Journal of Computers Vol. 28, No. 5, 2017, pp. 178-189
doi:10.3966/199115992017102805016

Research on Forecast Model of the Air-conditioning System in Data Center Based on Neural Network

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Received 25 October 2016; Revised 13 June 2017; Accepted 26 June 2017

Abstract. This paper introduces the relevant information about data center. The concept of data center is increasingly popular. This paper summarizes the domestic and foreign scholars research about the current situation of optimization and energy-saving about the air-conditioning system in data center and most scholars still come to stay in the study of the optimization of the equipment and control some equipment in order to achieve the purpose of energy optimization, but there is almost no research on predictive control. This topic applied predictive control to the entire air conditioning system. And it introduced the basic principles of predictive control, the policy-related knowledge of forecast model and data collection strategy. This paper introduces emphatically the BP neural network algorithm principle and application. By determining the amount of inputs and outputs and using BP neural network established the forecast model of the air conditioning system in data center. Eventually the model achieved the expected forecast results with MATLAB simulation and test.

Keywords: air-conditioning system, BP neural network, data center, forecast model

1 Introduction

With the deepening of information technology, more and more users need to process large amounts of data and information exchange, and accordingly more and more enterprises begin the construction of the data center. Therefore specialized data center services companies have emerged to provide professional data services to other agencies. In order to meet the competition and requirements of the market and industry, these companies must continually invest human and material resources to strengthen the hardware, and more research and development (R & D) buildings are built with this situation. One of the core R & D center— the data center's size has gradually expanded. As the scale of data center is increasing, its energy consumption is also increasing and the air conditioning and refrigeration equipment and auxiliary equipment are the main factors. More and more data centers take PUE (Power Usage Effectiveness) value as a key indicator, and increasingly pursue lower PUE [1]. Building green energy-efficient data center has become the industry consensus [2]. Green energy-saving data center has been from concept to reality.

Thus, the predictive control technology applied to the air conditioning system in data center, which can establish accurate and reliable forecast models. So cold source supply in accordance with the load demand has very important significance for energy-saving of air conditioning system. Meanwhile, the predictive control technology applied to the air conditioning system in data center is the precondition to achieve optimal operation of the air conditioning system. Common methods of forecast model are Exponential Smoothing (ES), Genetic Algorithm and BP neural network. The BP neural network is the most widespread application method. These advantages of self-learning, self-organizing ability and fault tolerance about BP neural network are superior to other algorithms [6].

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2 Situation Research of Data Center Air Conditioning System

The modality of a data center air conditioning system has a close relationship with the size, weather conditions of location etc. The upgrade of data center's IT equipment and expansion of the data center scale has a direct impact on the air conditioning and refrigeration technology. According to the statistics report (referred TC9.9) of American Society of Heating Refrigeration and Air Conditioning Engineers (ASHRAE) Technical Committee 9.9, one-third of the total electricity was consumed by the air conditioning and refrigeration systems in data center data. In order to promote energy conservation of data centers, the Ministry of Industry and Information Technology in the "Industrial Energy saving" twelfth five "plan" put forward the goal that "by 2015, data center PUE values for an 8% decline", so it is necessary to study energy-saving control of air conditioning system in data center. Through the investigation we found that the current energy saving of air conditioning system in data center mainly focus on the preliminary design and equipment selection through investigation, including several ways [9]: energy-saving of air-conditioning equipment, air distribution and layout optimization, rational use of natural cold source. However, the study of the application of predictive control theory on the data center air conditioning system that is used to optimize control is rarely.

The energy saving control simulation of air-conditioning system in data center started earlier abroad. Yuri Y. Lui proposed considerations and precautions that is needed to be considered when the data center utilizes economizer to save energy, compared two form of energy-saving effects that economizer respect to cooler serial and parallel and put forward that it is needed to reset the water temperature of the cooling tower when using different running strategies [4]. Luca Parolini presents distributed predictive control strategy that stratifies data center and modularizes data center. There are three main control layers, the bottom is used to handle fast dynamic process, the intermediate layer is responsible for thermal management and coordination of the underlying controller, the top is the control layer of data center. With a modular thought to solve the problem is under the control rule to meet the constraints to make the data center's performance maximization by providing a number of performance indicators and constraints .

Wang Jun in Tongji University proposed the scheme based on predictive control of energy-saving data center, this scheme is based on the server and air conditioning power model. Chongqing University used someone data center for the study. Using DEST software simulated and analyzed the hourly load and load characteristics. On this basis, they put forward the possibility of using the outdoor cold source refrigeration for the cooling room and designed a new wind operation mode. Nanjing University of Aeronautics and Astronautics had a research through the cooling tower cooling system and concluded that when outdoor wet bulb temperature reaches a certain condition, you can close the cooler and instead of directly cool by the cooling tower. Simulation analysis verified the energy efficiency of the system and the feasibility in transition season and winter.

Through the status of home and abroad research, it is found that these researches only aimed at a part of the air conditioning system and did not consider the impact that various devices made of the air-conditioning system coupled each other as a whole, especially the establish of the entire air-conditioning system forecast model. This paper applies predictive control based on BP neural network to the entire air conditioning system to establish an accurate forecast model, it is important for the air conditioning system to make the cold source supplying in accordance with the load demand, which is the pre-condition to achieve optimal operation of the air conditioning system.

3 Air Conditioning System in Data Center Introduction

3.1 Characteristics of Air Conditioning System in Data Center

The required cooling load is higher for per unit area in data room. Different from civil building air conditioning system, the main purpose of the air conditioning system in data center is to eliminate the rack heat dissipation to ensure the normal operation of data room [4]. Operating mode of air conditioning system is seven days a week, 24 hours a day are in a cooling state. The entire air conditioning system is affected by energy policy and other areas, thus the way to provide cold source quite different. In this paper, the research air conditioning system in data center is in the North. According to the advantages of weather conditions, in the chiller integrated water side economizer, so the cooling mode is no longer a single refrigerator refrigeration.

As the seasons change, the outdoor temperature is different, according to the outdoor wet bulb temperature and the cooling water change, air conditioning system in data center has three different refrigeration forms, refrigerator refrigeration in summer, plate heat exchanger and cooling tower refrigeration in winter, refrigerator and plate heat exchanger refrigeration in transition season. When the outdoor temperature low in winter, cooling tower fan produce condensate through high-speed operation. The condensed water is supplied to the heat exchanger by pump, cooling chilled water in the heat exchanger.

This paper mainly studies summer conditions. In summer it mainly is the refrigerator refrigeration, at this moment the plate heat exchanger does not work as the same as ordinary air conditioning refrigeration. Fig. 1 is the working condition figure of air conditioning system in summer after simplifying the system principle diagram.

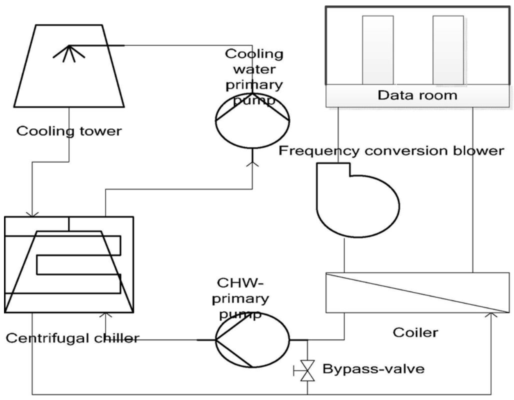

Fig. 1. Refrigeration system schematic diagram in summer

In this paper, the system model of the air conditioning system in data center is established based on TRNSYS. Fig. 2 is the operating mode switching model.

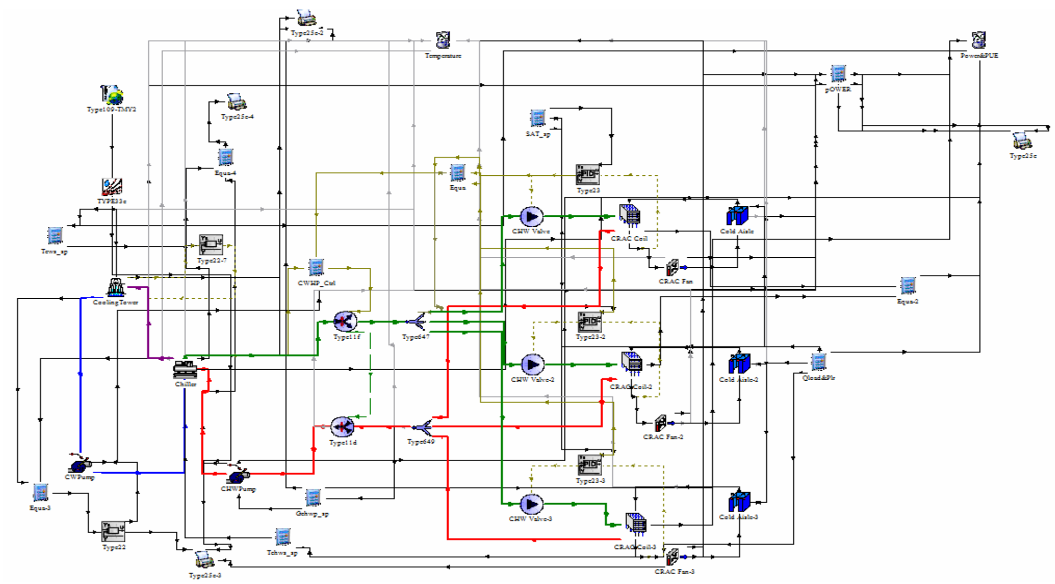

Fig. 2. Model of data acquisition

3.2 Energy Efficiency Index PUE in Data Center

PUE value is a measure of the standard about power usage effectiveness in data center. The smaller the PUE explains, the more energy saving about data center is. But, the premise of saving energy must meet the environmental requirements of IT equipment of data room and provide sufficient cooling capacity. PUE value is closely related to the energy consumption of air conditioning system, so you can find the relation between PUE and energy consumption of the air conditioning system equipment through the PUE value formula transformation. PUE value is closely related to the energy consumption of air conditioning system, so you can find the relation between PUE and energy consumption of the air conditioning system equipment through the PUE value formula transformation.

PUE is the ratio of total data center energy consumption and energy consumption of IT equipment. The total energy consumption of data center which is the sum of the energy consumption of IT equipments, electrical equipments and air-conditioning energy consumption. PUE power factor is the ratio of lighting and other power supply equipments and IT equipments. PUE refrigeration factor is the ratio of air conditioning systems equipments and energy consumption of IT equipments. Power factor can be reduced by reasonable lighting and energy-saving measures. The key to energy saving is the size of the air conditioning refrigeration factor.

3.3 Analyzing Method about Air Conditioning System Energy Conservation in Data Center

The superscript numeral used to refer to a footnote appears in the text either directly after the word to be discussed or – in relation to a phrase or a sentence – following the punctuation sign (comma, semicolon, or period). Footnotes should appear at the bottom of the normal text area, with a line of about 5cm in Word set immediately above them [1].

4 Air Conditioning System in Data Center Introduction

4.1 Overview of the BP Neural Network

In 1985, D. Rumelhart and McClellan put forward BP neural network which is a kind of back propagation learning algorithm used for the forward multi-layer neural. At present BP algorithm and its application are the most important among the training forward neural network learning algorithm, and BP algorithm is also the foundation of forward network which can be widely used.

As can be seen from Fig. 3, a BP neural network model contains a hidden layer, network input layer and network output layer [7-8]. Individual neuron between the adjacent layers interconnected corresponds to a connection weight of each other.

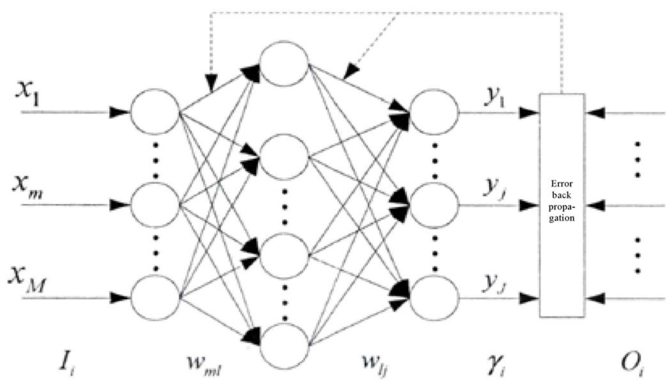

Fig. 3. The BP neural network model

Here we assume that in a BP neural network model, there are M neurons in the Input layer, using linear unit excitation function, the corresponding input for dimensional vector. There are L neurons in Hidden layer, excitation function to remember to f_1. There are J neurons in Output layer, excitation function to remember to f_2. In addition, the expectation output O_i are J dimensional vector. w_{ml} and w_{lj} are respectively the $m-th$ neurons in input layer to the $l-th$ neurons in hidden layer and the $l-th$ neurons in hidden layer to the $j-th$ neurons in output layer the weights of connections between neurons. ϑ_l and θ_j are respectively the $l-th$ in hidden layer neurons and the $j-th$ output layer neuron in output layer the threshold value. v_l is said the $l-th$ output neurons in hidden layer, it will be passed to the output layer neurons as a part of the input, y_j is said the actual output about the first j neurons in output layer.

Here, the three layers BP neural network are as an example to show the derivation about BP learning algorithm and the iterative learning formula. Assuming that the BP neural network training sample set $\{I_i, O_i\}_{i=l}^{N}$, $I_i = [I_{i1}, I_{i2}, \cdots, I_{im}, \cdots, I_{iM}]^T$ corresponds $[x_1, x_2, \cdots, x_m, \cdots, x_M]^T$ of neural network's input, $O_i = [O_{i1}, O_{i2}, \cdots, O_{ij}, \cdots, O_{iJ}]^T$ as output sample. In addition, $\eta > 0$ as learning rate is used to adjust the degree and speed of the weights in BP neural network. The following is divided into three parts to introduce the BP learning algorithm.

The signal forward propagation.

The output of the first l neurons in hidden layer can be derived as:

$$v_l = f_1\left(\sum_{m=1}^{M} w_{ml} x_m - \vartheta_l\right), \ l = 1, 2, \cdots, L, \quad \textbf{(1)}$$

The output of the $j-th$ neurons in output layer can be derived as:

$$y_j = f_2\left(\sum_{l=1}^{L} w_{lj} v_l - \theta_j\right), \ j = 1, 2, \cdots, J, \quad \textbf{(2)}$$

Corresponding to the $i-th$ samples of neural network learning error function as follows:

$$E = \frac{1}{2}\sum_{j=1}^{J}\left(y_j - O_{ij}\right)^2, \quad \textbf{(3)}$$

BP learning algorithm of error back propagation and weights updated.

(1) Connection weights between The $l-th$ neurons in hidden layer to the $j-th$ neurons in output layer, the following update formula:

$$\Delta w_{lj} = -\eta\frac{\partial E}{\partial w_{lj}} = -\eta\frac{\partial E}{\partial y_j}\cdot\frac{\partial y_j}{\partial w_{lj}} = \eta\left(O_{ij} - y_j\right)\cdot f_2^{'}\cdot v_l, \quad \textbf{(4)}$$

Among, making $\delta_{ij} = \left(O_{ij} - y_j\right)\cdot f_2^{'} = e_{ij}\cdot f_2^{'}$, $e_{ij} = O_{ij} - y_j$, $f_2^{'}$ for excitation function $f_2(u)$ for the independent variables of u derivative (and when values for $\sum_{l=1}^{L} w_{lj} v_l - \theta_j$).

The same available:

$$\Delta\theta_j = -\eta\frac{\partial E}{\partial\theta_j} = -\eta\frac{\partial E}{\partial y_j}\cdot\frac{\partial y_j}{\partial\theta_j} = -\eta\left(O_{lj} - y_j\right)\cdot f_2^{'} = -\eta\cdot\delta_{ij}, \quad \textbf{(5)}$$

(2) Incremental change of the connection weights between the first m neurons in the input layer to the $l-th$ neurons in hidden layer incremental change the following formula:

$$\begin{aligned}\Delta w_{ml} &= -\eta \frac{\partial E}{\partial w_{ml}} \\ &= -\eta \sum_{j=1}^{J} \frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial v_l} \cdot \frac{\partial v_l}{\partial w_{ml}} \\ &= \eta \sum_{j=1}^{J} \left(O_{ij} - y_j\right) \cdot f_2^{'} \cdot w_{lj} \cdot f_1^{'} \cdot x_m \\ &= \eta \cdot x_m \cdot \sum_{j=1}^{J} \sigma_{ijl}\end{aligned}, \tag{6}$$

Among, making $\sigma_{ijl} = \delta_{ij} w_{lj} f_1^{'}$, $f_1^{'}$ for excitation function $f_1\left(u\right)$ for the independent variables of u derivative (and when values for $\sum_{m=1}^{M} w_{ml} x_m - \vartheta_l$)

The same available:

$$\Delta \vartheta_l = -\eta \cdot \sum_{j=1}^{J} \sigma ijl\,, \tag{7}$$

The weights of network update formula. The next round of network learning and training of neurons connection weights are obtained according to the connection weights of each layer neurons of incremental changes to the iterative update, So for each training sample $i \in \{1, 2, \cdots, N\}$ update formula is:

$$\begin{cases} \theta_j \leftarrow \theta_j + \Delta\theta_j \\ w_{ij} \leftarrow w_{ij} + \Delta w_{ij} \end{cases}, \forall j = 1, 2, \cdots, J \text{ and } l = 1, 2, \cdots, L\,, \tag{8}$$

$$\begin{cases} \vartheta_l \leftarrow \vartheta_l + \Delta\vartheta_l \\ w_{ml} \leftarrow w_{ml} + \Delta w_{ml} \end{cases}, \forall l = 1, 2, \cdots, L \text{ and } m = 1, 2, \cdots, M\,, \tag{9}$$

From the above derivation, BP neural network trains the weights by using error function to calculate the weights' derivative, which requires the individual neurons excitation function that must be continuously differentiable. Because the Sigmoid function not only has these properties, but also has the amplitude between -1 and 1 ,monotonous straight and a series of advantages, so the BP neural network is widely used in the design of the function.

4.2 Data Collection

Artificial neural network can approximate nonlinear systems with arbitrary precision. In the process of forecast model identification, it does not require the establishment of specific mathematical model, but it must have sufficient input and output corresponding data. By algorithm to train data, which can respond the non-linear relationship between input and output data [6] and this non-linear relationship is saved by weight and threshold form. Therefore, the key to neural network forecast model is getting an effective and comprehensive sample data.

In this paper, the model of the whole control system is established with TRNSYS software. TRNYSY integrates air conditioning system's each device module, the data sampling model can be built through connection and construction of those modules. Eventually we use established sample strategy to collect data.

Neural network forecast model training results is good or bad completely depending on their accuracy and generalization ability evaluated. The premise condition that ensures these two indicators is that data collection which needs to take all possible scenarios of system running into consideration. Data collection should also meet all ranges of control strategies' implementation [5]. Specific sampling program is as follows:

Here are 8760 hours in one year. The sampling time is between 3624-5088 hours in this paper and in summer the running simulation step size of the established model is 0.5 minutes. The data are sampled with the data acquisition module of TRNSYS and the data acquisition interval is 10 min.

After the data collection strategy is determined, system started with the established platforms of data collection for data acquisition. Parts of the collected data sample are shown in Fig. 4.

TIME	Tcws	Tchws	Tcha	Qcp	Qchp	Twb	Qfuhe	PUE	Tsf
4800	18	18	2	10	10	16.86	191.25	0	18
4800.12	15.87	14.84	5.78	15.89	17.59	22.09	191.39	1.23	18.39
4800.25	17.25	14.84	6.96	17.26	20.25	22.07	191.54	1.2	21.94
4800.38	18.4	14.84	11.71	18.4	18.36	22.04	191.71	1.23	21.26
4800.5	19.38	14.84	11.53	19.41	18.54	22	191.9	1.19	21.68
4800.62	20.2	14.85	11.46	20.22	18.12	21.97	192.1	1.19	21.06
4800.75	20.96	14.85	11.42	20.98	18.26	21.92	192.32	1.19	21.21
4800.88	21.62	14.85	11.42	21.64	18.06	21.87	192.56	1.2	20.95
4801	22.2	14.86	11.42	22.23	18.07	21.82	192.82	1.19	20.91
4801.12	22.89	14.86	11.41	22.89	18	21.75	193.12	1.19	20.84
4801.25	23.69	14.87	11.41	23.68	17.97	21.67	193.43	1.19	20.79
4801.38	24.48	14.87	11.41	24.5	17.92	21.58	193.78	1.2	20.73
4801.5	25.28	14.88	11.41	25.29	17.9	21.49	194.16	1.2	20.7
4801.62	26.09	14.88	11.41	26.08	17.87	21.4	194.57	1.2	20.66
4801.75	26.89	14.89	11.41	26.88	17.84	21.31	195.02	1.2	20.64
4801.88	27.7	14.9	11.41	27.69	17.82	21.22	195.51	1.21	20.62
4802	28.52	14.9	11.41	28.5	17.8	21.13	196.04	1.21	20.61
4802.12	29.33	14.91	11.41	29.32	17.78	21.03	196.6	1.21	20.6
4802.25	29.92	14.92	11.41	29.96	17.76	20.94	197.21	1.21	20.59
4802.38	29.3	14.93	11.41	29.32	17.74	20.85	197.87	1.25	20.59
4802.5	27.98	14.94	11.41	28	17.72	20.75	198.57	1.24	20.59
4802.62	26.94	14.95	11.4	26.96	17.72	20.66	199.31	1.24	20.62
4802.75	26.1	14.96	11.4	26.12	17.72	20.56	200.09	1.24	20.65
4802.88	25.43	14.98	11.4	25.45	17.73	20.46	200.93	1.24	20.71
4803	24.88	14.99	11.4	24.89	17.74	20.37	201.8	1.23	20.77
4803.12	24.42	15	11.4	24.44	17.76	20.28	202.71	1.23	20.87
4803.25	24.04	15.02	11.4	24.06	17.77	20.19	203.66	1.23	20.93
4803.38	23.73	15.03	11.4	23.74	17.78	20.11	204.65	1.23	21.03

Fig. 4. Collected part of the data

Because the actual input and output of the system are not between [0,1], but the input and output of the neural network are required generally between [0.1], so after the input and output data are obtained, they should first be subjected to normalization processing and the data are converted to values between [0,1], and then these data are normalized using neural network system. There are many forms of normalization methods, there assumes utilizing following formula.

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{10}$$

Among them, x for system data that sits outside of the interval [0, 1]. $x_{\max}$ and $x_{\min}$ respectively are the maximum and the minimum in the data of the system. y is the system data that x is normalized.

For the output of the neural network, there is a need that data should be reversed the normalized processing and network output value between [0, 1] is converted to a system's actual output. And corresponds to formula (11) of the reverse normalization is as follows:

$$x = y\left(x_{\max} - x_{\min}\right) + x_{\min}, \tag{11}$$

Among them, y is a value in the interval [0, 1], $x_{\max}$ and $x_{\min}$ respectively are the maximum and the minimum in the data of system. x is the actual output for the system after the reverse normalization.

Generalization ability is mainly refers to the network for untrained data's extrapolation ability. If network appears over fitting phenomenon, its generalization ability will decline. From the perspective of theory analysis, there are many factors that influence multilayer forward feedback neural network generalization ability. One of the effective methods of improving neural network generalization ability is just using the size of the network for function approximation. However, in the process of practical application, it is often hard to do. Generally speaking, the obtained data can be divided into three subsets in the condition of a limited number of cases namely the training set, checking set and testing set, which can effectively improve the generalization capability of forward feed neural networks.

Kolgmogrov theorem states that even if there is only one hidden layer of BP neural network, any continuous function approximation can be arbitrary approximated as long as the number of hidden layer nodes is enough. Based on this, most of the BP neural network adopts the model structure of a hidden layer. In practice, the topological structure of the BP neural network is mainly determined by input layer, hidden layer and output layer and the number of nodes in each layer. In the process of determining input nodes, because it is difficult to determine which factors are the main factors that influence the practical problems, so principal component analysis method is usually adopted, and which is a repeated process of trial and error. The number of output nodes depends on the needs of the practical problems. Kawashima defined that there is a suggestion that the number of network hidden layer nodes is 2n+1, but the methods of experiment are also usually adopted in practical application to determine the number of network nodes.

5 The Forecast Model Based on BP Neural Network

5.1 Determination of the Amount Input and Output of Air Conditioning System in Data Center

The object of this research topic is the air conditioning system of a data center, the total cooling load of data center air conditioning system is about 13855kw, system configures 4 (3 with 1 standby) 4572kw centrifugal chillers (including one table storage unit). Chillers, cold plate heat exchangers, cooling towers, cooling water pump and a cooling water pump utilize the way of the group of 1-on-1.

The purpose of the research is to make the entire system to achieve energy saving and optimization to reduce the energy consumption indicator— PUE value in data center PUE value by means of applying predictive control algorithm to adjust parameters of air conditioning system in data center according to changes in load and outdoor weather conditions. Since the purpose of the research is to apply the control algorithm to adjust the parameters of the air-conditioning system in data center according to the changes of load and outdoor weather conditions, so as to reduce energy consumption indicators PUE of data centers. Therefore, output parameters of air conditioning system in data center for the forecast model [3, 5] are PUE value and cooler cooling capacity (optimization of air conditioning systems needs to consider the load and simultaneously cooling mechanism's cooling capacity is also asked to meet demands). By the analysis of PUE we get that the key to reduce the PUE value is to reduce the coefficient of the air conditioning system's cooling factor, while cooling factor's size is mainly related to the energy consumption of each air-conditioning's refrigeration device. The main factors influencing cooling tower's energy efficiency are outdoor wet bulb temperature, cooling water flow, etc; While the main factors affecting the cooling tower's energy efficiency are chilled water's supplying water temperature, chilled water's flow, load and so on; The end portion is mainly affected by air temperature, load, etc. So various elements should be considered and there is a terminal determination that the input parameters for the forecast model are chilled water's supplying temperature, chilled water's supplying temperature, air temperature, cooling water's pump flow ratio, chilled water's pump flow ratio, outdoor wet bulb temperature, PUE value and the amount of cold mechanism.

Finally, cooling load forecast model's time step length is selected for one hour according to the practical application requirements of the data center air conditioning system.

5.2 The Structure and Design of BP Neural Network

Kolgmogrov theorem shows that in terms of the forecast model for data center air conditioning system, it is sufficient to use a hidden layer for the requirements. While the selection of the number of hidden layer nodes is also very important, so far there is not a good analysis formula to express and only by the method of experience and experiment to determine. This paper relays on Kolmogorov theorem and references experience.

Formula (12), (13) and (14) to determine terminal formula.

$$K < \sum_{i=0}^{n} C_{n_1}^{i}, \tag{12}$$

K is the number of sample, n is respectively the number of input layer nodes and hidden layer nodes, when $i > n, C_{n1} = 0$.

$$n_1 = \log_2 n, \tag{13}$$

here n is the number of neurons in the input.

$$n_1 = \sqrt{n+m} + a, \tag{14}$$

m , n respectively is the number of neurons in the input and in the output, a is constant between 1 to 10.

Formula (13) commonly is used to deal with data compression of BP neural network. In this paper, prediction model of air conditioning system in data center was used of function's fitting function of BP neural network and the effect is better when selecting (14). Among them, m is 7，n is 2, while the specific value of a is determined through repeated test method.

Normalization is an important step in the process to predict when the neural network is used. In the stage of neural network learning, there is a need that all input data and the corresponding output values should be processed with normalization, and that is, data are processed into decimals values between 0 and 1.The parameters of this paper take following normalization process method:

Chilled water's supplying temperature

$$t_1' = \frac{t_1 - t_{1\min}}{t_{1\max} - t_{1\min}}, \tag{15}$$

Water temperature of cooling water

$$t_2' = \frac{t_2 - t_{2\min}}{t_{2\max} - t_{2\min}}, \tag{16}$$

Air output

$$s' = \frac{s - s_{\min}}{s_{\max} - s_{\min}}, \tag{17}$$

The fan rotation speed ratio

$$r' = \frac{r - r_{\min}}{r_{\max} - r_{\max}}, \tag{18}$$

Outdoor wet bulb temperature

$$b' = \frac{b - b_{\min}}{b_{\max} - b_{\min}}, \tag{19}$$

Cooling water flow rate

$$l' = \frac{l - l_{\min}}{l_{\max} - l_{\min}}, \tag{20}$$

PUE

$$PUE' = \frac{PUE - PUE_{\min}}{PUE_{\max} - PUE_{\min}}, \tag{21}$$

Load

$$P' = \frac{P - P_{\min}}{P_{\max} - P_{\min}}, \tag{22}$$

6 Data Center Air Conditioning System Forecast Model Training and The Analysis Of Simulation Results

6.1 The Training of BP Neural Network

The calculation process of BP neural network model, that is to say, learning engineering mainly has two phases. First, input known training samples, by setting the network structure and the last iteration of the weights and thresholds. From the first layer of the backward calculate each neuron network output. The second stage amended weights and thresholds, and modified the weights and thresholds from the last layer forward to calculate the effect on total error (gradient). The above two processes, alternately repeatedly until reach the convergence. Matlab's Neural Network Toolbox offers a variety of learning algorithm. This paper uses a LM - (levenberg - marquardt) algorithm, with the characteristics of the fast convergence rate and the high precision. The transformation function of neurons in hidden layer adopts hyperbolic tangent function Tansig, output transformation function uses the Purelin function. Neural network adopts Trainlm training function.

At the beginning, using random initialization, a new neural network function and parameter Settings shown in the Table 1.

Table 1. Prediction model structure and parameter setting of BP neural-network

The neural network type	A single hidden layer BP neural network
Number of input layer nodes	7
Number of output layer nodes	2
Number of hidden layer nodes	15
The transfer function of neurons	'log*sig*',' *purelin*' (Excitation function)
Learning function	'*learngd*' (Weights and threshold value of gradient descent)
The performance function	'*msereg*' (The weighted mean square error)
Network training function	'*trainbr*' (Bayesian regularization method)
Initialization of weights and thresholds	'*initnw*' (Nguyen-Widrow)
The biggest training time	5000Epochs
The target of error	0

6.2 Predicted Results and Error Analysis

After the network training, you need to verify this model to determine training is available. Through the input values of the original sample, call sim function into the trained model simulation to get the corresponding output values. Finally compare the simulation value and the actual value of the model to determine whether a deviation within the scope of the permit, then to determine whether the model is available. To determine whether the model is available.

After neural network structure and parameters determined, trains the neural network model in the MATLAB, the training results of forecasting model of air conditioning system in data center as shown in Fig. 5. When in 301 steps the variable mu value is maximum, the training has to stop. In the process of training error surface gradient is more and more small, which increases the number of parameters effectively. At the same time, the error sum of squares tends to stabilize, which states the network generalization ability is very good.

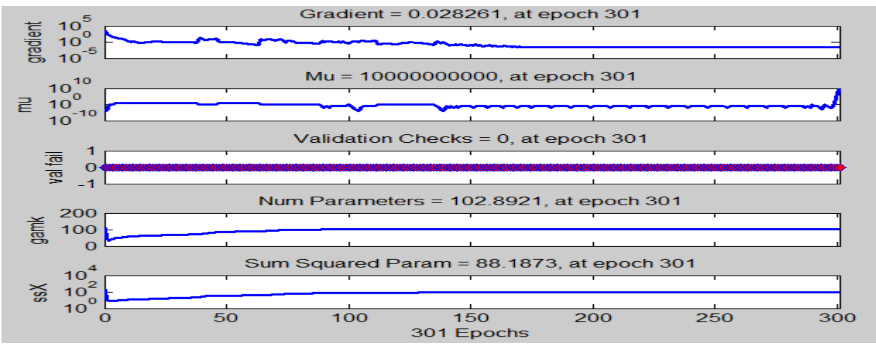

Fig. 5. Changes in the data center air conditioning system forecast model in neural network training process parameters

In the acquisition of data, this paper randomly chose 600 data samples for testing the trained network. Fig. 6 and Fig. 7 respectively give the forecast model of network output of the test sample and the actual output of the comparison chart. The abscissa is the number of sample test data, the ordinate is output value after normalization, respectively the PUE value and load size of the next moment.

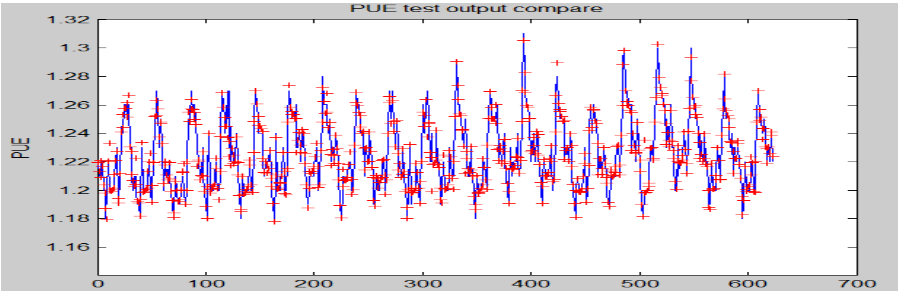

Fig. 6. Comparison of the data center air conditioning system PUE value of the test sample and the actual output of the network output

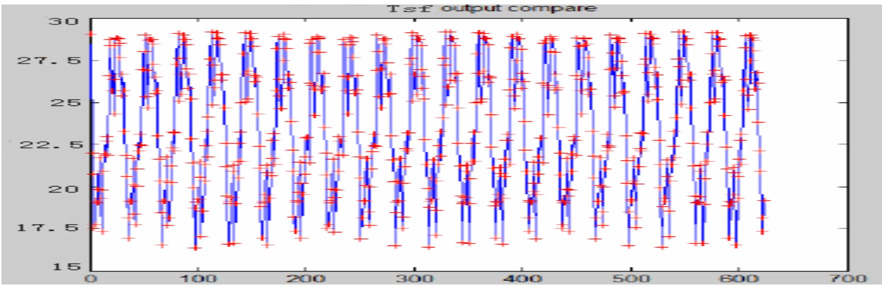

Fig. 7. Comparison of actual output and network

Fig. 8 and Fig. 9 described test sample error between actual output and the network model output. For PUE value, it's test error is between 0.2～0.2, the error of load is between 0.03～0.03, the error is relatively small.

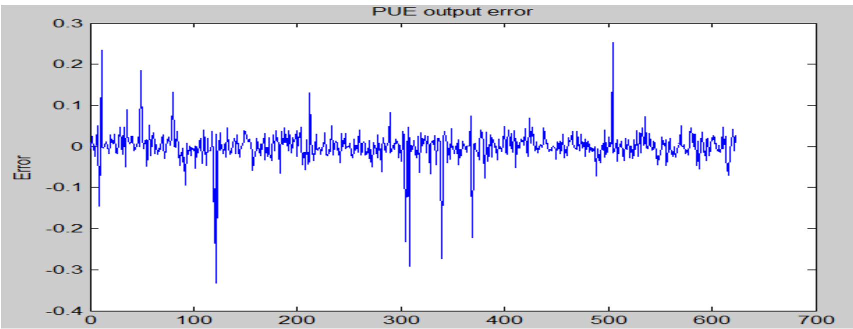

Fig. 8. PUE value of the test sample error

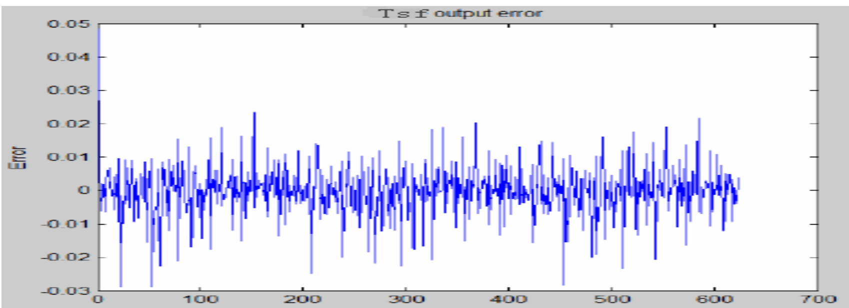

Fig. 9. Load test sample value error

7 Summary

This article describes the commonly used method to establish a data center air conditioning system forecast model, in which BP neural network has a unique advantage. Here the prediction model of air conditioning system in data center is established with BP neural network, and the predicted results is good. The established model has a good foundation for optimization to use the existing model to predictive control. Simulation in MATLAB described neural network has good nonlinear mapping ability, and established a non-linear forecast model of air conditioning system data center, the model with a large lag brought great convenience.

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