Artificial neural network analysis based on genetic algorithm to predict the performance characteristics of a cross flow cooling tower

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Abstract. Cooling tower of air conditioning has been widely used as cooling equipment, and there will be broad application prospect if it can be reversibly used as heat source under heat pump heating operation condition. In view of the complex non-linear relationship of each parameter in the process of heat and mass transfer inside tower, In this paper, the BP neural network model based on genetic algorithm optimization (GABP neural network model) is established for the reverse use of cross flow cooling tower. The model adopts the structure of 6 inputs, 13 hidden nodes and 8 outputs. With this model, the outlet air dry bulb temperature, wet bulb temperature, water temperature, heat, sensible heat ratio and heat absorbing efficiency, Lewis number, a total of 8 the proportion of main performance parameters were predicted. Furthermore, the established network model is used to predict the water temperature and heat absorption of the tower at different inlet temperatures. The mean relative error MRE between BP predicted value and experimental value are 4.47%, 3.63%, 2.38%, 3.71%, 6.35%,3.14%, 13.95% and 6.80% respectively; the mean relative error MRE between GABP predicted value and experimental value are 2.66%, 3.04%, 2.27%, 3.02%, 6.89%, 3.17%, 11.50% and 6.57% respectively. The results show that the prediction results of GABP network model are better than that of BP network model; the simulation results are basically consistent with the actual situation. The GABP network model can well predict the heat and mass transfer performance of the cross flow cooling tower.

1. Introduction

Reversibly used cooling tower (RUCT) can be used as heat source under heat pump heating operation condition, and has distinctive advantages and application prospect. At present, RUCT technology has been applied in the central air conditioning system of public buildings in China [1, 2], and has shown better energy saving effect [3, 4].

In RUCT, the flow, heat transfer and mass transfer occur simultaneously and are coupled with each other. It is a complex and irreversible thermodynamic process.In fact, many influence parameters affect heat and mass transfer characteristic. At the same time, considering RUCT under cross flow condition and heat pump system under heating operation condition, there were uncertainties about the situation that air contacted directly with water, the influence that environment parameters changed instantaneously, and the influence that terminal load changed instantaneously, all of which caused that the accurate mathematical method could not be utilized to illustrate. The multi-layer neutral network can be utilized to analyze non-linear problem. Currently, neutral network has been widely used in practice in the field of heating, ventilation and air conditioning, and 80%-90% situations apply BP network or its development form [5,6]. Qi et al. [7] combined the ANN method with the conventional method and present the model of shower cooling tower with accuracy and adaptively, and presented the ANN technique could determine the performance of shower cooling towers under various operating conditions.Wu et al. [8] combined back-propagation (BP) training with principal component analysis, the three-layer ANN model with a tangent sigmoid transfer function at hidden layer with 11 neurons and a linear transfer function at output layer was obtained, and the results reveal that ANN model can be used effectively to predict the performance characteristics of the cross flow RUCT .

In this paper, the BP neural network model based on genetic algorithm optimization (GABP) was applied to better analyze the complex non-linear relationship between each parameter in the heat and mass transfer process of wet air and water inside cooling tower. Using this GABP model, 8 main performance parameters of RUCT under cross flow condition, specifically outlet air dry-bulb temperature, wet-bulb temperature, outlet water temperature, heat absorption capacity, sensible heat ratio, heat absorption efficiency, proportion of condensate water and Lewis number, was conducted with predictive analysis. The research results can be used as a basis for performance prediction, evaluation and optimal design of cross flow RUCT.

2. The GABP neural network model for a cross flow RUCT

2.1. BP network model

In the cross flow RUCT, theheat -mass exchange process between wet air and chilled wateris a nonlinear problem. The multilayer neural network can be used to analyze the nonlinear problems, and has been widely used in the actual neural network in HVAC field [9], and 80%-90% network used BP or on the basis of the evolution of the form. In 1986, the BP network was proposed by Rumelhart and McCelland as a multilayer feed forward network trained by error back propagation algorithm. It is one of the most widely used neural network models. The BP network can learn and store a large number of mapping relations between input and output patterns without revealing the mathematical equations describing such mappings. BP algorithm not only solves the learning problem of multilayer perception, as the core of the feed forward network, but also embodies the best part of the neural network and promotes its continuous development. In this paper,the BP network algorithm is selected mainly includes the following steps: (1)set variables and parameters, and initialize the network; (2) calculate the hidden layer output; (3) calculate the output layer; (4) calculate error; (5) determine whether the end of the iteration algorithm; (6) update the weights and threshold.

Many previous literatures [10-12] believe that 3-layer BP network model of which hidden layer number is 1 has good characteristic to capture non-linear pattern, so long as choosing the proper neuron number in hidden layer, and a nonlinear function can be approximated with high precision. Therefore, 3-layer BP network is used in preference in this paper. By training different functions which include trainlm, trainrp, traincgb, traincgf, traincgp, et. al respectively, the result of training error finally show that the training function trainlm of Levenberg Marquardt applied in BP network model of RUCT under cross flow condition in this paper is with relatively small training error. The correlation coefficient r=0.9751, the coefficient of determination R2=0.9508, and the mean relative error MRE=1.74%. Hence training function trainlm is used in this paper to conduct calculation.

At present, there are many empirical formulas [13,14] to roughly determine hidden layer node number. Based on these empirical formulas, hidden layer node number is determined within the range of 6-15. Then they are tested and adjusted one by one repeatedly, and node number is chosen which has the minimum training error. BP network RUCT under cross flow condition in this paper uses 1300 sets of previous experimental data, and randomly chooses 1000 sets of data as sample for training, 300 sets of data as sample for verification. When hidden layer node number is 13, the correlation coefficient r=0.9751, the coefficient of determination R2=0.9508, the mean relative error MRE=1.74%, and acceptance of error is good.

In the final established BP network model ,there are 6 nodes in input layer, denoting inlet air dry-bulb temperature, inlet air wet-bulb temperature, inlet water temperature, inlet water mass flow rate, inlet air mass flow rate and water-spraying density of RUCT under cross flow condition respectively. There are 8 nodes in output layer, representing outlet air dry-bulb temperature, outlet air wet-bulb temperature, outlet water temperature, heat absorption capacity, sensible heat ratio, heat absorption efficiency, proportion of condensate water and Lewis number Le of RUCT under cross flow condition respectively. The range of input parameters are listed separately: inlet air dry-bulb temperature ranges 3.0-15.0 °C, inlet air wet-bulb temperature ranges 2.0-15.0 °C, inlet water temperature ranges 0-8.8 °C, inlet water mass flow rate ranges 7.4-17.1 kg/s, inlet air mass flow rate ranges 13.2-28.3 kg/s, and water-spraying density ranges 3.3-7.6 kg/(m2·s).

2.2. Realization of the BP neural network model based on genetic algorithm (GA) optimization

Although the BP network algorithm is currently the most widely used neural network algorithm, there are still many problems which mainly including: learning speed of BP algorithm is slow, training failure possibility of network is relative big, and it is likely to be in the over fitting state. As a kind of optimization method with good versatility and wholeness, GA is naturally used in the training process of BP network.

(1) Initialization

This paper adopts real coding method, namely cascade weight and threshold of BP network in a certain order, and an array of real numbers is formed. The array consists of weight connecting input layer and hidden layer of network, threshold of hidden layer, weight connecting hidden layer and output layer, and threshold of output layer, which is a chromosome of genetic algorithm.

In BP network of this paper, network structure is 6-13-8, which means that input layer has 6 nodes, hidden layer has 13 nodes, and output layer has 8 nodes. There are totally 182 nodes and 21 thresholds, thus the number of optimized parameter in genetic algorithm is 203.The number of weights and thresholds is shown in table 1. The number of nodes in the input layer, the hidden layer and the output layer is R, S1 and S2 respectively, and the encoded length is:

$$S = R \cdot S_1 + S_1 \cdot S_2 + S_1 + S_2 \tag{1}$$

Table1. Determination of weight and threshold number.

Weight connecting input layer and hidden layer	Threshold of hidden layer	Weight connecting hidden layer and output layer	Threshold of output layer
78	13	104	8

Supposing that the code of weight and threshold are both binary numbers, the binary code length of individual is 2030. The first 780-bit encode for weight connecting input layer and hidden layer, 781-bit-910-bit encode for hidden layer threshold, 911-bit-1950-bit encode for weight connecting hidden layer and output layer, 1951-bit-2030-bit encode for output layer threshold.

(2) Determination of fitness function

S connection weights of initial population are assigned to BP network, and the input signal is transmitted forward. Sum E of absolute errors between predicted output and expected output is set as value of individual fitness F, and set fitness function as:

$$F = k\left(\sum_{i=1}^{n}\left|y_i - o_i\right|\right) \tag{2}$$

Where n is number of network output node; $y_i$is expected output of the *i* node of BP network; o_i is predicted output of the *i* node; *k* is factor.

(3) Selection

This paper uses roulette method which makes the selection based on fitness scaling method. The first step is to calculate fitness of each individual in population. Then order all individuals in population by their fitness, and this sequence distributes chance Pi of selection of each individual. The individual with higher fitness will be more likely to be selected, and the probability to be selected is smaller for individual with lower fitness. In this way, the evaluation criteria of genetic algorithm and BP network integrate together. The smaller sum of absolute error, the better performance of network.

(4)Crossover

The crossover method between the k chromosome $a_k$and the l chromosome al is shown as follow:

$$\begin{cases} a_{k,j} = a_{k,j}(1-b) + a_{l,j}b \\ a_{l,j} = a_{l,j}(1-b) + a_{k,j}b \end{cases} \tag{3}$$

(5)Mutation

Choose $a_{i,j}$ which is the j gene of the *i* individual to proceed mutation, mutation operation method is as follow:

$$a_{i,j} = \begin{cases} a_{i,j} + (a_{i,j} - a_{\max}) \cdot f(g) & r \ge 0.5 \\ a_{i,j} + (a_{\min} - a_{i,j}) \cdot f(g) & r < 0.5 \end{cases} \tag{4}$$

Where$a_{max}$is the upper bound of gene $a_{i,j}$, $a_{min}$is the lower bound of gene $a_{i,j}$, $f(g) = r_2(1 - g / G_{\max})$,r2 is a random number, g is the iteration, G_{max} is the maximum number of optimization, r is the random number in the interval of [0,1].

(6)Creation of the new population

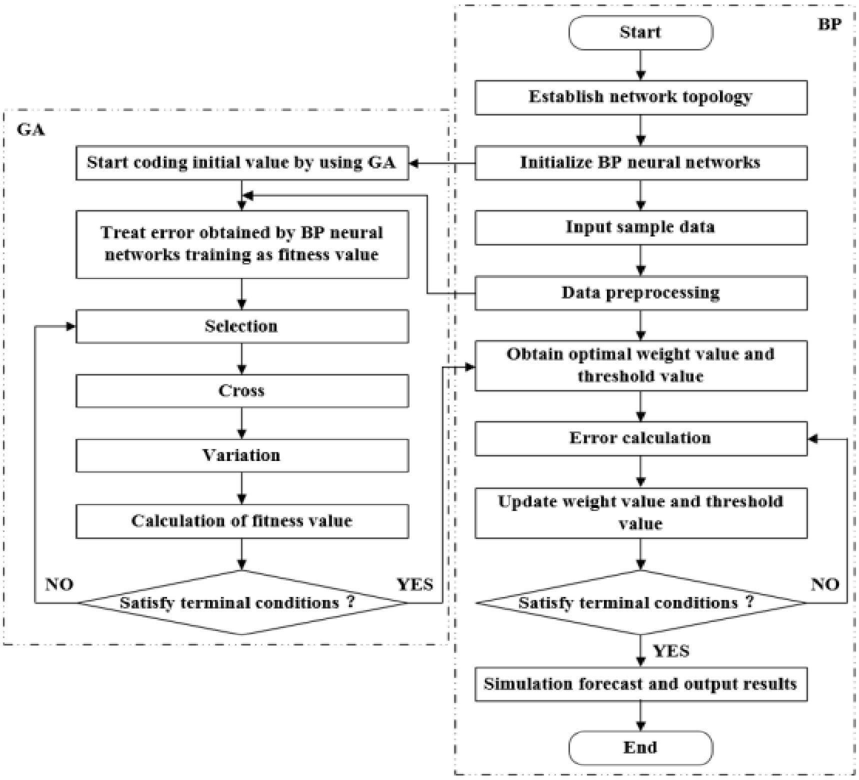

Figure 1. The program flow diagram of BP network optimized by GA.

The new individual is produced by calculation of crossing and mutation for the origin individual, and the new population is created by inserting all new individuals to the origin population. Connecting weights of BP algorithm are updated by individuals in new population. Calculate individual fitness repeatedly, and set the calculation error standard or the iteration number to decide whether the update is terminated. If meeting the requirement, then decode, and set the connecting weight of optimized network as initial of BP network. The program flow diagram of BP network optimized by GA is shown in Figure 1.

The running parameters of genetic algorithm in this paper are set as Table 2: because the data of weight and threshold matrix is too much, they are not listed specifically here, and the minimum error reaches 8.5632. After getting the optimized initial weight and threshold, the training curve in two cases separately with random weight, threshold and optimized weight, threshold can be obtained. Through comparison error of test sample with optimized initial weight and threshold reduces from 13.8571 to 8.5632, and error of training sample reduces from 33.8174 to 24.3398. Therefore, test result of test and training sample of BP network are both improved significantly.

Table2. Running parameter setting of genetic algorithm.

Population size	Int lchrom	Individual lengths	Generation gap	Crossover rate	Mutation rate
50	30	20	0.95	0.7	0.01

2.3. Analysis on predicted correlation of GABP network

Figure 2 to Figure 9 indicate the functional relationship between predicted value and experimental value of 8 output parameters (outlet air dry-bulb temperature, outlet air wet-bulb temperature, outlet water temperature, heat absorption capacity, sensible heat ratio, heat absorption efficiency, proportion of condensate water and Lewis number Le of RUCT under cross flow condition).

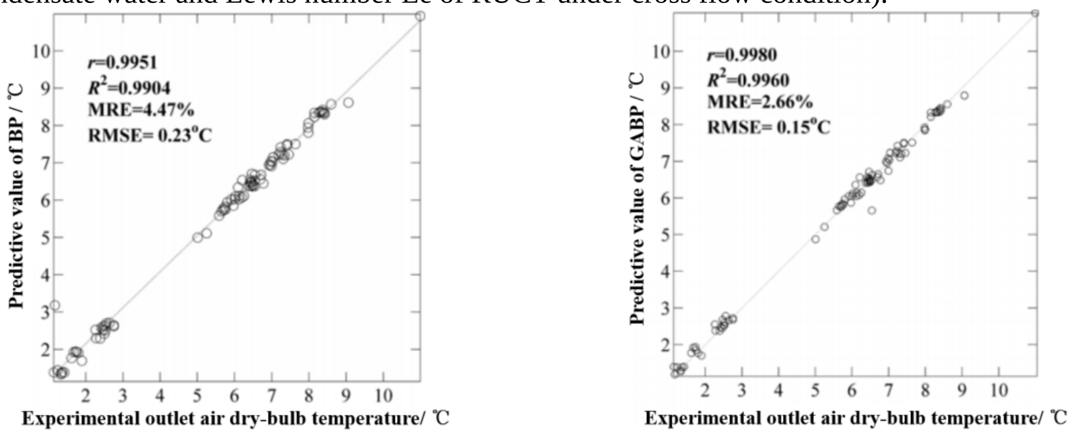

Figure 2. Correlation curve ofoutlet air dry-bulb temperature.

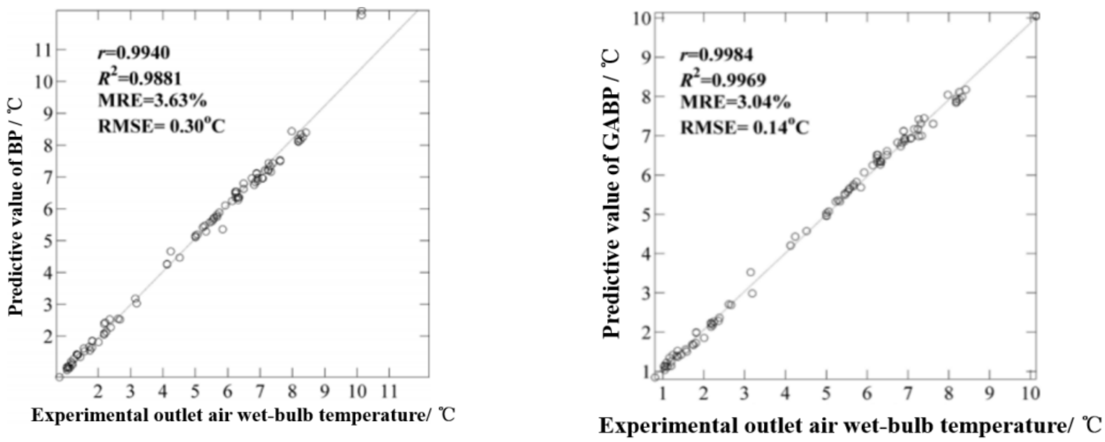

Figure 3. Correlation curve of outlet air wet-bulb temperature.

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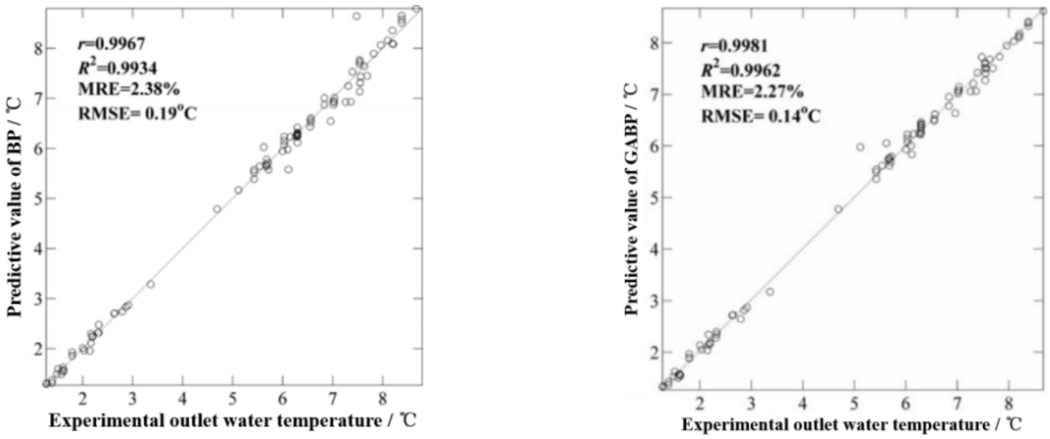


Figure 4. Correlation curve of outlet water temperature.

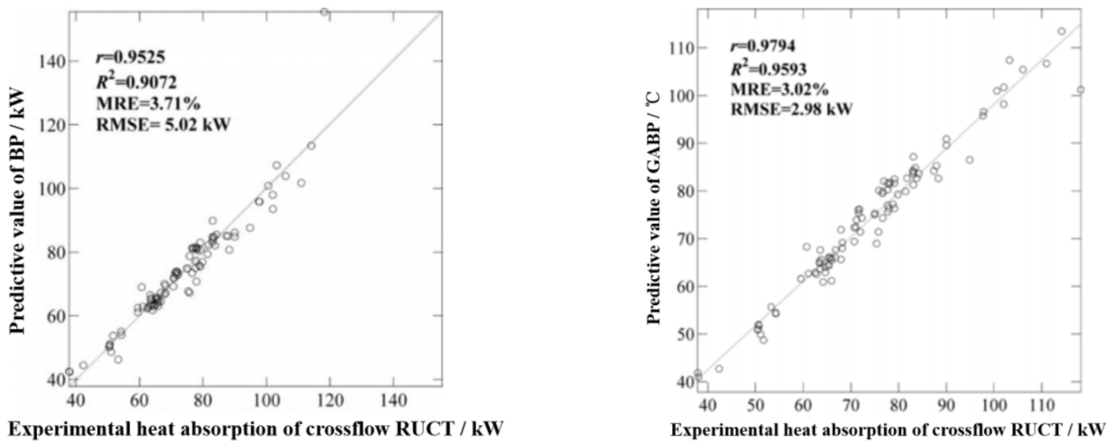


Figure 5. Correlation curve of heat absorption capacity.

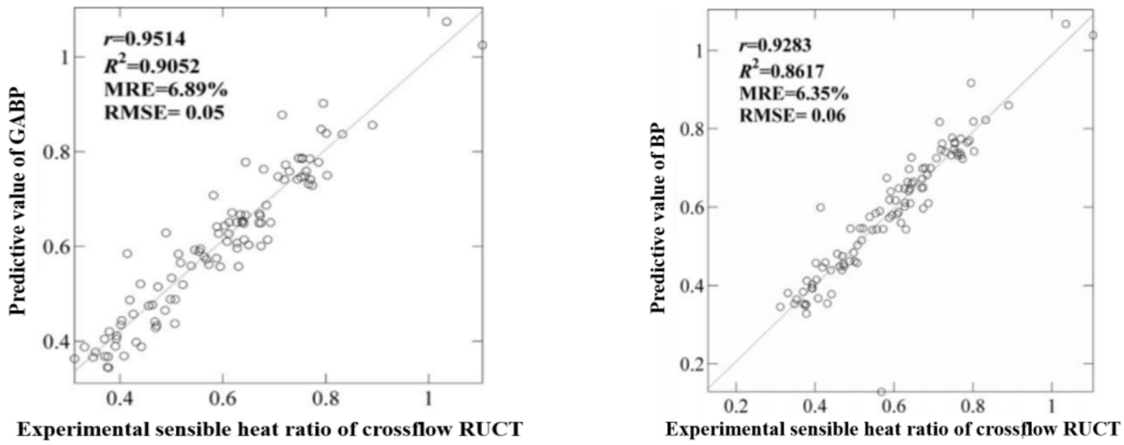


Figure 6. Correlation curve of sensible heat ratio.

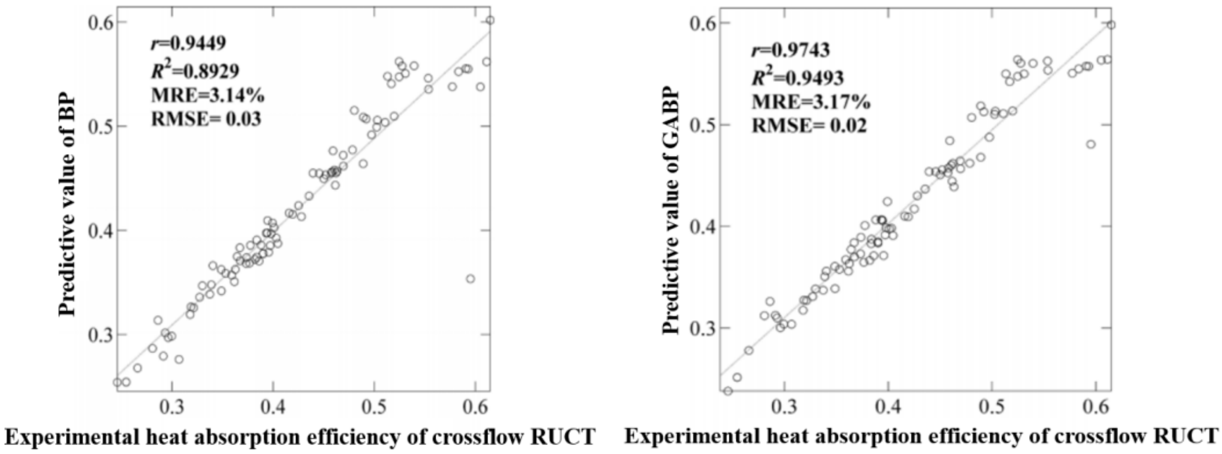


Figure 7. Correlation curve of heat absorption efficiency.

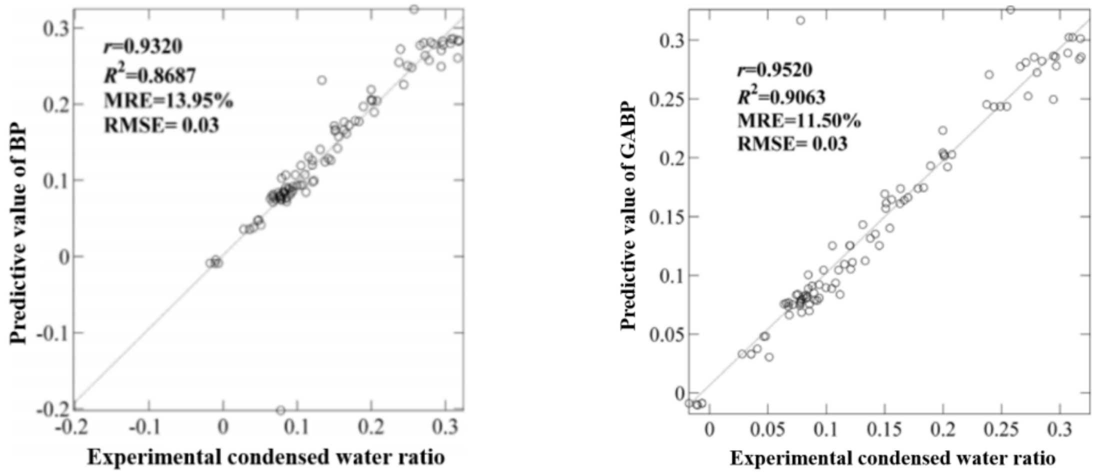


Figure 8. Correlation curve of proportion condensate water.

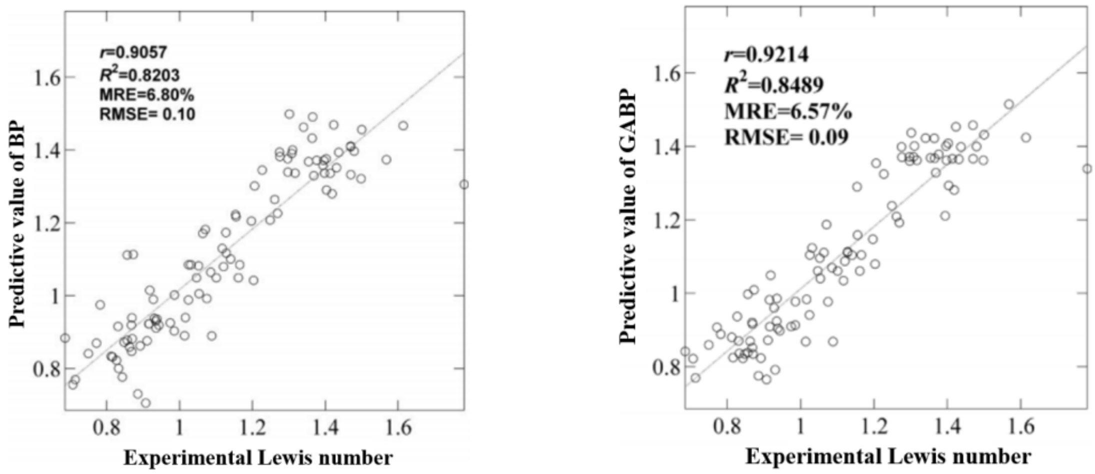
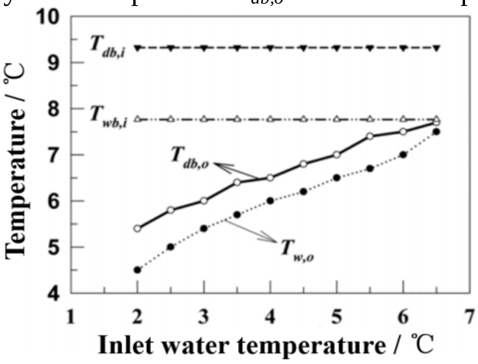


Figure 9. Correlation curve of Lewis number.

The results show that the correlation coefficient r between BP predicted value and experimental value of 8 main performance parameters are 0.9951, 0.9904, 0.9967, 0.9525, 0.9283, 0.9449, 0.9320 and 0.9057 respectively; the coefficient of determination R2 between BP predicted value and experimental value are 0.9904, 0.9881, 0.9934, 0.9072, 0.8617, 0.8929, 0.8687 and 0.8203 respectively;the mean relative error MRE between BP predicted value and experimental value are 4.47%, 3.63%, 2.38%, 3.71%, 6.35%,3.14%, 13.95% and 6.80% respectively; the root mean square error RMSE between BP predicted value and experimentalvalue are 0.2°C, 0.3°C, 0.2 °C, 5.0kW, 0.06, 0.03, 0.03 and 0.10 respectively. The correlation coefficient r between GABP predicted value and experimental value are 0.9980, 0.9984, 0.9981, 0.9794, 0.9514, 0.9743,0.9520 and0.9214 respectively; he coefficient of determination R2 between GABP predicted value and experimental value are0.9960, 0.9969, 0.9962, 0.9593, 0.9052, 0.9493, 0.9063 and 0.8489respectively; the mean relative error MRE between GABP predicted value and experimental value are 2.66%, 3.04%, 2.27%, 3.02%, 6.89%, 3.17%, 11.50% and 6.57% respectively; the root mean square error RMSE between GABP predicted value and experimental value are 0.2 °C, 0.1 °C, 0.1 °C, 3.0 kW, 0.05, 0.02, 0.03 and 0.09 respectively. It can be seen that, regardless of correlation coefficient r, coefficient of determination R2, mean relative error MRE, and root mean square error RMSE, GABP is better than BP, whose error is in theextent permitted and predicted result is more accurate. Since value of Lewis number Le is calculated by many formulas, rather than the directly measured data in experiment, comparing predicted value with experimental value of network, error is relative big. Finally it can be concluded that the prediction accuracy of GABP network model is increasingly higher than BP network.

2.4. Application of GABP network performance prediction model of cross flow RUCT

Figure 10 is predictions for RUCT under cross flow condition's outlet water temperature $T_{w,o}$, outlet air dry-bulb temperature $T_{db,o}$ and heat absorption capacity Q by applying GABP network model.



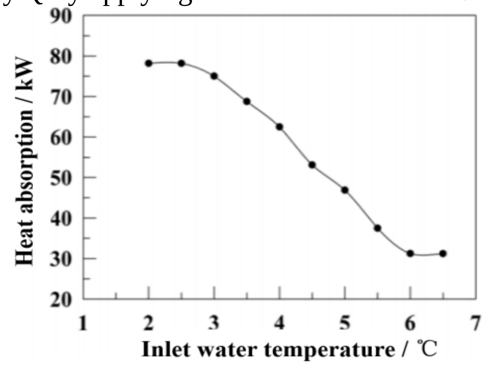


Figure 10.GABP prediction of outlet air temperature,outlet water temperature and heat absorption capacity.

Inputs of model are as following: inlet air dry-bulb temperature$T_{db,i}$ is 9.3°C, wet-bulb temperature $T_{wb,i}$ is7.8°C, mass flow rate ma is 15.9kg/s, inlet water mass flow rate mw is 7.4kg/s, and water-spraying density q is 3.3kg/(m2·s). Adjusting inlet water temperature continuously, variation of outlet air dry-bulb temperature, outlet watertemperature and heat absorption capacity are predicted by using GABP model. Refer to the correlation curve in Figure 10, when inlet water temperature rises gradually from 2.0°C to 6.5°C, outlet air dry-bulb temperature of RUCT under cross flow condition changes from 5.4°C to 7.7°C, and outlet water temperature changes from 4.5°C to 7.5°C. According to the prediction in Figure 10, heat absorption of RUCT under cross flow condition reduces gradually from 78.2 kW to 31.2 kW. The variation trend of 3 performance parameters along with inlet water temperature predicted by GABP is substantial in accordance with the partial experimental result, which means that the established GABP network model can well predict heat and mass transfer performance of cross flow RUCT under heat condition.

3. Conclusions

In this paper, based on the experimental data, using genetic algorithm (GA) to find the optimal weight threshold for the BP network, the three layer GABP network model 6-13-8 to predict the transverse RUCT performance parameters is established, and the prediction results of performance parameter are compared with the traditional BP network model. The mean relative error MRE between BP predicted value and experimental value are 4.47%, 3.63%, 2.38%, 3.71%, 6.35%,3.14%, 13.95% and 6.80% respectively; the mean relative error MRE between GABP predicted value and experimental value are 2.66%, 3.04%, 2.27%, 3.02%, 6.89%, 3.17%, 11.50% and 6.57% respectively.The results show that the prediction results of the GABP network model are better than the BP model, and the error is within the allowable range. It shows that using the GABP network model to evaluate the performance of cross flow RUCT can achieve higher accuracy.

Taking experimental data of cross flow RUCT as the basic input condition, the influence of inlet temperature on effluent temperature, outlet air dry bulb temperature, and heat absorption capacity are predicted by GABP network model. The results show that the variation law of the predicted parameters with the inlet water temperature of GABP model is basically consistent with some experimental results.The GABP network model established in this paper can predict the heat and mass transfer performance of cross flow RUCT well.

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References
[1] Song YQ, Ma HQA and LONG WD 2011 Application and analysis of energy tower heat pump technology in air conditioning engineering *J. HV&AC* **41(4)** 20-23
[2] An QX. 2014 Energy Tower in Training’s Hostel of Jiangsu Province *J. Building Energy & Environment* **33(3)** 94-96
[3] Xu ZHY. 2014 The Heating Performance Study of Open Type Heat Source Tower Heat Pump Technology in Hot Summer and Cold Winter Area. D. Chongqing University
[4] Li NP, Zhang D, Cheng JL, et al. 2015 Economic analysis of heat pump air conditioningsystem of heat-source tower *J.Shenzhen University Science and Engineering* **32(4)** 404-409
[5] Mohanraj M, Jayaraj S and Muraleedharan C 2015 Applications of artificial neural networks for thermal analysis of heat *J. International Journal of Thermal Sciences* **90** 150-172
[6] Mohanraj M, Jayaraj S and Muraleedharan C. 2012 Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems—A review J.Renewable and Sustainable Energy Reviews **16(2)** 1340-1358
[7] Qi X.N., Liu Z.Y. and Li D.D 2008 Numerical simulation of shower cooling tower basedon artificial neural network *J. Energy Conversion and Management* **49(4)** 724–732.
[8] Wu JSH, Zhang GQ, Zh Q, Zhou J andWang Y 2011 Artificial neural network analysis of the performance characteristics of a reversibly used cooling tower under cross flow conditions for heat pump heating system in winter *J. Energy and Buildings* **43** 1685-1693
[9] Mohanraj M, Jayaraj S and Muraleedharan C 2012 Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems—A review *J. Renewable and Sustainable Energy Reviews* **16(2)** 1340-1358
[10] Abbassi A and Bahar L 2005 Application of neural network for the modeling and control of evaporative condenser cooling load *J.Applied Thermal Engineering* **25(17–18)** 3176-3186
[11] Gandhidasan P and , Mohandes MA 2011 Artificial neural network analysis of liquid desiccant dehumidification system *J. Energy* **36(2)** 1180-1186
[12] Li N, Xia L, Shiming D, et al 2012 Dynamic modeling and control of a direct expansion air conditioning system using artificial neural network *J. Applied Energy* **91(1)** 290-300
[13] F.Xin. 2000 Basic Theory and Method of Neural Net Intelligence. M. Southwest Jiaotong University
[14] Pu J, Liu G and Feng X. 2010 Application of the cumulative energy approach to different air conditioning systems J. Energy and Buildings **42(11)** 1999-2004