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The Application of Recurrent Artificial Neural Network in Chiller Energy Analysis Simulation

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Abstract: In recent years, due to the rapid development of high-tech industry, air-conditioning equipment has become an essential facility. However, the power consumption of the air-conditioning equipment is considerably high, accounting for 40~50% of the total building electricity consumption. The air-conditioning equipment includes chiller, pump, fan, cooling tower fan motor; therefore, how to reduce energy consumption and improve energy utilization will be a very important topic. This study used the sensors on the site to collect historical data of load change for analysis and conducted simulation and verification using the artificial neural recurrent network and MATLAB. The frequency of cooling tower fan was set as the output parameter and two groups of modules were established to effectively predict the frequency of cooling tower fan by rainfall to optimize the cooling water fan rotational frequency, in order to reduce power consumption of the cooling tower in different environmental conditions for energy saving.

Key words: Artificial neural network, MATLAB, cooling towers, electricity consumption

INTRODUCTION

With the flourishing development of the high-tech industries, different types of buildings have been installed with the central air conditioning system. There are a substantial number of new or existing central air-conditioning systems. In most cases, the cooling tower operates in parallel connection with the central air conditioning system. Previously, the cooling tower fan runs in fixed frequency, resulting in waste of energy due to improper control of operation (National Science Council, 2005).

The cooling tower power consumption accounts for parts of the air-conditioning equipment. In the design and planning of general air conditioning systems, the system maximum air conditioning load is often determined by highest external temperature and maximum indoor load to determine the chiller rated capacity and the cooling tower size is determined by the chiller rated capacity (Shih, 2004). However, the times of proper operation of the

cooling tower fan in the load are rare. Therefore, this study used the neural recurrent network to simulate the frequency of cooling tower fan and established the forecast models for rainy days and days without rain. The proper frequency of cooling tower fan in different climatic conditions was the major research direction for the energy conservation of today's central air conditioning chiller system. This study used the artificial neural network, historical data of load change for analysis on the site to collect and conducted simulation and verification effectively predict the frequency of cooling tower fan to optimize the cooling water fan rotational frequency, in order to reduce power consumption of the cooling tower in different environmental conditions for energy saving.

PRINCIPLE ARCHITECTURE AND METHOD

Cooling principle of the cooling tower: The most important cooling device of the water-cooled chiller is the

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cooling tower. In recent years, the frequency conversion technology has been applied in the cooling water fan control to adjust the rotating speed of the cooling fan with the cooling load to achieve the purpose of capacity control (Bureau of Energy, 2008). The working principle of the cooling tower is as follows: the high temperature cooling water flows to the cooling tower after heat exchange to be sprayed in the surface of the heat dissipation material by nozzles through the distribution tubes to form water droplets. Then, the water contacts the cool air absorbed by the cooling tower fan. Heat exchange reaction between the hot water and the cool air takes place. Meanwhile, a small part of the hot air has been evaporated and the absorption evaporation heat will reduce the temperature of the cooling water and results in low temperature cooling water.

The cooling tower's efficiency of heat abstraction, air web bulb temperature and cooling tower fan operational frequency are closely related. When the weather becomes hot, the cooling water temperature in the cooling tower rises and the host power consumption rises accordingly. If the cooling tower remains running at a fixed frequency, the temperature of the cooling water will rise. To keep the cooling water at a fixed level, the rotation of the cooling fan should be speed up and thus, the power consumption will rise as a result. Similarly, when the weather becomes cool, the cooling water temperature reduces and the host power consumption will drop accordingly. If the cooling tower keeps the fixed rotation speed, the cooling water temperature will reduce. If the cooling water temperature is fixed, the rotation speed must be reduced and thus, the power consumption will reduce consequently (Liu and Tsai, 2008).

Frequency of cooling tower fan and power consumption:

The operational frequency of the cooling tower fan is related to the overall power consumption of the air conditioning system. If the frequency of cooling tower fan can be effectively forecasted, the energy conservation can be effectively achieved.

At present, there are three methods to control the fan volume commonly seen in the air conditioners for general buildings as illustrated in Fig. 1 (Kao, 1997):

- Inlet vane control
- Discharge damper control (discharge damper control)
- Variable speed motor control

As seen from the fan power consumption and air flow relationship curve, using frequency converter to control the fan to change the motor rotational speed is the optimal and effective energy saving method.

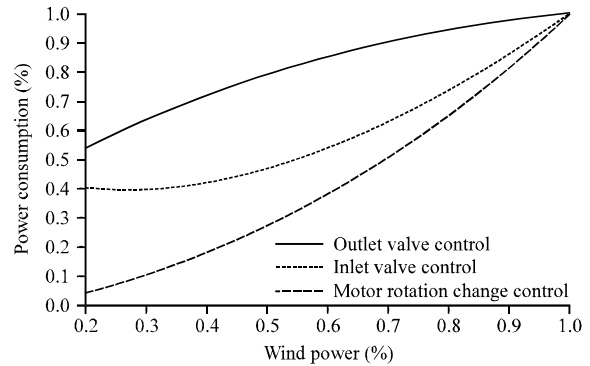


Fig. 1: Curve of the relation between the fan power consumption and air flow

According to the fan law, if the cooling water tower fan frequency can properly change the rotational frequency through frequency converter, thus, realizing energy saving.

The fan law principle is illustrated as shown in Eq. 1 (Yu and Chan, 2008):

$$\frac{H1}{H2} = \left(\frac{D1}{D2}\right)^5 \times \left(\frac{N1}{N2}\right)^3 \times \frac{\rho1}{\rho2} \tag{1}$$

where, H: power consumption (j/s), D: impeller diameter (mm), N: fan rotation speed (deg/s), ρ: air density (g cm⁻³).

If only the rotation speed (density and diameter remain unchanged) is changed and the inlet/outlet wind temperature pressure gap is not great, D1 = D2, ρ1 ≈ ρ2, as shown in Eq. 2:

$$\frac{H1}{H2} = \left(\frac{N1}{N2}\right)^3 \tag{2}$$

In Eq. 1, the fan motor power consumption and the third power of the fan rotation speed are in a proportional relationship. If the rotation speed is changed with fixed density and diameter, by Eq. 2, the power consumption of the fan motor is proportional to the third power of the air flow.

If the frequency of cooling tower fan can be effectively controlled, the fan motor power consumption can be reduced to save the chiller power consumption (Yu and Chan, 2008; Saidur *et al.*, 2011). This study used the recurrent artificial neural network and MATLAB methods to analyze, simulate and forecast the module of the frequency of cooling tower fan for the optimization of the cooling tower fan frequency.

Artificial neural network: The traditional difficulty in building the mathematical model is the need of

assumptions to simplify the environment and build physical model or mathematical equation when facing complex and non-linear problems. When using the artificial neural network to process complex problems, it does not need to define the problem complexity and solve any calculus equation or other mathematical equation. At present, in many scientific fields, models simulating biological system (Artificial neural network) have been attempted to solve some problems that cannot be solved in the past for the following causes (Chang and Chang, 2005).

- **Fast association speed:** the training process of the artificial neural network takes more time to adjust the inter-neuron connection weight. When the weight value is confirmed, the output of the input data or data forecast should be compared and thus the speed is faster than traditional models
- **Easy to network architecture:** network architecture is more open. The maintenance and updating are easier, requiring the addition of new information and adjustment of network architecture for training
- **Fault-tolerant feature:** artificial neural network in operation has ultra high level of fault tolerance. If the input data brings noise interference, the overall artificial neural work can operate normally

The basic concept of artificial neural network is to simulate human neural system. Its architecture is composed of many non-linear computing units (neuron) and many connections of such computing units. The computing units mainly operate in parallel and dispersive patterns. By the conversion of non-linear function, it can effectively analyze a large amount of data with learning capabilities. In addition, the artificial neural network does not require any assumption. With ample historical learning data, it can conduct analysis. The artificial neural network can be divided into two major categories by learning model (Chang and Chang, 2005; Yeh, 2001):

- **Supervised learning:** In the learning process, it will present the neural network input and output parameters to promote the network modification of the weight during the training process. By the repeated adjustment of the network connections in the training process, the network output and target output values can be reduced
- **Unsupervised learning:** It requires input variable only. In other words, it does not need to modify weight values to improve the neural network output and thus it is applied in classification problems

The artificial neural network has many functional features similar to human brain and the major three functions are as follows (Chang and Chang, 2005):

- **Learning process:** Artificial neural network learning process can be done by a number of methods to build the neuron connection, modify the weights of the connected neurons and adjust the threshold values of the neuron activation function or the combination of the above methods
- **Recalling process:** When the artificial neural network receives an input, it will produce an output value according to the network architecture. This is the recalling process. The effectiveness and robustness of an artificial neural network are determined by whether the recalling process is fast and effective
- **Inductive inference process:** It observes and describes the overall characteristics from parts of a system. Regardless of inference from special cases to the overall event or the recognition of one or a few examples, it defines the object type

Recurrent artificial neural network: Recurrent artificial neural network is a commonly seen dynamic neural network, consisting of at least one feedback layer. This is the main difference from the feed-forward artificial neural network, as shown in Fig. 2. It has no restriction regarding the interconnection of artificial neurons, allowing the neurons to feed back to each other. As feedback provides local memory or temporary memory, the dynamic artificial neural network can simulate the systems that are hard to simulate by the static artificial neural network. The recurrent network architecture can be divided into (Yeh, 2001):

- Feedback from the input layer or the hidden layer to the input layer
- Links exist between various processing units of the layer
- Neurons are arranged not in a hierarchical system but in a layer. The neurons are interconnected. As shown in the Fig. 2, in network propagation, at least one neuron does not propagate forward

Elman network is a simple recurrent artificial neural network with architecture as shown in Fig. 3. In the artificial neural network of single hidden layer, the feedback item is fed back by the input vector of the hidden layer neurons to the input vector of the input layer which is named as the context unit. The weight of the

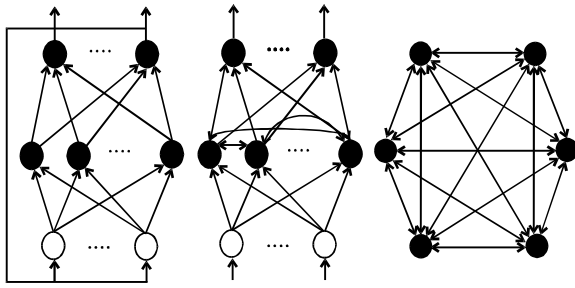


Fig. 2: Recurrent artificial neural network architecture diagram

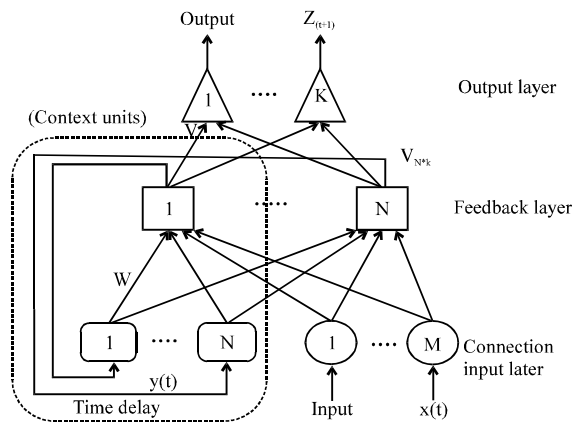


Fig. 3: Elman artificial neural network architecture diagram

context unit is fixed. The weights are modified by the network supervised learning and error back propagation algorithm (Yeh, 2001).

As shown in Fig. 3, if there are M input layers, K output layers and N feedback processing layers, X(t) is the input vector at t of M×1, then, the output vector at T+1 of K×1 is Z(t+1). Y(t) is the output of the “feedback processing layer”, in addition to the input of the “output layer”, it feeds back to the “connection input layer” at the delay of one unit time to connect X(t+1) to form the input vector in (N+M)+1 dimensions of U(t+1). The U(t)’s ith unit can be presented as u_i(t), if i belongs to Set A, the u_i(t) is represented as the actual input value x_i(t), if i belongs to Set B, it means u_i(t) is the feedback input value of Y_i(t): (Yeh, 2001).

$$u_i(t) = \begin{cases} x_i(t) & \text{if } i \in A \\ y_i(t) & \text{if } i \in B \end{cases}$$

The network forward-feed propagation is to add up the multiplication of the input value x_i(t) and corresponding weight w_{ji}(t) to get net_j(t) which is converted by a non linear function of f(·) to get the

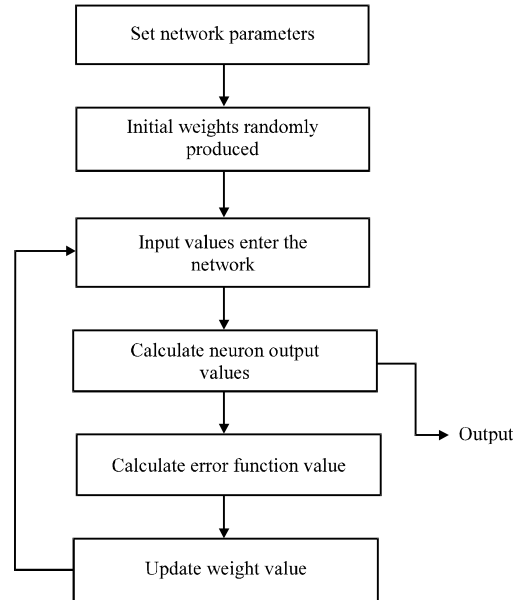


Fig. 4: Real time feedback computation process diagram

“feedback processing layer” output y_i(t). Next, the multiplications of the y_i(t) and corresponding weight are added up to get net_k(t) which is converted by a non-linear function f(·) to obtain the “output layer” output of Z_k(t). The RTRL network output equation can be represented by the following output equation:

$$net_j(t) = \sum_{i \in A \cup B} w_{ji}(t-1)u_i(t-1)$$

$$y_i(t) = f(net_j(t))$$

$$net_k(t) = \sum v_{kj}(t)y_j(t)$$

$$z_k(t) = f(net_k(t))$$

Real-time recurrent learning: Real-time recurrent learning (RTRL) is the most commonly used training equation of the recurrent artificial neural network. This algorithm uses the network connection weight vectors for real time adjustment. When new information is input, the network continuously implements the information program functions and gradually updates the connection weight values according to the errors. The real-time feedback algorithm program is as shown in Fig. 4. The steps are as shown in (Yeh, 2001):

- Set initial connection weight values
- Input the first time unit X into the network to calculate Y and Z and feed back Y to the “connection layer” after the delay of one unit time

- Calculate the error between the network output value and the target value
- Calculate ΔV and update weight accordingly
- Calculate ΔW and update weight accordingly
- Input next time X and repeat the above steps

ARTIFICIAL NEURAL NETWORK MODEL CONSTRUCTION

Build parameter model: Use MATLAB to convert the input variables and output variables into the vector $R \times Q$ matrix.

Data mean value and standardization: As the input and output parameters are different in unit and the artificial neural network requires the same unit for analysis, the unit mean value and standard normalization should be conducted. The preset function is used for conversion to normalize the input and output data, making the data set standardized.

$$[pn, meanp, stdp, tn, mean, stdt] = prestd(p,t)$$

Where:

- pn = The normalized input vector $R \times Q$ matrix
- p = The $R \times 1$ vector consisting of the mean value of P
- stdp = The $R \times 1$ vector consisting of the standard deviation of P
- tn = The normalized input vector $S \times Q$ matrix;
- t = The $S \times 1$ vector consisting of the mean value of T
- stdt = The $S \times 1$ vector consisting of the standard deviation of T

The normalized input and target values fed back by function are pn and tn respectively, making the two have zero mean value and standard deviation at 1. Vectors meanp and stdp contain the initial input mean value and standard deviation. Vectors meant and stdt contain the initial mean value and standard deviation. After the training of the network, the above conversion vectors can be used to convert any input for the network in the future to allow the network to effectively conduct numerical computation and analysis.

Data analysis: The experimental purpose is to use the first day historical data to establish the artificial neural network module and use the historical data of in the second morning in the module to analyze and simulate the data of the second day. Both days require the same mean value and standard deviation. A total of 1060 samples from the two days are form into the same matrix for mean value and standard normalization. Next, the module is applied to compare the historical data of

the morning of the second day with the simulation value. Hence, the data are divided into two parts, the first part is consisted of 709 samples and the second part is consisted of 351 samples of the morning of the second day. However, modification should be done as the data sum of each day is different.

Data set training and verification: The size command is used to check the size after conversion to divide the data set into the training subset and verification subset. The data of the previous day are used as the training subset and the data of the next day are used as the verification subset.

Parameter descriptions:

- **net.trainParam.lr:** network module's learning rate
- **net.trainParam.epochs:** the maximum learning times of the network module
- **net.trainParam.goal:** the tolerable MSE set for the network module

Using the learning rate, the change in weight can be determined and the maximum learning times of the network module are then set. When the network training times have reached the set maximum times or the network output value and expected target value MSE have reached range, the training will stop.

Build network architecture: When using the Elman artificial neural network architecture and the real-time recurrent learning for training, the network hidden layer neuron activation function is the tangent dual-bending curve transfer function (tansig) and the output layer neuron activation function is the linear transfer function (purelin). Initially, the hidden layer is expected to have 12 neurons and the output layer has only one target. Therefore, a neuron is set, the training function is traingdx, the weight and the partial weight learning function is learnqdm.

Simulation and anti-standardization: After the network simulation, the result is converted into the same unit with the initial target value. Next, the use command poststd function is used for conversion to match the network output value with the normalization target tn. The normalized network output value a and the initial target value are in the same unit.

Compare the verification results: The actual measurements of the fan frequency. Instructions are used to the comparison Bode diagram of the verification results and fan frequency measurements.

EXPERIMENTAL RESULTS AND ANALYSIS

This experiment used the historical data measured by the monitoring system of the central air conditioning system in a research institute. The historical data of the two parameters that affect the cooling tower heat dissipation capability factors were used to conduct simulation analysis of correlation via the neural recurrent network before testing the effectiveness of the artificial neural network module using the historical data.

The training and verification of cooling tower frequency module: In this experiment, the recurrent artificial neural network was used to train and verify the historical data. In addition, a forecast module was built to forecast the cooling tower fan operational frequency in the morning of the second day. The feasibility of the module was verified by the comparison of the prediction value and actual value. The previous day cooling water temperature was used as the input parameter (p), then the cooling tower frequency was the output parameter (t). The above data were used for training to establish the forecast module and the data of the following morning were inputted to verify the feasibility of the module. The cooling tower heat dissipation capability was affected by the external wet ball temperature and external humidity change. Therefore, this experiment conducted simulation prediction in conditions without rain.

Sunny day module prediction results: In this experiment, the maximum training times was set as 1000 times and the tolerable MSE was 0.001. When the training times have reached 1000 times, although the MSE has not reached the set value, the maximum training times of 1000 would be satisfied; therefore, the training stops. The MSE value was 0.234 as shown in Fig. 5. Figure 6 illustrates the relationship between training target and network output value. Figure 7 illustrates the relationship between the target verification and network output value. The average temperature gap of the external wet ball in the two days was 0.167°C, indicating that the weather differences were not significant. As shown in Fig. 6 that the trends of the target verification and network output value were identical, indicating that the module simulation effects were good.

This study used the established network module to simulate the condition without rain and predict the next day cooling tower fan frequency values. The comparison of the actual measurements and simulation values is as shown in Fig. 8. The Bode diagram of the cooling tower fan motor frequency measurement values and simulation value are also shown in Fig. 8. As

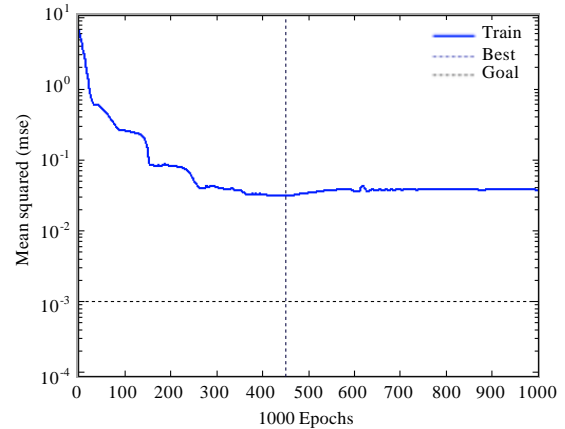


Fig. 5: Relationship between times of the network training and MSE

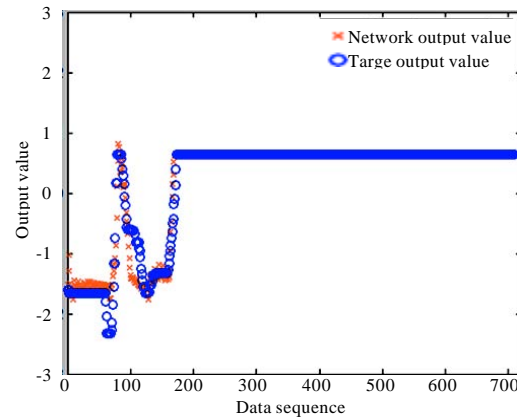


Fig. 6: Training target and network output value

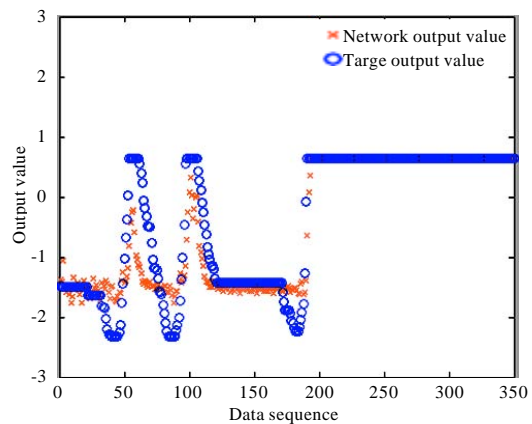


Fig. 7: Target verification and network simulation output value

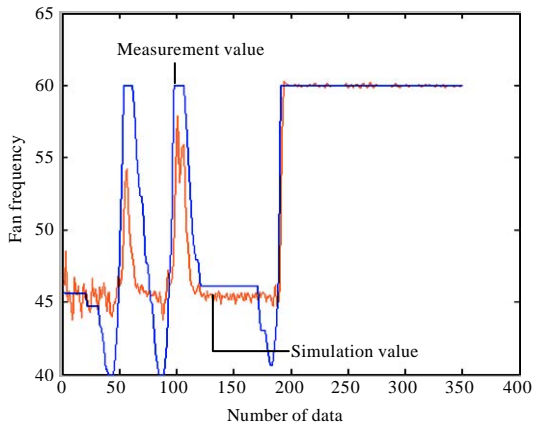


Fig. 8: Comparison of the second day fan frequency original value and simulation value

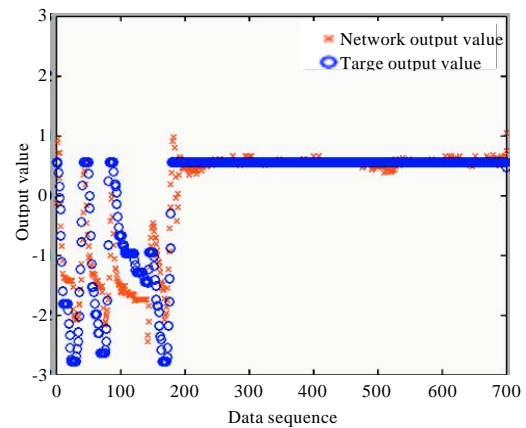


Fig. 10: Training target and network output value

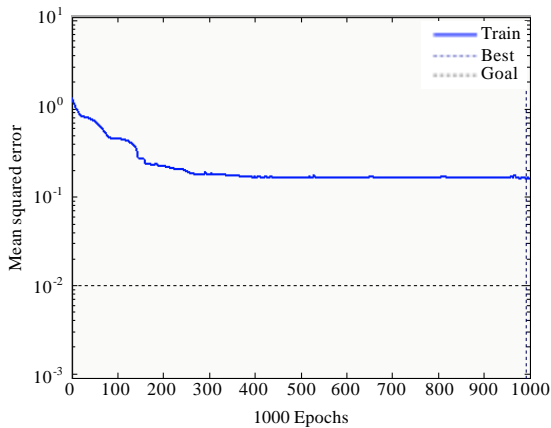


Fig. 9: Relationship of training times of the network and MSE

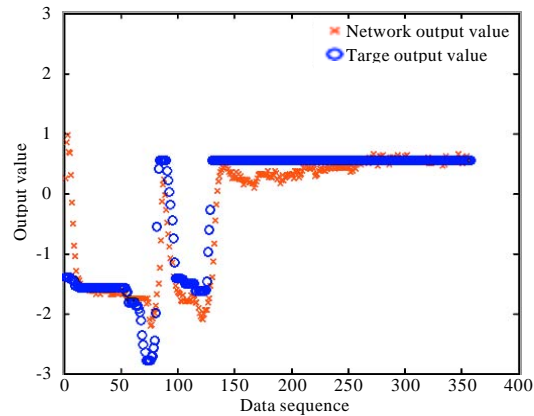


Fig. 11: Target verification and network simulation output value

seen, the trends of the simulation value and the measurement values were considerably identical. Hence, the feasibility of the module to simulate the frequency of cooling tower fan was high.

Rainy day module prediction results The training times of the network has reached the maximum times and therefore, the training stops. As shown in Fig. 9, the MSE value is 0.163. Figure 10 illustrates the relationship between the training target and network output. Figure 11 illustrates the relationship between the target verification and network output value. The average temperature gap of the external wet ball in these two days was 0.562°C. The first day rainfall was 39.5 mm and the second day rainfall was 50.5 mm; thus, the rainfall difference was not significant. As shown in Fig. 11, target verification and network output value were well matched, indicating that the simulation values were accurate.

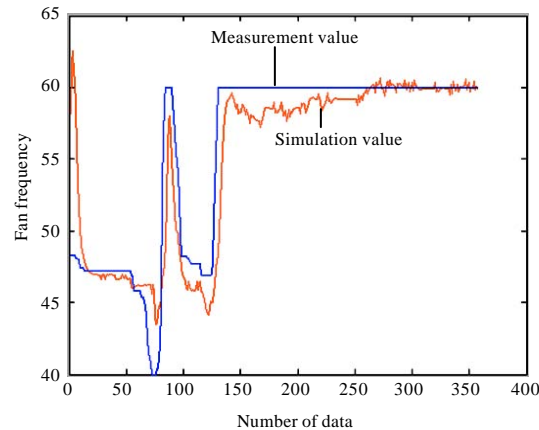


Fig. 12: Comparison of the original value and simulation value of the fan frequency on the second day

This study used the established network module to simulate the conditions in rainy days and predict the cooling tower fan frequency in the next day. The comparison of the actual values and simulation values is as shown in Fig. 12. The average error value of the cooling tower fan motor frequency measurement (blue) and simulation value (red) Bode diagram was 0.122. The trends of the simulation values and the actual curve were close, proving that this module can effectively predict the cooling tower fan operating frequency in rainy days.

CONCLUSION

According to the analysis of the power consumption of the entire air conditioning system, chiller is the major power consumption equipment. In particular, in major semiconductor and wafer plants, the cooling load is at least more than 10 thousand tonnage. In addition, the host will operate continuously throughout the year. Therefore, the power consumption is considerable in terms of air conditioning power consumption.

This study used use the MATLAB software to build the neural recurrent network module and explored the cooling water temperature and cooling tower fan frequency of the historical data to predict the cooling tower fan operating frequency. The historical data of the cooling tower fan frequency and cooling water temperature were used for training and verification. The modules were established by weather condition. The simulation prediction values revealed that the cooling tower fan often operates in high frequency. According to the fan law, the fan motor power consumption and the third power of the fan rotating speed are in a proportional relationship. If the cooling tower fan frequency can be properly controlled according to the climatic conditions, the overall cooling tower power consumption can be effectively reduced.

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