity, solar radiation intensity, wind speed, wind direction, the indoor load (personnel and equipment).

PCA [8] uses a feature matrix to make the patterns to be projected into a new space which makes patterns being projected from a high- dimensional space into a low-dimensional space. The steps of PCA can be summarized as follows. (1) Computing the scatter matrix of patterns. (2) Computing the feature values and feature vectors. (3) Sorting feature values from large to small. (4) Choose more than 85% of the principal components and make the corresponding feature vectors as a projection matrix. (5) Using the projection matrix to map the patterns in the original space into a new space and the space dimension is based on the size of the corresponding feature vectors in this projection matrix.

There are many factors that affect the load of the air conditioning systems. The influencing factors are divided into internal disturbance and external disturbance of the air conditioning area. From the theoretical level, any factors that affect the formation of air conditioning system load can be used as input parameters of neural network prediction model. Generally speaking, the increase of input parameters can increase the nonlinear mapping ability of neural network, and getting the higher prediction accuracy, smaller prediction error. But this will also produce many drawbacks, such as computer solution time will be greatly extended, and the control system will become more complex and make the owners of the initial capital investment increased significantly. Most importantly, in practical engineering applications, many influencing factors can not be measured and recorded directly.

The most important parameters affecting the load are the outdoor weather parameters, the utilize of the indoor space and the opening of the equipment. The selection of input parameters plays a key role in the neural network modeling process. For the air conditioning system load prediction, the potential input parameters include the following parameters: outdoor air pressure; outdoor air density; wind speed, wind direction; solar radiation intensity; indoor staff and equipment load (outdoor temperature); outdoor temperature.

The principle of input parameter selection is to remove the parameters with less predictive correlation and to retain the parameters that are highly correlated with the prediction. This paper adopts the PCA method to select the input parameters of the prediction model by repeated experiments. After data analysis, the potential input parameters have been reduced to the following parameters: outdoor temperature; outdoor relative humidity; solar radiation intensity; wind speed, wind direction; indoor load (personnel and equipment).

Outdoor temperature is the primary determinant of air conditioning system load, which is positively correlated with air conditioning system load. At the same time the relative humidity is also one of the major external disturbances affecting air conditioning load, which shows the change of latent heat. Therefore, both are used as input parameters.

Solar radiation is the main reason for the rise of outdoor air temperature, its impact on air conditioning load is relatively large. So choosing the solar radiation intensity as one of the input parameters.

The influencing factors of air conditioning system load also include wind speed and wind direction. In practical engineering applications, the direction of the wind is often expressed in sixteen orientations. Wind direction is a parameter that can not be described by specific data. Considering the wind direction data obtained in the practical engineering application, this paper uses the projection technique to project the obtained wind direction data to the east and north respectively. The wind speed (northward) and wind speed (eastward) obtained by the projection technique are used as the two input parameters of the load forecasting neural network model.

In addition to the above meteorological parameters, the internal disturbance occupies a large proportion in the air conditioning load, so it is considered as one of the input parameters of the neural network.

In summary, this paper based on the neural network load forecasting model has the following six input signals: outdoor temperature T_{out} *(k)*; outdoor relative humidity RH_{out} *(k)*; solar radiation intensity *i (k)*; outdoor wind speed (north) $S_{nort}h$ *(k)*; outdoor wind speed (east) S_{east} *(k)*; indoor load (personnel and electrical Device) Q_{in} (*k*).

2.2 Neural Networks Structure

Based on Kolmogorov's theorem [9], a limited number of hidden layer is enough to solve the problem of nonlinear and hysteresis. Three-layer neural network can approximate any nonlinear function, thus this paper set up only one hidden layer for the load prediction model. In this paper with related empirical formulas (1) and (2) [10] for reference, the number of neurons in hidden layer are mainly decided by trial and error experiment and test relative prediction error

$$k < \sum_{i=0}^{n} C_N^i \tag{1}$$

$$m = \sqrt{n+l} + \alpha \tag{2}$$

Where n is input layer nodes, l is output layer nodes, m is the number of hidden layer nodes, k is training sample number, and α is trial and error constant which scope is [1~10]. Using relevant empirical formulas (1) and (2) can calculate that the number of hidden layer nodes scope is [4~14].

In this paper, the performance evaluation index is adopted by the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{l=1}^{N}\left(\frac{q_l - \hat{q}_l}{\hat{q}_l}\right)^2} \times 100\% \tag{3}$$

Where N is the total number of samples, predictive value of $\hat{q}_l$ is q_l.

In order to determine the optimal number of neurons in hidden layer, it is necessary to compare the experimental trial and error. The network to achieve the best results that considering the network error and network generalization performance when the number of hidden layer nodes is 12. The experimental comparison results as shown in Table 1.

Table 1. Page margins

Hidden layer (neurons number)	RMSE
8	0.0131
9	0.0147
10	0.0132
11	0.0150
12	0.0118
13	0.0145
14	0.0148

2.3 Weight of the Network

It has been always one of the difficult research topics of the network on how to obtain effective information from BP neural network model. To a certain extent, the performance of optimal training model reflects the complex non-linear relationships between input variables and output variable, which can be explained through network weight and bias information. When output layer only involves one neurode, the influences of Input variables on output variable are directly presented in the influences of input parameters on the network. Simultaneously, in case of the connection along the paths from the input layer to the hidden layer and along the paths from the hidden layer to the output layer, it is attempted to study how input variables react to the hidden layer, which can be considered as the impacts of input variables on output variable.

According to Lee, Huang, Dickman and Jayawardena [11], the relative importance of individual variable between input variables and output variable can be expressed as:

$$I = \frac{\sum_{i=1}^{H} ABS\left(w_{ji}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{H} ABS\left(w_{ji}\right)} \tag{4}$$

Where w_{ji} is the connection weight from i neurode in the input layer to j neurode in the hidden layer, ABS is an absolute function, N, H are the number of input variables and neurodes in the hidden layer, respectively.

2.4 Topology of BP Neural Network

The output of the load prediction model is the next moment area load Q(k+1). This paper established a neural network load prediction model with 3 layer including 6 input layer nodes, 12 hidden layer nodes and 1output layer node. The network topology is shown in Fig. 1.

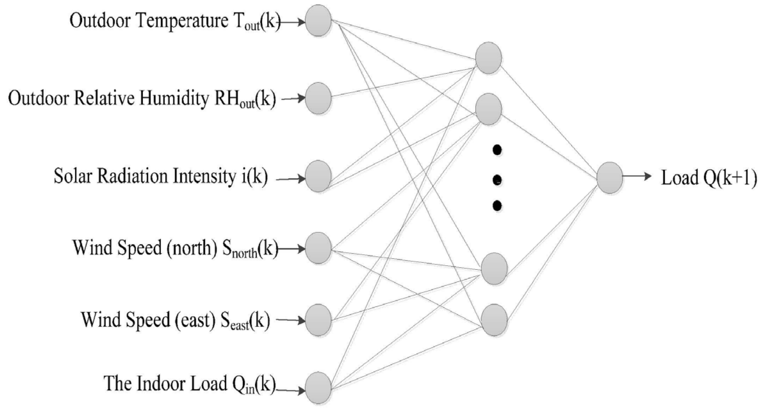

Fig. 1. Topology of the three layer neural network for load prediction

3 Sample Data Acquisition and Preprocessing

3.1 Sample Data Acquisition

The whole cooling period is from 1st June to 30th September (2928 hours). Take the dataset of July and August (1488 hours) as training data, the testing (320 hours) and validation data (320 hours) are generated from the rest months randomly. Sampling interval is 10 minutes. In order to win state-output nonlinear relation in the sample data, using the training dataset to train the neural network, and saving the data in the form of weights and thresholds. Validation dataset is necessary which is used to prevent excessive training (fitting), and test dataset of a group of independent data used for testing purposes.

3.2 Sample Data Preprocessing

Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and/or lacking in certain behaviors or trends, and is likely to contain many errors. Data preprocessing is a proven method of resolving such issues. Data preprocessing prepares raw data for further processing.

In this paper, using the measured data in the study of load prediction algorithm. There may be some error data or large deviation data because of many factors such as volatility of acquisition instrument. These abnormal data does not express the running status of air conditioning system, so must use technical means to get rid of them. For the air conditioning system, the acquisition of data must be kicked out when presenting one of the following two situations: one is that data present large mutation compared with other data on similar moment. The other is that the curve shape or peak time of data operation parameters has big deviation which date is adjacent.

3.3 Normalization

Cooling load in the building is affected by many factors which are measured by different units and have big differences of data value. If using those data to train prediction model, training time will be significantly longer, and even appears the situation that training cannot final convergence. Therefore the inputs of BP neural network should be normalized to improve modeling efficiency. In this study, all inputs would be mapped to [0,1] with normalizing function as:

$$x_i = \frac{\left(x_{di} - x_{d\min}\right)}{\left(x_{d\max} - x_{d\min}\right)} \tag{5}$$

$$t_i = \frac{\left(y_{di} - y_{d\min}\right)}{\left(y_{d\max} - y_{d\min}\right)} \tag{6}$$

Where x_i is input value that after normalized, x_{di} is original input value, t_i is the normalized target value, and y_{di} is the original target value.

After the normalization processing, the data's value range between 0 and 1. Using these data as the input of the neural network model will get the corresponding output data between 0 and 1. These data cannot express physical meaning, therefore, it is necessary to denormalize the output data in order to restore the real physical significance. After the normalization processing data as follow:

$$y_{pi} = y_{d\min} + o_i \left(y_{d\max} - y_{d\min} \right) \tag{7}$$

Where y_{pi} is the reduced value of the predicted output, and o_i is the predicted output value.

4 Model Training

4.1 Improved Algorithm

After the model structure been settled down, the next work is to get the training and testing data. The BP neural network algorithm, which successfully complements the learning of the feed forward networks, is widely used. However the standard BP neural network algorithm has some inherent defects [12], and there are still some problems difficult to solve. These problems are usually related to the structure and algorithm, and they will become worse while dealing with some large practical tasks.

First, the generalization ability of neural network is relatively not good. These phenomena may occur in most supervised learning algorithms. In practical use, it was found that a trained neural network using supervised learning algorithm including Back-propagation algorithm can reach very high accurate rate. However, it is difficult that the training set covers all possible types of exemplars. And the generalization ability of an over-trained Back-propagation neural network usually may fall down.

Second, introducing the nonlinear activation function to the multilayer neural network makes the error surfaces very complex and quite harsh. It suggests that there are many local minimum points in these surfaces. The Back-propagation algorithm based on a gradient search is likely to sink in local minimum and thus may not yield the exact mapping.

The common shortcomings of the main relevant literature can be summarized as follows: (1) It can not ensure global optimization and overfitting problem when using BPNN to predict load of the air conditioning system. (2) Most of the work did not based on the optimal choice of the input variables of BPNN. It possibly results in the duplicate impacts of the duplicated inputs on the outputs. (3)The issue of evaluating neural network performance goes far beyond assessing the ability of the network to generalize to a validation or testing data set.

Because of shortcomings of the BP network, the researchers put forward many improved algorithm. Improved algorithm and its corresponding MATLAB training function is shown in Table 2.

Table 2. Algorithm and its corresponding training function

Algorithm description	The training function	Algorithm description	The training function	Algorithm description
The steepest decline in BP algorithm	traingd	Quasi-newton algorithm	BFGS algorithm	trainbfg
Momentum BP algorithm	traingdm		OSS algorithm	trainoss
Vector variable BP algorithm	traingx	Variable gradient algorithm	Fltcher-Reeves correction algorithm	traingf
Resilient BP algorithm	trainrp		Polak-Ribiere correction algorithm	traincgp
L-M algorithm	trainlm		Powell-Beale reset algorithm	traincgb
Bayesian regularization algorithm	trainbr		SCG algorithm	trainscg
Algorithm description	The training function	Algorithm description	The training function	Algorithm description

In this paper, we used the Bayesian regularization BP neural network (BRBPNN) to predict the load of air conditioning system. The advantage of this model is that it can automatically select the regularization parameters and integrate the characteristics of high convergent rate of traditional BPNN and prior information of Bayesian statistics.

4.2 Genralization

The theoretical foundation by applying BP neural networks to identify the object model is to find out the implicitly mapping relationship between input and output in the limited sample data. This can reach the function of generalization [13] which can get appropriate output data from untrained input data. The so-called generalization rate, which is one of the most important indexes of target recognition system, means the recognition accurate rate to the new unlearned exemplars after the neural network learned a definite number of training exemplars.

The generalization ability of neural network is relatively not good. These phenomena may occur in most supervised learning algorithms. An overfitting phenomenon exists in the BP network. The overfitting means that as long as the network is allowed to be sufficiently complicated, the BP network can minimize the error of the training sample set. However, in the case of a limited number of samples, the generalization ability of the network will decrease. This indicates that there is a relation between the learning ability and the generalization ability. When using BP neural network model in specific application which kind of algorithm to be chosen to train neural networks is worth discussing. Generally speaking, compared with other algorithms, using the L-M algorithm to train the neural network means the smaller square error (MSE) and the fastest convergence speed [14]. But the generalization ability of the network will be strongest when using the Bayesian regularization algorithm to train neural network. Bayesian regularization algorithm is a useful method for improving generalization of neural networks. This algorithm was firstly presented by Mackay [15] and then applied to Levenberg-Marquardt training algorithm by Foresee and Hagan [16].

Under the same conditions, this paper use different training function to train the neural network. Results show that using trainbr training function can get better fitting effect and generalization ability that compared with other algorithm function.

4.3 Theory of Bayesian Neural Network

In this paper, the regularization method can be used to improve generalization ability of the network and the training objective function F is denoted as:

$$F = \alpha E_W + \beta E_D \quad \textbf{(8)}$$

$$P(\alpha, \beta \mid D, M) = \frac{P(D \mid \alpha, \beta, M) P(\alpha, \beta \mid M)}{P(D \mid M)} \quad \textbf{(9)}$$

Where E_W is the square sum of weight of the network, E_D is the square sum of residual between network response values and objective values, α and β are the parameters of objective function (regularization parameter), whose values demonstrate that the emphasis of the network training depends on the decrease of output residual or the network volume. It is well known that the crux of regularization method is how to select and optimize the parameters of objective functions through Bayesian statistics.

According to Bayesian rule, if α and β are assumed to satisfy uniform distribution, then when the likelihood of $P(D \mid \alpha, \beta, M)$ is maximized, the probability of posterior distribution of α and β in (9) will be up to the maximal value. Assuming the residual and the weight are stochastic variables and based on the Bayesian rule, (10) is obtained:

$$P(w \mid D, \alpha, \beta, M) = \frac{P(D \mid w, \beta, M) P(w \mid \alpha, M)}{P(D \mid \alpha, \beta, M)} \quad \textbf{(10)}$$

Where w is the weight of the network. Supposing the residual and the weight accord with Gaussian distribution, then

$$P\left(D \mid w,\beta,M\right)=\frac{\exp\left(-\beta E_D\right)}{Z_D\left(\beta\right)}$$
$$P\left(w \mid \alpha,\right)M=\frac{\exp\left(-\alpha E_W\right)}{Z_W\left(\alpha\right)} \tag{11}$$

To ensure that $P\left(D \mid \alpha,\beta,M\right)$ becomes regularization factor of (10), and (12) can be denoted:

$$P\left(w \mid D,\alpha,w\beta,M\right)=\frac{\exp\left(-F\left(w\right)\right)}{Z_F\left(\alpha,\beta\right)} \tag{12}$$

If (11) and (12) are taken into (10), so (13) is achieved as follows.

$$P\left(D \mid \alpha,\beta,M\right)=\frac{Z_F\left(\alpha,\beta\right)}{Z_W\left(\alpha\right)Z_D\left(\beta\right)}$$
$$Z_F\left(\alpha,\beta\right)=\left(2\pi\right)^{N/2}\det\left(H\right)\exp\left(-F\left(w^{MP}\right)\right) \tag{13}$$
$$Z_W\left(\alpha\right)=\left(\pi/\alpha\right)^{N/2},Z_D\left(\beta\right)=\left(\pi/\beta\right)^{n/2}$$

$$H=\beta\Delta^2 E_D+\alpha\Delta^2 E_W \tag{14}$$

Where $Z_F\left(\alpha,\beta\right)$ is Hessian matrix of the objective function (F). When logarithm method and derivation method are respectively applied to (13), and supposing differentiation equation is equal to 0, then $P\left(\alpha,\beta \mid D,M\right)$ is maximized and posterior probability of weight is minimized. At this moment, the formulas of α and β are expressed: $\alpha^{MP}=\frac{\gamma}{2E_W\left(w^{MP}\right)}$, $\beta^{MP}=\frac{n-\gamma}{2E_D\left(w^{MP}\right)}$,

$$\gamma=N-\alpha^{MP}trace^{-1}\left(H^{MP}\right) \tag{15}$$

Where n is the number of sample set, N is the total amount of network parameters, γ is the number of effective parameters, which relatively have more impacts on the reduction of error function. Initially assuming α and β according with Levenberg-Marquardt algorithm, the minimal value of $F\left(w\right)$ can be obtained by iterative training of BRBPNN. Updating α and β based on (15), then obtain the optimal value of posterior distribution, search the minimal value of the new $F\left(w\right)$, and finally train iteratively until convergence.

4.4 ANN Model Parameters Setting

The topology structure and parameters setting of air conditioning system load prediction model based on neural network were shown in Table 3.

Table 3. The neural network topology and parameters setting of the load prediction mode

Neural network type	Single hidden layer BP network
Input layer node number	6
Output layer node number	1
Hidden layer node number	12
Transfer function of neurons	‘logsig’,‘purelin’ (excitation function)
Learning function	‘learngd’ (weights/threshold of gradient descent)
Neural network type	Single hidden layer BP network
Input layer node number	6

5 Load Prediction Using the Neural Network Model

An office building located in Beijing, China is selected randomly to justify the feasibility that based on BP neural network to establish the building cooling load prediction model. The total building area is 14,9570m^2, among which the ground area is 118390m^2, the underground area is 31180m^2. Building shape coefficient is 0.15 and office number around 800. The object shows in Fig. 2.

Fig. 2. The object

The building's refrigeration station system consists of the following design: Water chiller adopt two centrifugal water chillers of 1458 kw; Chilled water pump adopts two centrifugal pump power of 18.5 kW; Cooling water pump adopts two power of 15 kw centrifugal pumps; Cooling tower adopts two square cooling tower of 5.5 kW. The device information is shown in Table 4. The whole cooling period is from 1st June to 30th September and its sample interval is 10 minutes. The purpose is using the constructed BP neural network load prediction model to forecast the future load in 1 day.

Table 4. The identification results

Equipment serial number	Equipment name	Equipment parameters	Equipment sets
1	centrifugal water chillers	refrigerating capacity of 1458 kw, power of 334 kW	2
2	centrifugal chilled water pumps	Power of 18.5 kw, flow rate of 316 m3/h, head of 38 m	2
3	centrifugal cooling water pump	Power of 15 kw, flow rate of 353 m3/h, head of 32 m	2
4	square cooling tower	air volume of 11500 m3/h, Power of 5.5 kw	2

The air conditioning load prediction test is in MATLAB environment based on model parameters setting in Table 3, and parameters corresponding change situation in the process of testing is shown in Fig. 3. Where gradient parametric curves expressed the error of surface gradient change in test process. Parameter *mu* is a select variable, its different value represents different ways of learning, namely Newton learning method and gradient learning method. At the same time, the parameter *mu* is a judgment variable. The training process is stopped when *mu* is bigger then $mu\_\max$ which decided by set value of $mu\_\max$.

The linear regression about the network output and the corresponding expected output is shown in Fig. 4. Figure shows, there has the high value of linear correlation R between the model output and the corresponding target output which is 0.9646, therefore the conclusion that the forecast effect is good because model output can track well corresponding to the target output and the model is better fitting the nonlinear relationship between the air conditioning system load and its related influencing factors can be inferred.

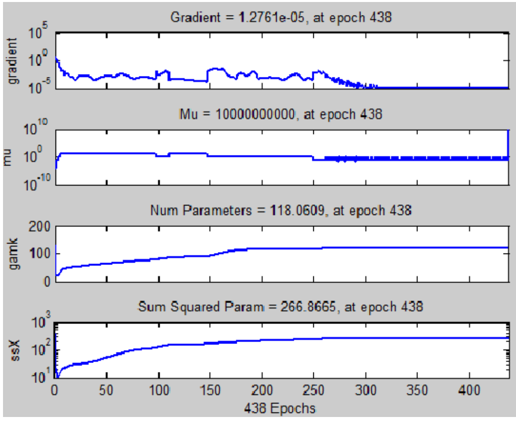

Fig. 3. The changing process of each parameter in the network training stage

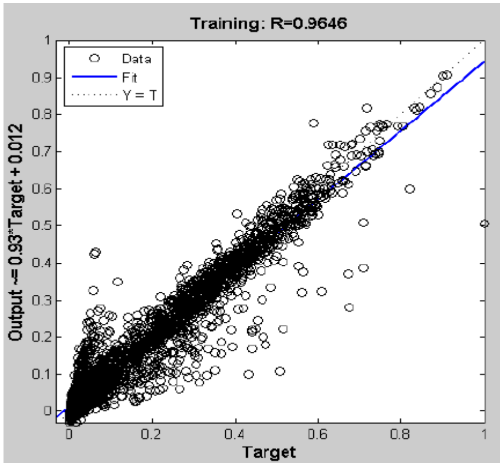

Fig. 4. The linear regression about the network output and the corresponding expected output

The predicting error is shown in Fig. 5, and the comparison of the predicting load based on BP neural network and the actual load is shown in Fig. 6. According the graph can see that although some error extents between the output and the corresponding target output though model test, the error mostly maintained between 0.02-0.05. The root mean square error (RMSE) is 1.18% by calculation which error range is acceptable in engineering application. In terms of prediction accuracy, model structure and training algorithm of the load prediction model of air conditioning system in this paper is relatively good, that can reflect the inherent nonlinear mapping relation with relatively high precision of input-output sample data.

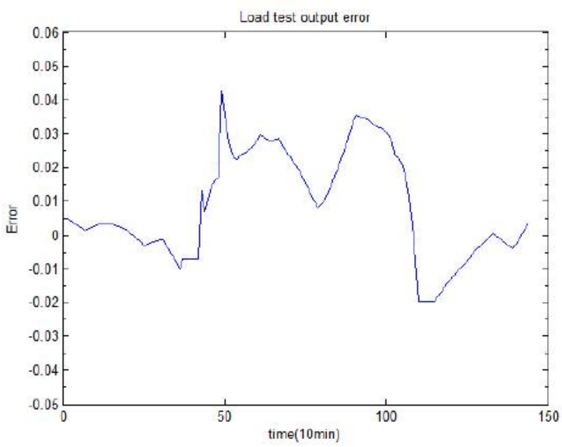

Fig. 5. The results about cooling load prediction error of 168 sets test samples

Using the one day data of test set sample to do test experiments, the comparison of the predicting load based on BP neural network and the actual load is shown in Fig. 6. Where the solid line connection is the target output curve, and '+' represents the output value of the neural network model simulation test result. By the graph, we can conclude that there has good fitting between model test output and the corresponding target output. Though affected by the weather factors such as time-varying parameters, the load prediction value will follow better when the load of air conditioning system sudden changing. Those show that the neural network load prediction model can be applied to practical engineering project of air conditioning system cooling load prediction.

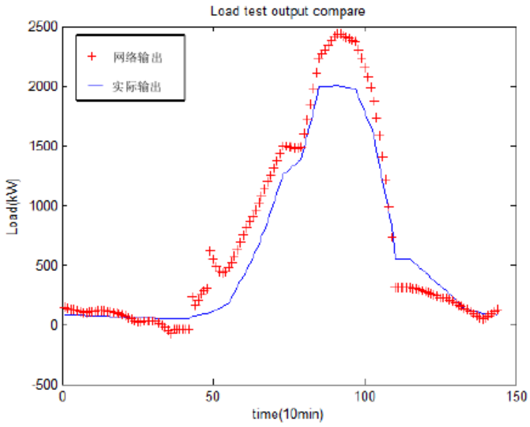

Fig. 6. The cooling load comparison results of the calculated output load with the prediction output load

By the above results can be seen, the characteristics of the neural network load prediction model constructed in this paper is its simple structure, the required input parameters only for outdoor temperature, outdoor relative humidity, the intensity of solar radiation, wind speed, wind direction and indoor Load. At the same time, it avoids the tedious unsteady heat transfer calculation. And the model is well described the complex nonlinear relationship between building air conditioning load and the input parameters, the prediction model has a certain practical engineering Value.

6 Conclusion

In this paper, BP neural network and its improved algorithm are investigated for the prediction of building cooling load. The input parameters are selected based on PCA method. Meteorological parameters and indoor heat disturbance are taken by using BP neural network as inputs and the load prediction is conducted as output. Testing results show that improved BP neural network based on Bayesian regularization method has better generalization ability than traditional BP neural network in building cooling load prediction model and improved BP neural network model meets the requirement of accuracy of RMSE error for building cooling load.

The biggest characteristic of the load prediction model built in this paper is simple structure that avoids the tedious unsteady heat transfer calculation. The results show the complex nonlinear relationship between the building air conditioning load and input parameters can be got effectively, therefore the predictive model have some practical value in engineering.

However, due to experimental conditions and time constraints, the delay effect of meteorological parameters that caused by cold load delay of building heat capacity is not taken into account in the predictive model input parameters. Therefore, it is necessary to further study the outdoor temperature, humidity and solar radiation intensity of the delay effect on the air conditioning system load.

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