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Performance prediction of wet cooling tower using artificial neural network under cross-wind conditions

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Abstract

This paper describes an application of artificial neural networks (ANNs) to predict the thermal performance of a cooling tower under cross-wind conditions. A lab experiment on natural draft counter-flow wet cooling tower is conducted on one model tower in order to gather enough data for training and prediction. The output parameters with high correlation are measured when the cross-wind velocity, circulating water flow rate and inlet water temperature are changed, respectively. The three-layer back propagation (BP) network model which has one hidden layer is developed, and the node number in the input layer, hidden layer and output layer are 5, 6 and 3, respectively. The model adopts the improved BP algorithm, that is, the gradient descent method with momentum. This ANN model demonstrated a good statistical performance with the correlation coefficient in the range of 0.993–0.999, and the mean square error (MSE) values for the ANN training and predictions were very low relative to the experimental range. So this ANN model can be used to predict the thermal performance of cooling tower under cross-wind conditions, then providing the theoretical basis on the research of heat and mass transfer inside cooling tower under cross-wind conditions.

Keywords: Cross-wind; Cooling tower; Heat and mass transfer; BP network

1. Introduction

Cooling towers play an important role in the cool-end system of power plant, and its cooling capacity can affect the total power generation capacity directly. The cooling efficiency is highly sensitive to environmental conditions [1], particularly for most cases under the cross-wind conditions. However, for the conventional design of cooling towers, the impact of cross-wind, which actually exists in most cases, has not been paid much attention. Therefore, it is really crucial to delve the influence of cross-wind regarding the heat and mass transfer performance of cooling towers.

Many literatures which are related to heat and mass transfer performance of cooling towers under windless conditions, can be found [2–7], and works on heat and mass transfer performance of cooling towers under cross-wind conditions are also done by some researchers [8–11]. In addition, Q. Wei [12], M.D. Su [13], Du Preez, Kröger [14,15] and Z. Zhai [16] et al. have researched the effect of cross-wind on heat transfer performance of dry-cooling towers, to some extent. These works focused on the dry-cooling towers. D.D. Derksen and T.J. Bender [17–19] studied the influence of cross-wind on the heat transfer performance of wet cooling towers by means of wind tunnel experiments and numerical calculation. But these works mentioned in literatures [17–19] did not make an agreement with the geometry similarity and dynamic similarity between model tower and prototype tower.

As seen from the above summary, very few researchers studied the cross-wind influence on heat and mass transfer characteristic of Natural Draft Counter-flow Wet Cooling Tower (NDWCT). In fact, many parameters affect heat and mass transfer characteristic of NDWCT. What's more, the influence is non-linear, and these parameters are interactional and intercoupling. So it is difficult to study this by using the classical mathematical modeling. However, the artificial neural networks (ANNs) have the characteristic which can catch preferably non-

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Nomenclature

a	actual output (experimental output)	
b	predicted output (network output)	
c	constant	
K	the sample number	
$\dot{m}$	the circulating-water flow rate	L/min
m	the node number in the output layer	
MSE	the mean square error	
n_1	the node number in the hidden layer	
n	the node number in the input layer	
R	the correlation coefficient	
T	temperature	°C
ΔT	the temperature difference	°C
V	the wind velocity	m/s
$v_{k,j}$	the weight between hidden layer vectors and output layer vectors	
$w_{j,i}$	the weight between input layer vectors and hidden layer vectors	

Greek symbols

μ_a	mean value of a set	
μ_b	mean value of b set	
θ	dry bulb temperature of air	°C
τ	wet bulb temperature of air	°C
η	cooling coefficient of efficiency	%

Subscripts

a	air
in	inlet
i, j, k	the number of nodes
lim	limit
out	outlet

linear rule. And some researchers pointed out that the BP network which includes one hidden layer may approach to a nonlinear function arbitrarily, that is, the three-layer BP network may achieve the mapping from I dimension (input layer) to K dimension (output layer) [20]. So the thermal performance prediction of NDWCT under cross-wind conditions is done by adopting ANN technology in this paper.

As reviewed by Kalogirou [21], the ANN models of energy systems have been recently studied by numerous investigators [22–27], for example, condenser, boiler, nuclear power plant, refrigerant and heat exchanger etc. Among them, Yasar Islamoglu [27] used ANN model to predict heat transfer rate of wire-on-tube heat exchanger, and received a valuable conclusions. Very few researchers predicted thermal performance of wet cooling tower by ANN technique. M. Hosoz et al. [28] combined for the first time the ANN technique and performance prediction of wet cooling tower, but they did not consider effects of cross-wind on thermal performance of wet cooling tower. Therefore, the ANN technique is used to predict thermal performance of wet cooling tower under cross-wind conditions in this paper.

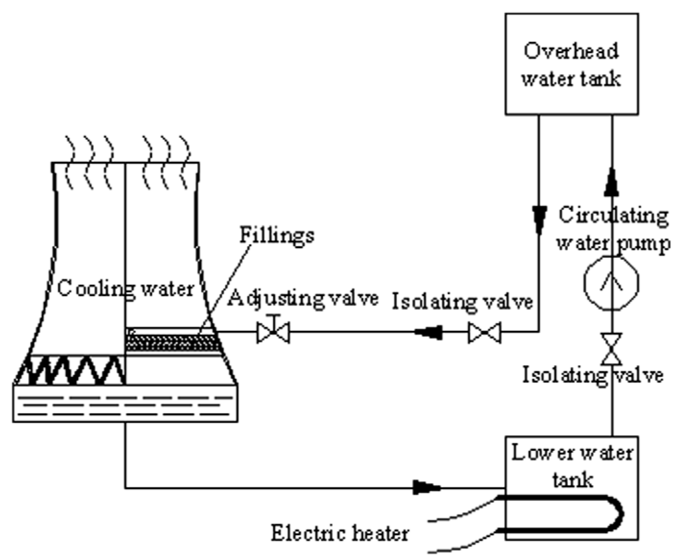

Fig. 1. Schematic diagram of experimental cooling tower.

2. Description of experiment

The key point in this paper is developing predicted model of BP network about wet cooling tower under cross-wind conditions, so the experiment parts are briefly introduced. The schematic diagram of experimental cooling tower is shown in Fig. 1. The model tower, adopted in this experiment, is made to simulate wet cooling tower of large-scale power plant according to similarity theory. And the proportion of model and prototype tower is 1:100. In addition, the test process also corresponds to dynamic similarity and thermodynamic similarity besides geometry similarity. The whole experimental course simulates the actual working process of wet cooling tower in power plant. Before doing experiments, the circulating water is heated up to the required temperature by several heaters, and then the circulating pump feeds the water to the overhead water tank. There are overhead water tank and lower water tank in this system in order to carrying out thermal state experiment and making circulating system steady. During the course of experiments, the circulating water enters into the model tower and goes through the fills from top to bottom, while the dry air flows through the fillings from bottom to top, and the heat and mass transfer are finished in the course of flow.

During this test, the relative temperature about water and air can be measured by using copper-constantan thermocouples. The dry bulb temperature and wet bulb temperature of environmental air are given by wet and dry bulb thermometer, and the humidity of wet air leaving the model tower is measured by thermo hygrometer. In addition, the wind velocity values are measured by the KA22 type anemoscope. The main measuring apparatuses are shown in Table 1.

Table 1
Measuring apparatus

Item	Measuring apparatus	Uncertainty
Wind velocity (m/s)	KA22 type anemoscope	0.01 m/s
Temperature (°C)	copper-constantan thermocouple	0.1 °C
	wet and dry bulb thermometer	0.1 °C
Humidity (%)	thermo-hygrometer	0.1%
Pressure (kPa)	manometer	0.01 kPa
Water flow rate (L/min)	rotameter	0.1 L/min

In this experiment, the volume flow rate of circulating water is 2, 4, 6, 8, 10 and 12 L/min. Furthermore, the circulating temperature is relatively higher in order to make the experiment more obvious, which is 40, 45, 50 and 55 °C . The inlet wind velocity at the windward side of tower, which is produced by the lower fan, is 0 m/s for the windless state, 0.2, 0.3, 0.4, 0.5, 0.6 and 0.8 m/s. This wind velocity value is measured at middle part of air inlet. According to the distribution of natural wind above ground [29] and the vertical distance between the two fans in this experiment, the top level wind velocity which is produced by the upper fan, is about 0 m/s for the windless state, 0.4, 0.6, 0.8, 1.0, 1.2, and 1.6 m/s. If not pointing out specially, the wind velocity mentioned in the following text is the speed value which is produced by the lower fan. In addition, the experimental range of dry bulb temperature is 28.5–33.5 °C, the experimental range of wet bulb temperature is 23.0–27.5 °C.

Assuming that the other parameters, especially atmosphere pressure and wet bulb temperature of air, are uniform, the circulating water temperature difference ΔT and cooling efficiency coefficient η can be considered as the performance indices of wet cooling tower. The expressions of ΔT and η are given by

$$\Delta T = T_{\text{in}} - T_{\text{out}} \tag{1}$$

$$\eta = \frac{T_{\text{in}} - T_{\text{out}}}{T_{\text{in}} - T_{\text{lim}}} = \frac{\Delta T}{T_{\text{in}} - T_{\text{lim}}} \tag{2}$$

where T_{in} and T_{out} are the inlet and outlet temperature of circulating water respectively, and T_{lim} is the cooling limit, that is, the wet bulb temperature of inlet air. In addition, in the later analysis, it is assured that the wet bulb temperature is invariable for cases with any operating conditions.

3. Model of ANN

3.1. Three-layer BP network

Three-layer BP network used in this paper is shown in Fig. 2. $w_{j,i}$ represents the weights between the input layer vectors and hidden layer vectors, and $v_{k,j}$ represents the weights between the hidden layer vectors and output layer vectors. The input layer has five nodes, including dry bulb temperature of inlet air θ_{in}, wet-bulb temperature τ_{in}, circulating water inlet temperature T_{in}, circulating water inlet mass flow rate $\dot{m}_{\text{in}}$ and inlet wind velocity V_{in}. And the output layer has three nodes, including circulating water outlet temperature T_{out}, temperature difference ΔT and cooling efficiency coefficient η. The hidden layer has six nodes.

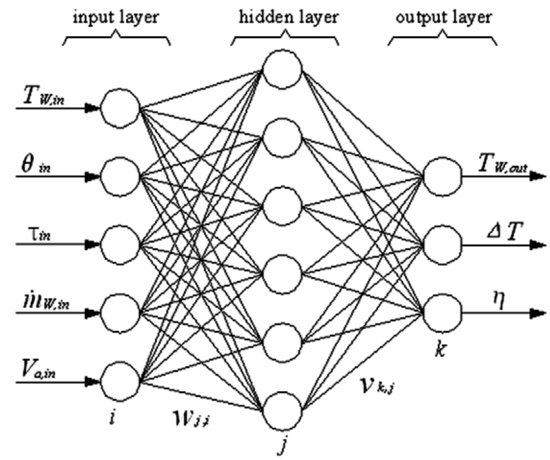

Fig. 2. The structure of ANN for modeling the experimental model tower.

The network part is implemented under the Matlab environment, and the activation function is chosen as the tangent sigmoid function in the hidden layer and the purelin function in the output layer. There are 200 input–output pairs, thereinto, 120 pairs were employed for training set, and the remaining 80 pairs were regarded as the testing the network. All the 200 input–output pairs were normalized to fall in the interval $[-1, 1]$ in order to improve the predicted agreement. The normalization and anti-normalization functions of training data are premnmx and postmnmx function, respectively, and the normalization and anti-normalization functions of testing data are tramnmx and postmnmx function. During the course of training, many training functions can be adopted, including trainlm, traingd, traingdm, traingdx, and traincgb and so on. It is proved that the traingdm function adopting the gradient descent method with momentum is used to act as the training function in this paper, because it has higher stability and faster convergence rate [30].

In this paper, correlation coefficient (R) and mean square error (MSE) are acted as the characteristic parameters to assess the agreement of training and prediction. R is a measure of how well the variation in the predicted outputs is explained by the experimental values, and the R value between the experimental values and predicted outputs is defined by [28]

$$R = \frac{\operatorname{cov}(a, b)}{\sqrt{\operatorname{cov}(a, a) \cdot \operatorname{cov}(b, b)}} \tag{3}$$

where $\operatorname{cov}(a, b)$ is the covariance between the a and b sets which represent the experimental and network output sets, respectively, and is given by

$$\operatorname{cov}(a, b) = E\lfloor (a - \mu_a)(b - \mu_b) \rfloor \tag{4}$$

where E is the expected value, μ_a and μ_b are the mean value of a set and b set, respectively. In addition, $\operatorname{cov}(a, a)$ and $\operatorname{cov}(b, b)$ are the auto covariances of a and b sets, respectively, and are expressed by

$$\operatorname{cov}(a, a) = E\lfloor (a - \mu_a)^2 \rfloor \tag{5}$$

$$\operatorname{cov}(b, b) = E\lfloor (b - \mu_b)^2 \rfloor \tag{6}$$

The R values closer to $+1$ indicate a stronger agreement of training and predicted values, while the values closer to -1

indicate a stronger negative relationship between training and prediction.

The mean square error is calculated from

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(a_i - b_i)^2 \tag{7}$$

The less MSE is, the better fit results are.

3.2. Determination of the number of nodes in the hidden layer

The performance of an ANN is affected by the characteristic of the network, such as the number of hidden layer and the number of nodes in hidden layer. But up to now, there is not a definite method to choose the optimal number of hidden layer and the number of nodes in hidden layer. General speaking, the ANN model which has one hidden layer can meet with simulative requirements [20]. So the model of one hidden layer is used in this paper.

Three formulas which are used to determine the node number in hidden layer are given by Eqs. (8)–(10) [31],

$$\sum_{i=0}^{n} C_{n_1}^{i} > K \tag{8}$$

where K is the sample number, if $i > n_1$, $C_{n_1}^{i} = 0$.

$$n_1 = \sqrt{n+m} + c \tag{9}$$

where c is a constant which belongs to [1, 10].

$$n_1 = \log_2 n \tag{10}$$

When there is only one hidden layer in this ANN model, according to Ref. [32], the calculated formula of node number in hidden layer is defined by,

$$n_1 = \sqrt{mn} \tag{11}$$

Another empirical formula is put forward in Ref. [33]. It can be used to determine the node number in hidden layer, and the expression is given by

$$n_1 = \sqrt{0.43mn + 0.12m^2 + 2.54n + 0.77m + 0.86} \tag{12}$$

In the above five formulas (Eqs. (8)–(12)), n_1 is the node number in hidden layer, m is the node number in output layer, n is the node number in input layer.

According to above five formulas, it is received that the range of node number in hidden layer is from 4 to 13. The training results are shown in Table 2, where the node number in hidden layer is 4, 5, 6, 7, 8, 9 and 10. From Table 2, the training results have a better agreement by analyzing R and MSE when the node number in hidden layer is 6. So the ANN model in this paper chooses six nodes in hidden layer.

4. Results and discussion

4.1. The correlation analysis of training results by using the developed ANN model

By many trials, the R of training results is rather closer to +1 and the results have the least MSE when the node number in hidden layer is 6. The correlation analysis curves between the ANN training and the experimental values are described in Figs. 3–5. Results show that the R of training and experimental values on outlet water temperature T, ΔT and η is 0.999, 0.998 and 0.995. And the corresponding MSE is 0.044 °C, 0.066 °C and 0.53%. Therefore, the R and MSE come to a higher accuracy. It is obvious that the training values are in good agreement with the experimental values.

Table 2
Training results under different node number in hidden layer

Performance parameter	Output parameter	4	5	6	7	8	9	10
R	T_{out}	0.992	0.998	0.999	0.998	0.997	0.995	0.991
	Δt	0.995	0.998	0.998	0.997	0.995	0.992	0.990
	η	0.991	0.992	0.995	0.994	0.992	0.990	0.985
MSE	T_{out} (°C)	0.064	0.049	0.044	0.048	0.052	0.058	0.065
	Δt (°C)	0.072	0.065	0.066	0.073	0.070	0.079	0.087
	η (%)	0.71	0.62	0.53	0.59	0.68	0.75	0.92

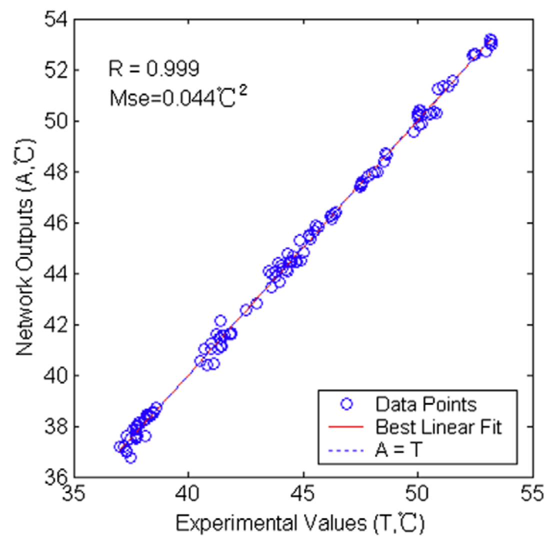

Fig. 3. The ANN training values for outlet water temperature vs. the experimental value.

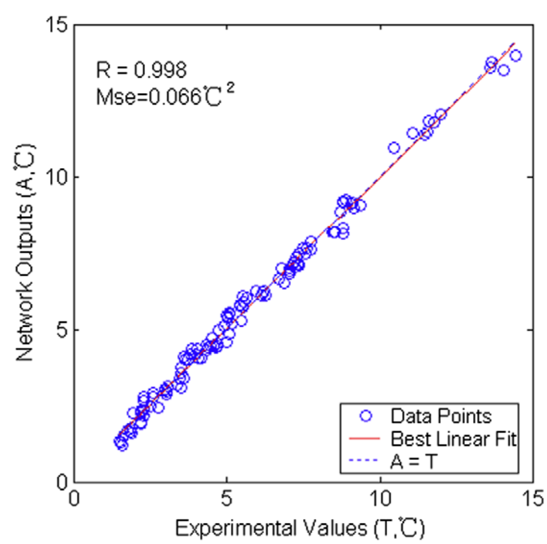

Fig. 4. The ANN training values for temperature difference ΔT vs. the experimental value.

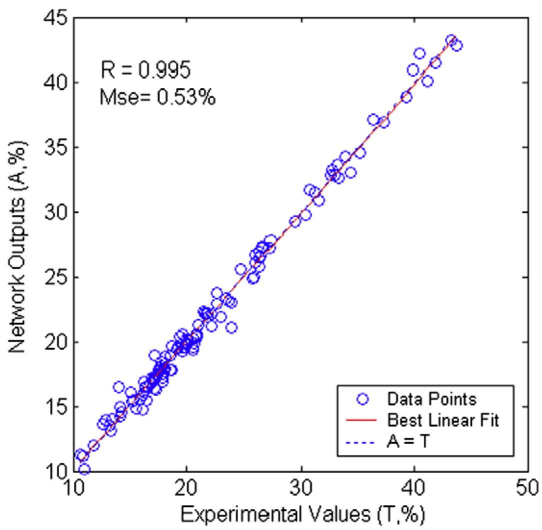

Fig. 5. The ANN training values for cooling coefficient of efficiency η vs. the experimental value.

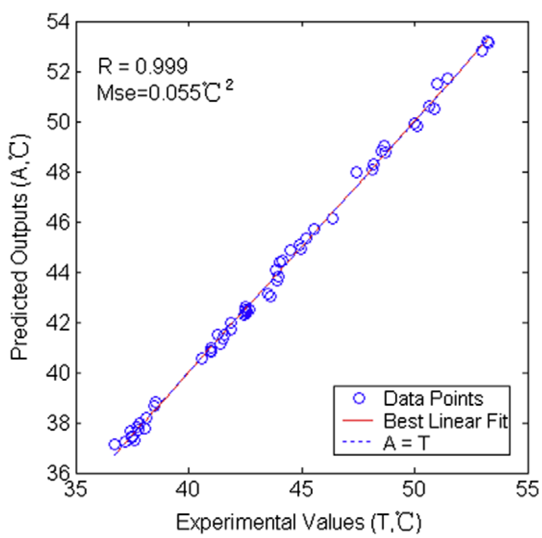

Fig. 6. The ANN predicted values for outlet water temperature vs. the experimental value.

It is claimed that A and T represent the network output values/(training values) and experimental values, respectively in Figs. 3–5. And $A = T$ represents one straight line on which the network output values are equal to experimental values.

4.2. The correlation analysis of predicted results by using the developed ANN model

The correlation analysis curves between the ANN predicted values and the experimental values are shown in Figs. 6–8. Note that in the prediction part, the comparisons were made using values which are the remaining 80 input–output pairs.

The relational curves between the predicted outlet water temperatures and the experimental ones are depicted in Fig. 6. The ANN predictions for this parameter can reach to a R of 0.999, a MSE of 0.055 °C. Results show that the predictions of ANN to the outlet water temperature are quite accurate and have very good agreement according to the characteristic parameter R and MSE.

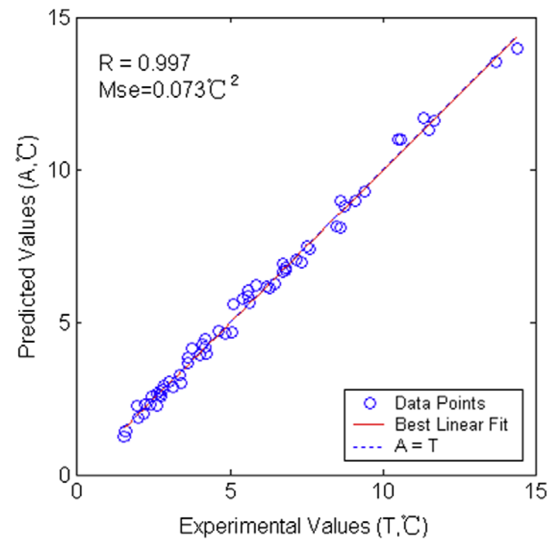

Fig. 7. The ANN predicted values for temperature difference ΔT vs. the experimental value.

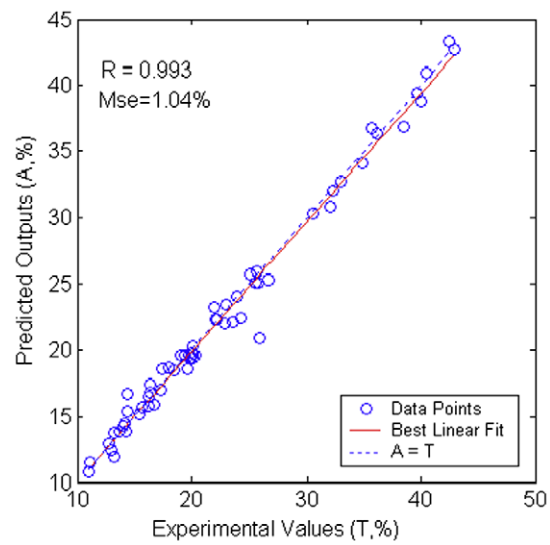

Fig. 8. The ANN predicted values for cooling coefficient of efficiency η vs. the experimental value.

The predicted values for ΔT as a function of the experimental ones are shown in Fig. 7. For this parameter, the ANN comes to a R of 0.997, a MSE of 0.073 °C. Results demonstrate that the predictions of ANN to the temperature difference have better agreement. But compared with the predictions of outlet water temperature, the ANN predictions for ΔT have poorer agreement. Because ΔT is received from Eq. (1), it has a relatively poor uncertainty. And this uncertainty affects the training process, so leading to a slight poor agreement.

The relational curves between the predicted efficiency coefficients η and the experimental ones are reported in Fig. 8. The ANN predictions for this parameter can get a R of 0.993, a MSE of 1.04%. It is obvious that the ANN predictions for η have poorer agreement than outlet water temperature and ΔT predictions. η is received from Eqs. (1) and (2), not determined

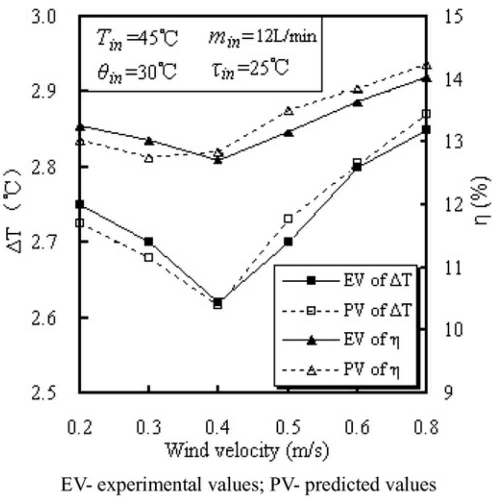

Fig. 9. The comparisons of predicted and experimental values about ΔT and η under cross-wind conditions.

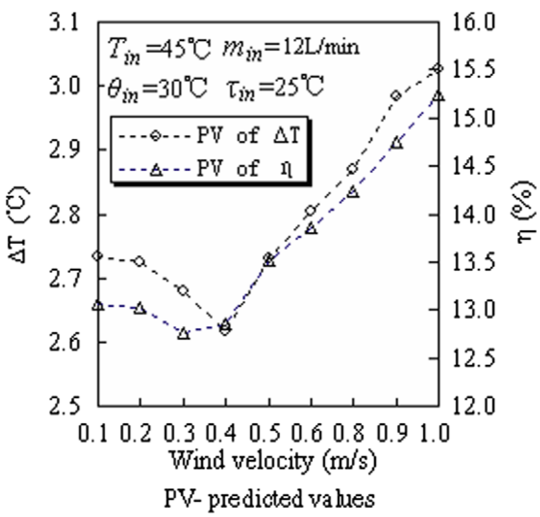

Fig. 10. The ANN predicted curves of cross-wind effect on ΔT and η.

directly from the measurements, so it has a relatively poor uncertainty. But the error is still in the tolerance and the predicted results are still right.

It is claimed that A and T represent the predicted output values and experimental values, respectively in Figs. 6–8. And $A = T$ represents one straight line on which the predicted output values are equal to experimental values.

5. The performance predictions by using the developed ANN model under cross-wind conditions

In fact, an important characteristic of the ANN model is that the developed ANN can be used to analysis the effects of the input parameters on the outputs. In order to visualize these effects, the ANN predictions for temperature difference ΔT and efficiency coefficient η as a function of the wind velocity were indicated in Figs. 9–10. In this paper, our main intention is studying cross-wind effects on heat and mass transfer performance, that is, the effects of cross-wind on temperature difference and efficiency. And the effects of other input parameters on the outputs are shown in Ref. [34].

Fig. 9 depicts the changes in the predicted values and experimental values of ΔT and η with respect to the cross-wind velocity when the other four input parameters are kept constant, that is, the circulating water flow rate and inlet water temperature are equal to 12 L/min and 45 °C, and the dry bulb and wet bulb temperature of inlet air are equal to 30 and 25 °C. The range of wind velocity belongs to the experimental values which are 0.2–0.8 m/s. Analysis shows that the maximum mean absolute relative error in the predicted values and experimental values of ΔT and η are 1.10% and 2.57%, respectively in Fig. 9. It is also shown that the predicted values are in good agreement with experimental values in Fig. 9.

In addition, Fig. 9 indicates that ΔT and η decreases firstly, then increases with the increase of cross-wind velocity when the other four input parameters are kept constant. Because the cross-wind is harmful to heat and mass transfer inside cooling tower when the wind velocity is lower, that is, a lower cross-wind velocity destroys the well-proportioned and axisymmetric air dynamic field at air inlet of bottom, and then reduces the air rate inside tower, so deteriorates the heat and mass transfer performance. But the cross-wind becomes helpful when the wind velocity increase to about 0.4 m/s. Because the air rate inside tower increases when wind velocity reaches to 0.4 m/s, and larger wind velocity intensifies the turbulence in tower, so enhances the heat and mass transfer performance. These results are accordant with the literature [35]. So the ANN predicted results to ΔT and η are quite right.

The parameter values in Fig. 10 are the same as those in Fig. 9 except for the wind velocity values. Fig. 10 indicates the ANN predicted curves of cross-wind effects on ΔT and η, but it is claimed that the range of cross-wind velocity is 0.1–1.0 m/s which is beyond the range of experimental values. Although the agreement of the predictions can not be given, it is observed that the ANN results in agreeable curves for the predicted parameters.

In conclusions, Figs. 9 and 10 show the influences of cross-wind on ΔT and η. It is concluded from these two figures that the developed ANN model can predict the thermal performance of natural draft wet cooling tower under cross-wind conditions.

6. Conclusions

(1) The ANN model for prediction of thermal performance on natural draft wet cooling towers is developed successfully in this paper, and the improved BP algorithm, the gradient descent algorithm with momentum, is used in this model. In this ANN model, the number of nodes in the input layer, hidden layer and output layer is 5, 6 and 3. The nodes in the input layer are dry bulb temperature of inlet air, wet-bulb temperature, circulating water inlet temperature, circulating water inlet mass flow rate and inlet wind velocity. The nodes in output layer are circulating water outlet temperature, temperature difference and cooling efficiency coefficient.

(2) The correlation coefficient (R) and mean square error (MSE) are used to assess the performance of ANN model. This

ANN model demonstrated a good statistical performance with the correlation coefficient in the range of 0.993–0.999, and the MSE values for the ANN training and predictions were very low relative to the range of the experiments.

(3) In order to show the usefulness of this ANN model, the effects of cross-wind on ΔT and η are predicted by using the developed ANN model. Results indicate that the network outputs are in good agreement with the actual values. So this ANN model can be used to predict the thermal performance of natural draft wet cooling tower under cross-wind conditions.

References

[1] E. Ding (Ed.), Air Cooling Techniques in Power Plants, Water and Electric Power Press, Beijing, 1992.

[2] J.C. Kloppers, D.G. Kröger, The Lewis factor and its influence on the performance prediction of wet-cooling towers, International Journal of Thermal Sciences 44 (2005) 879–884.

[3] J. Smrekar, J. Oman, B. Širok, Improving the efficiency of natural draft cooling towers, Energy Conversion and Management 47 (2006) 1086–1100.

[4] J.C. Kloppers, D.G. Kröger, A critical investigation into the heat and mass transfer analysis of counter flow wet-cooling towers, International Journal of Heat and Mass Transfer 48 (2005) 765–777.

[5] S.P. Fisenko, A.I. Petruchik, A.D. Solodukhin, Evaporative cooling of water in a natural draft cooling tower, International Journal of Heat and Mass Transfer 45 (2002) 4683–4694.

[6] S.P. Fisenko, A.A. Brin, A.I. Petruchik, Evaporative cooling of water in a mechanical draft cooling tower, International Journal of Heat and Mass Transfer 47 (2004) 165–177.

[7] P. Naphon, Study on the heat transfer characteristics of an evaporative cooling tower, Int. Communication of Heat and Mass Transfer 32 (2005) 1066–1074.

[8] J.F. Kenneay, H. Fordyce, Plume recirculation and interference in mechanical draft cooling towers, in: Cooling Tower Environment—1974, Energy Research and Development Administration, 1975.

[9] J.G. Ribier, Study of performances on site and on a model of large natural drought cooling towers, in: Fifth IAHR Cooling Tower Workshop, 1980.

[10] Y. Caytan, An investigation of the performance of natural draft cooling towers under cross wind conditions, Performed using small scale heated models in a hydraulic channel, in: Fifth IAHR Cooling Tower Workshop, 1980.

[11] A.F. Du Preez, D.G. Kröger, Investigation into the influence of cross-wind in the performance of dry-cooling towers, in: 8th Cooling Tower and Spraying pond Symposium, 1992.

[12] Q.D. Wei, B.Y. Zhang, K.Q. Liu, X.D. Du, X.Z. Meng, A study of the unfavorable effects of wind on the cooling efficiency of dry cooling towers, Journal of Wind Engineering and Industrial Aerodynamics 54–55 (1995) 633–643.

[13] M.D. Su, G.F. Tang, S. Fu, Numerical simulation of fluid flow and thermal performance of a dry-cooling tower under cross wind condition, Journal of Wind Engineering and Industrial Aerodynamics 79 (3) (1999) 289–306.

[14] A.F. du Preez, D.G. Kröger, Investigation into the influence of cross-wind on the performance of dry-cooling towers, in: 8th Cooling Tower and Spraying Pond Symposium, 1992.

[15] A.F. du Preez, D.G. Kröger, The effect of the heat exchanger arrangement and wind-break walls on the performance of natural draft dry-cooling towers subjected to cross-winds, Journal of Wind Engineering and Industrial Aerodynamics 58 (1995) 293–303.

[16] Z. Zhai, S. Fu, Improving cooling efficiency of dry-cooling towers under cross-wind conditions by using wind-break methods, Applied Thermal Engineering 26 (2006) 1008–1017.

[17] D.D. Derksen, T.J. Bender, D.J. Bergstrom, K.S. Rezkallah, A study on the effects of wind on the air intake flow rate of a cooling tower: Part 1. Wind tunnel study, Journal of Wind Engineering and Industrial Aerodynamics 64 (1996) 47–59.

[18] T.J. Bender, D.J. Bergstrom, K.S. Rezkallah, A study on the effects of wind on the air intake flow rate of a cooling tower: Part 2. Wind all study, Journal of Wind Engineering and Industrial Aerodynamics 64 (1996) 61–72.

[19] T.J. Bender, D.J. Bergstrom, K.S. Rezkallah, A study on the effects of wind on the air intake flow rate of a cooling tower: Part 3. Numerical study, Journal of Wind Engineering and Industrial Aerodynamics 64 (1996) 73–88.

[20] R. Hecht-Nielson, Theory of back propagation neural networks, Proceedings of the International Joint Conference on Neural Networks [C]. Washington 1 (1989) 593–605.

[21] S.A. Kalogirou, Application of artificial neural-networks for energy systems, Appl. Energy 67 (2000) 17–35.

[22] M.M. Prieto, E. Montanes, O. Menendez, Power plant condenser performance forecasting using a non-fully connected ANN, Energy 26 (2001) 65–79.

[23] D.J. Swider, A comparison of empirically based steady-state models for vapour-compression liquid chillers, Applied Therm. Eng. 23 (2003) 539–556.

[24] E. Arcaklioglu, Performance comparison of CFCs with their substitutes using artificial neural network, Int. J. Energy Res. 28 (2004) 1113–1125.

[25] H.M. Ertunc, M. Hosoz, Artificial neural network analysis of a refrigeration system with an evaporative condenser, Appl. Therm. Eng. 26 (2006) 627–635.

[26] S.A. Kalogirou, S. Panteliou, Thermosiphon solar domestic water heating systems: longterm performance prediction using artificial neural networks, Solar Energy 69 (2) (2000) 163–174.

[27] Y. Islamoglu, A new approach for the prediction of the heat transfer rate of the wire-on-tube type heat exchanger-use of an artificial neural network model, Applied Thermal Engineering 23 (2003) 243–249.

[28] M. Hosoz, H.M. Ertunc, H. Bulgurcu, Performance prediction of a cooling tower using artificial neural network, Energy Conversion and Management 48 (2007) 1349–1359.

[29] ZH.G. Zhao, Cooling Tower, China WaterPower Press, Beijing, 2001.

[30] J.R. Ju, R. Zhuo, Convenient realization of BP networks on Matlab, Journal of Xinjiang Petroleum Institute 11 (2) (1999) 42–46.

[31] F. Xin, Basic Theory and Method of Neural Net Intelligence. Chengdu, Southwest Jiaotong University Press, 2000.

[32] Q.S. Xie, Neural Net Method in Mechanical Engineering, China Machine Press, Beijing, 2003.

[33] Y.B. Yao, J.L. Wang, Research on raising BP network training speed, Information Technology 1 (2002) 4–6.

[34] M. Gao, F.-z. Sun, K. Wang, Y.-t. Shi, Y.-b. Zhao, Experimental research of heat transfer performance on natural draft counter flow wet cooling tower under cross-wind conditions, International Journal of Thermal Sciences 47 (2008) 935–941.

[35] C. Bourillot, J. Grange, J.M. Lecoeuvre, Effect of wind on the performance of a natural wet cooling tower, in: Fifth IAHR Cooling Tower Workshop, 1980.