Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 11 (16): 3008-3014, 2011
ISSN 1812-5654 / DOI: 10.3923/jas.2011.3008.3014

Chiller Energy Saving Optimization using Artificial Neural Networks

[1]Kuang-Cheng Yu, [2]Yung-Hsiang Hung, [3]Shi-hung Hsieh and [4]Shi-Je Hung
[1]Department of Refrigeration, Air-conditioning and Energy Engineering,
National Chin Yi University of Technology, Republic of China
[2]Department of Industrial Engineering and Management, National Chin Yi University of Technology
[3]Skytech Science, Technology Engineering Co., Ltd
[4]Department of Refrigeration, Air-conditioning and Energy Engineering,
National Chin Yi University of Technology, Republic of China

Abstract: In central air conditioning systems, chillers are the main cooling source. Chiller power consumption comprises 60% of the total power consumed by the system. The major parameters affecting chiller efficiency include cooling water pump efficiency, wet bulb temperature, cooling tower fan frequency, compressor high pressure and cooling water inlet temperature. This study focused on the use of neural networks to integrate, train and simulate the parameters to construct power saving modes. To deal with field load change, this study used neural networks and MATLAB to analyze and simulate the data collected from the field sensors to establish effective energy saving modules to adjust cooling tower fan operating frequency, optimize chiller load distribution and reduce chiller power consumption with various loads to achieve energy-saving goals.

Key words: Artificial neural network, MATLAB, optimization

INTRODUCTION

Since the industrial revolution, humans have depended on energy by exploiting oil and coal for stable economic growth, future resource shortages will inevitably occur. Impacted by geographical factors, Taiwan does not have many natural resources, forcing the importation of resources from other countries. Because of complex accessibility to resources and the slow development of new resources, energy saving is important for Taiwan.

Electricity is the mother of industry and of the most important energy for modern life. With rapid economic development of industry and commerce, electricity consumption will also increase in the future. Industrial and residential electricity consumption will increase. Taiwan has a subtropical climate. Taiwan is characterized by hot and humid summers, causing demand for air conditioning to increase which has promoted the development of refrigerating air conditioning industry. Due to the popularity of air conditioning equipment, air temperature changes are closely related to peak loads for power systems. For electric power loads, power consumption of air conditioning equipment accounts for 30% of the total power consumption during the summer. For central air conditioning systems, chillers are the primary cooling source and comprise 60% of the total power consumed by the system. Reducing energy consumption for air conditioning equipment and increasing energy use efficiency is crucial. In air conditioning system planning, the maximum load for the system is often decided by the highest outside air temperature and maximum room load. The chiller rated capacity depends on the system load. Chillers seldom operate under the maximum load of air conditioners and often work under various loads. The optimization of chiller operations under various loads is one of the main energy-saving methods for central air conditioning systems (Shih, 2004).

PRINCIPLES AND METHOD

Biological neural networks exemplified by human brain operation and thinking are mysterious. Artificial neural networks were created by human beings to simulate biological neural network information processing systems. Neural network theory began in the 1950s. Prior to 1980, expert systems were the most popular artificial intelligence networks available. Artificial neural network theory was ignored and has not matured since. After 1980, artificially intelligent expert systems had bottleneck complications. Extensive attention has been paid to

Corresponding Author: Kuang-Cheng Yu, Department of Refrigeration, Air-conditioning and Energy Engineering, National Chin Yi University of Technology, Republic of China Tel: (04)23924505 Fax: (04)23930062

artificial neural network systems. By far, new architectures and theories for artificial neural networks have been proposed. With the increase of the computer speeds, artificial neural networks have more powerful functions and are in wide use. Their characteristics are as follows (Chiang, 2005):

- **Filtering capability:** When the input signals have noise or data are incomplete, the input signals have less impact on the network than transitional mathematical model
- **Adaptive learning capability:** Adjust connection weights of two nodes; continuously adjust the weights until input and output is correct. This is called adaptive learning capability.
- **Multi-input-multi-output system:** Input layer is allowed to have any number of input nodes and the output layer is allowed to have any number of output nodes. Thus, neural network systems are multi-input-multi-output systems

Artificial neural network: Artificial neural networks are information processing systems that simulate biological neural networks. These are defined as:

... a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons and it processes information using a connectionist approach to computation. Artificial neurons are the simple simulation of the biological neurons and can obtain information from the external environment or other artificial neurons and transmit results to external environment or other artificial neurons.

Artificial neural networks are divided into two learning models (Chiang, 2005; Yeh, 2001):

- **Supervised learning:** In the training examples, given neural network input and output variables. During training, continuously supervise neural networks to correct weights and learn correspondence rule for the input variables and output variables. It is often used in model training
- **Unsupervised learning:** Only require input variables and not output variables. It is not necessary to correct weights for improving the output of neural networks and it is often used for classification

The supervised learning model is represented by Back-propagation Neural Network (BPNN). The basic theory for this network uses the steepest gradient descent method to minimize error functions. Back-propagation neural networks have functions for learning and parallel information processing which include learning and recalling processes:

- **Learning:** BPNN is a common method of teaching artificial neural networks how to perform a given task. Part of variable input data and output reference value is required to remove the data to be processed. It is used for the learning model. In the process of training data to be input into the BPNN, the steepest gradient descent method is used to repeatedly correct weights and biases until the error is converged to allowable values and the weights can be stored as the weights after learning. If the error is significant, then it will propagate back to the previous layer. The error-correction rule is used to adjust network weights. After learning, a series of expert experiences are stored in the weights
- **Recalling:** Recalling phase uses the weights and biases of expert experiences after learning the identification and classification for future data

The modification process of weights and biases has forward and backward propagations. These are referred to as back propagation neural networks.

Back-propagation neural network model: Back-propagation neural network model is shown in Fig. 1, including (Jiang *et al*., 2004):

- **Input layer:** This displays the network input variable and this number depends on demand

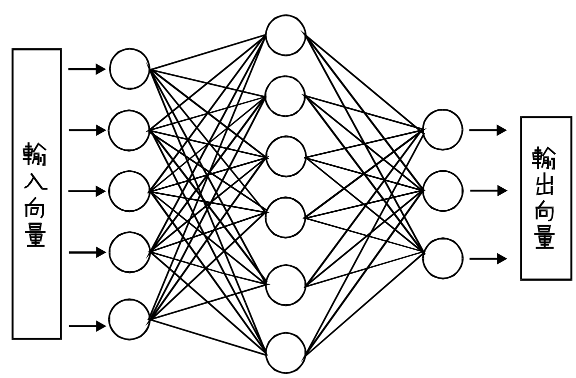

Fig. 1: Back-propagation neural network model structure

- **Hidden layer:** This displays the interactions between input processing units and the greater number of processing units there are, the slower the convergence is. But, minimum error (training error) can be achieved. If exceeding a certain number, then this is not helpful for minimizing (testing error). Currently, no method can determine this. The optimal number is confirmed by the test method
- **Output layer:** Displays network output variable and the number of processing units is decided by demand

BPNN input layer receives the signal input. The hidden layer and the output layer perform two operations: the linear sum and non-linear conversion of non-linear conversion function. The linear sum process is the product and sum of the first layer input (xi) and the connection weight (wji) plus biases (bi), the result is unit j plus sum uj. The non-linear conversion is used to obtain output value yj of unit j. The back-propagation neural network model flow chart is shown in Fig. 2.

The Equation is as follows (Huang and Huang, 1998):

$$u_j = \sum_{i=1}^{N} w_{ji} x_i + b_i$$

$$y_j = \varphi\,(u_j)$$

$$\varphi(u) = \frac{1 - e^{-u}}{1 + e^{-u}}$$

$$E = \frac{1}{2} \sum_{j \in C} (d_{j-y_j})^2$$

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \frac{\partial E}{\partial w_{ji}}$$

Air conditioning energy-saving principle: The Mollier refrigerant system recycle diagram is shown in Fig. 3.

Q_e: Refrigerating capacity
W: Compressor output power
C: (Performance coefficient): $\frac{Qe}{W}$

If reducing condensation temperature and pressure, because:

$$C.O.P' = \frac{Q_e'}{W'}$$

and Q_e>Q_e>, W'<W, P_C>P_C' So C.O.P' >C.O.P

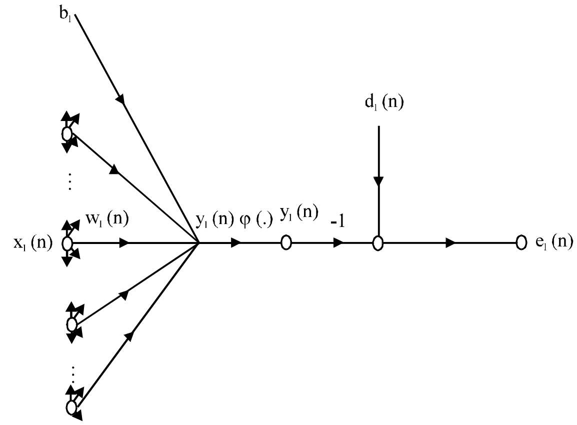

Fig. 2: Back-propagation neural network model flowchart

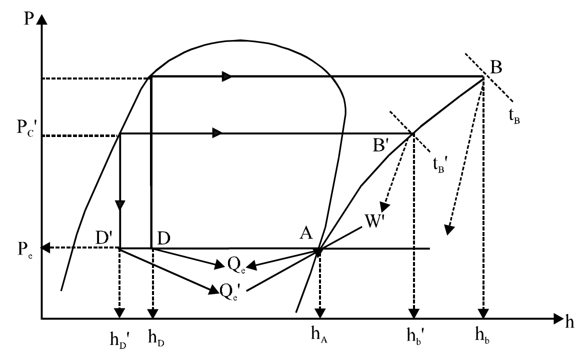

Fig. 3: Mollier recycle of reducing condensation temperature

System energy consumption decreases when condensation temperature and pressure reduce. Reducing cooling water input temperature can save chiller energy consumption. This study uses neural networks, i.e., back-propagation neural networks in a supervised learning model to train and simulate chiller parameters.

Experimental method: The experimental method employed historical data for the five parameters that affected cooling tower capacity. Cooling tower fan motor frequency, high pressure compressor, cooling water inlet temperature, cooling water pump frequency and temperature differences between cooling water inlet and outlet were used as input parameters (p) and the temperature differences between cooling water input and wet bulb were used as the output variable (t). The back-propagation neural network can be used to analyze this correlation. Further, the historical data from the last day were used to test the effectiveness of neural network modules. The network construction steps were as follows:

Step 1: We used MATLAB to convert the input parameters and output variables into vector R×Q matrix and the converted results were stored for test.

Step 2: Load data with MATLAB working space, normalize input, output objectives and set them to the zero mean and standard deviation to 1.

Step 3: Check converted data, we divided the data into training, verification and testing subsets; one quarter of the total data was used as the data verification set, the other quarter was used as the data testing set and last half was used as the data training set.

Step 4: We used Levenberg-Marquardt to set parameters, such as learning efficiency, learning objective and maximum number of training recycles.

Step 5: We used Levenberg-Marquardt for training and created a network for training. This study tested a two-layer network. This hidden layer within the network contained tangent sigmoidal transfer functions and the output layer had linear transfer function. According to this assumptions, the hidden layer would use five neurons, because there was only a single objective and, therefore, one output neuron was set.

Step 6: The plot error bar for training, verification and testing was used to check training progress.

Step 7: We introduced the data sets into the network and conducted linear regression for network outputs and the corresponding objectives. In this experiment, there was one input and one linear regression required. The historical data of p2 and t2 from the last days were used to normalize the input and the output objectives. By setting them as the zero mean and the standard deviation was 1.

Step 8: We conducted the network simulation analysis for the total data sets and did not normalize the network output.

Step 9: We analyzed and simulated the error between the output value and the actual value and performed a linear regression.

Step 10: We used constructed modules and simulated parameters.

EXPERIMENTAL RESULTS AND ANALYSIS

This study used the actual measured data from air conditioning systems from the research institute and back-propagation network analysis to find out the chiller

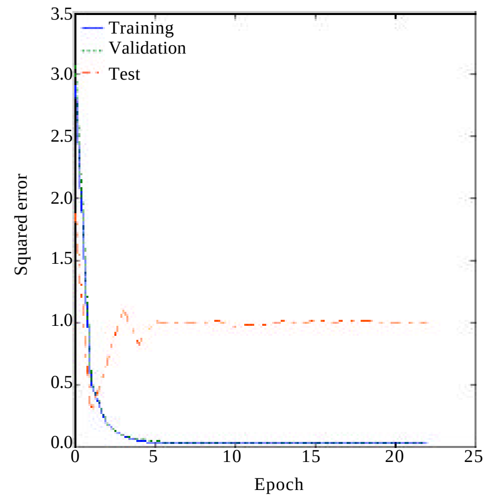

Fig. 4: Network training progress of simulation process

energy consumption weights and construct the network modules. The data from the second day were simulated to test modules and the simulated cooling water pump frequency was used to compare the simulated cooling water inlet temperature from the second day with actual results.

Result of training network modules: Figure 4 demonstrates the rationality of simulated results. The errors of the data testing set and data verification data have similarity. Further, no significant over-fitting occurred. The training process will stop when error verification was performed at 22 times epochs. The scatter plot for the output results is shown in Fig. 5. The five input and output parameters had a close relationship. The R-value represented the correlation coefficient of output and objective and was the measure of verification. If the value was 1, the objective and input had a perfect correlation. In this study, the R-value was 0.986, so the network consisted of the five input and output parameters was feasible. The network modules were used to simulate the data for the next day, sharp climate changes were excluded, because the data of two consecutive days had a correlation. If the R-value was higher, then the modules used the data from the first day to effectively simulate the data from the second day. The results are shown in Fig. 6. If the R-value was 0.853, then there was a slight difference. Nevertheless, the simulated data from the second day was effective.

Simulated temperature difference result using simulated fan motor frequency: The neural network module was stored as pro-model 1. The fan motor frequency and the temperature difference was represented by t and p. After relevant simulation training, the results are shown in

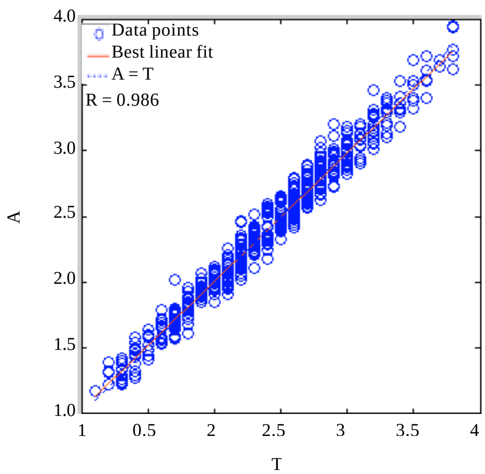

Fig. 5: Scatter plot of simulated output results

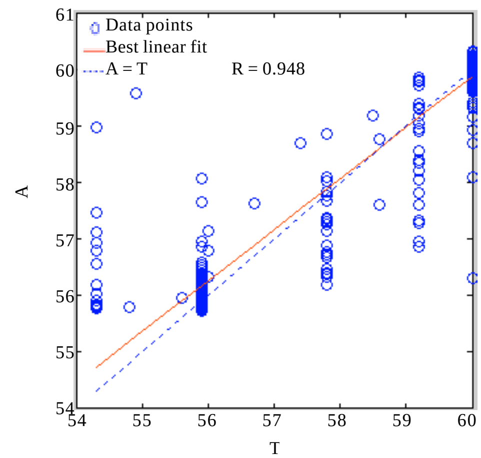

Fig. 7: Scatter plot of simulated output results

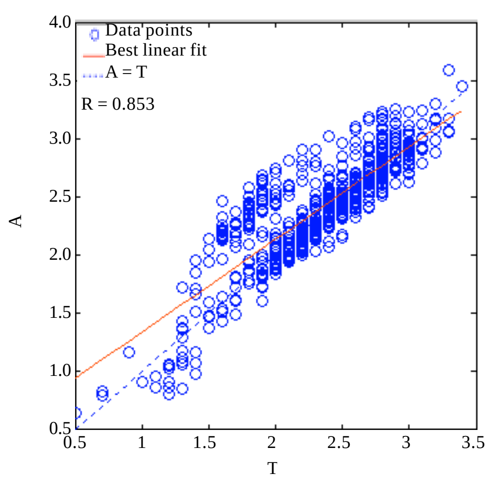

Fig. 6: Scatter plot of output results using the simulated data of the last day in the training network

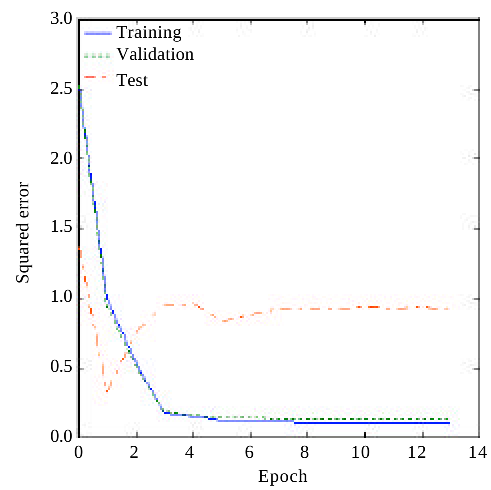

Fig. 8: Network training progress in simulation process

Fig. 7 and 8. The training results indicated that the correlation R-value was in the accepted range. The module is stored as pro-model 2. The temperature difference was gradually increased based on the historical data for temperature differences of 1.7°C. The pro-model 2 simulation frequency results are shown in Table 1. The simulated frequency was 58.394Hz when the temperature difference was set to 2.2°C. If increasing the temperature difference, then the simulated value of the water tower fan motor frequency had no significant change. The simulated frequency of pro-model 2 can propagate back to the simulated temperature difference of pro-model 1, as shown in Table 2. The simulated temperature difference was

Table 1: Analysis list of simulated frequency and temperature difference

Simulated result of Pro-model 2		Simulated result of Pro-model 1	
Temperature difference value (°C)	Simulated water tower motor frequency (Hz)	Simulated water tower motor frequency (Hz)	Simulated temperature difference (°C)
2.0	56.684	56.684	1.6979
2.1	56.966	56.966	1.7968
2.2	58.394	58.394	1.9003
2.3	59.104	59.104	1.9111
2.4	59.456	59.456	1.8572
2.5	59.343	59.343	1.876
2.7	59.788	59.788	1.8889
2.9	59.919	59.919	1.8884
3.2	60.025	60.025	1.8513
3.5	60.165	60.165	1.8505
3.6	59.943	59.943	1.8834
3.8	58.878	58.878	1.89

Table 2: Mean error

No. of day	Mean error
1	0.147
2	1.105
3	0.622
4	3.594
5	0.926
6	0.238
7	0.899
8	0.451
9	0.223
10	4.058
11	1.704
12	1.252

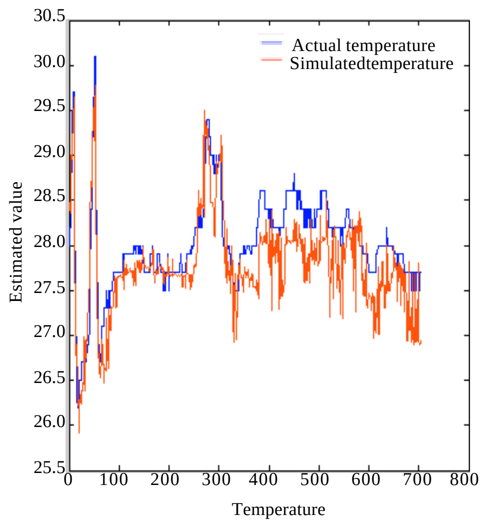

Fig. 9: Cooling water inlet temperature comparison

1.6979°C when the frequency was 56.684 Hz. If increasing the frequency, then the temperature difference had no significant change. Thus, the fan motor frequency was adjusted to 56.684 Hz when temperature difference was higher than 1.6979°C and increased of the fan motor frequency had no effect. As a result, the cooling water tower motor frequency would not work under full load of 60 Hz; reducing operation frequency can effectively reduce cooling water tower fan motor power consumption.

Adjusting cooling water pump frequency to simulate cooling water inlet temperature: The constructed network modules were used to simulate water pump frequency for the following day. The value was used to estimate cooling water inlet temperature and compared the estimated value to the actual value. Figure 9 shows the Bode diagram for the actual cooling water inlet temperature and the simulated cooling water inlet temperature. From this figure, two values were closer and the error difference was less than 0.5°C. The module had a high feasibility of simulating cooling water inlet temperature. Average error of estimated values of 12 days are shown in Table 2. The results indicated most errors were lower than 0.5°C. Because the climate changes frequently in Taiwan, the effectiveness of the network-based modules based on historical data was decided by climate stability. From Table 2, the fourth day and the tenth day had the greatest average errors. If two days had significant climate changes, then the effectiveness of the simulation prediction was lower. Therefore, network modules for different climates should be constructed.

CONCLUSIONS

In this analysis of air conditioning system power consumption, chillers are of the primary cooling source. Industrial semiconductor and wafer manufacturers require ten thousand ton refrigeration loads with chillers running year round. Air conditioning power consumption is considerable. The cooling water tower efficiency is closely correlated to wet bulbs. As the temperature of wet bulb changes, the fan motor frequency is adjusted to optimize the cooling effect to cool the water tower to maximize efficiency.

This study used back-propagation neural networks to analyze and classify chiller historical data. Present findings showed that the correlation and the feasibility of the simulated results. The cooling tower fan motor frequency can be adjusted to simulate temperature differences between cooling inlet water and wet bulbs. The known impacts of the cooling water tower fan motor frequency and cooling water pump frequency on cooling water inlet temperature. Further control cooling water inlet temperature can optimize the chiller energy efficiency. Future studies can use more sampling points to find greater regularity. In combination with PLC, the control equation can be used in field tests to achieve energy saving efficiency for air conditioning systems.

ACKNOWLEDGMENT

This study was financially supported by the National Science Council under the "Chiller Energy Saving Simulation and Measurement Optimization Research" of the University-Industry Cooperation Plan (Project No: NSC 99-2622-E-167- 005-CC3.). The authors would also like to thank Skytech Science and Technology Engineering Co., Ltd. for its additional funding and technical support.

REFERENCES

Chiang, C.H., 2005. Optimal chiller loading using simulated annealing. Masters Thesis, Department of Energy and Refrigerating Air-Conditioning Engineering, National Taipei University of Technology.

Huang, Y.W. and H.J. Huang, 1998. The study on the comfortable air-condition and energy-saving of air-condition system by fuzzy control. Chin. Refrig. Air Conditioning J., 39: 132-140.

Jiang, Y., Y. Yao, S. Deng and Z. Ma, 2004. Applying grey forecasting to predicting the operating energy performance of air cooled water chillers. Int. J. Refrig., 27: 385-392.

Shih, Y., 2004. A practical analysis in energy savings for facility HVAC-System Chiller. Master's Thesis, Department of Mechanical Engineering, Chung Yuan Christian University.

Yeh, Y., 2001. Application and Implementation of Artificial Neural Network Model. Ru Lin Books, Chnia, ISBN:957-499-313-2.