

Article

Prediction and Analysis of Dew Point Indirect Evaporative Cooler Performance by Artificial Neural Network Method

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Abstract: The artificial neural network method has been widely applied to the performance prediction of fillers and evaporative coolers, but its application to the dew point indirect evaporative coolers is rare. To fill this research gap, a novel performance prediction model for dew point indirect evaporative cooler based on back propagation neural network was established using Matlab2018. Simulation based on the test date in the moderately humid region of Yulin City (Shaanxi Province, China) finds that: the root mean square error of the evaporation efficiency of the back propagation model is 3.1367, and the r^2 is 0.9659, which is within the acceptable error range. However, the relative error of individual data (sample 7) is a little bit large, which is close to 10%. In order to improve the accuracy of the back propagation model, an optimized model based on particle swarm optimization was established. The relative error of the optimized model is generally smaller than that of the BP neural network especially for sample 7. It is concluded that the optimized artificial neural network is more suitable for solving the performance prediction problem of dew point indirect evaporative cooling units.

Keywords: dew point indirect evaporative cooling; air conditioning unit; PSO-BP neural network; performance prediction



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1. Introduction

Evaporative cooling technology is one of the key technologies for green, environmental protection and energy saving in the heating, ventilation, and air conditioning (HVAC) industry. It has been applied in various fields and industries including industrial buildings, residential buildings, rail transit, agricultural buildings, etc. Dew point indirect evaporative (DPIE) cooling technology is a breakthrough in improving energy efficiency. It uses the difference between the primary air-dry bulb temperature and the dew point temperature as the driving potential, which can overcome the theoretical limitation of traditional cooling technologies [1,2]. The traditional design method of air conditioning unit is generally to determine the specific performance parameters of the unit, then to analyze and infer the stable operation conditions, and finally to determine the relevant structural parameters of the unit. However, there are many factors that can affect the evaporative performance of an air conditioning unit [3], such as air-dry bulb temperature, relative humidity, total air volume, head wind speed, primary air volume, secondary air volume and secondary/primary air volume ratio. Due to this fact, it is difficult to accurately predict the performance of a DPIE air conditioning unit with mathematical models and experimental methods. Although many numerical and experimental models have been carried out to solve the problem in the past several years, the complicated model and high computation time is inevitable [4]. One effective measure is to use the artificial neural network (ANN) model to predict the

performance of DPIE cooling air conditioning units which can fully simulate and avoid product defects, reduce the research and development (R&D) cost, and shorten the R&D cycle of the unit [5]. Based on imitating the behavioral characteristics of animal neural networks, ANN has the advantages of self-learning and adaptive capabilities in terms of predicting the future behavior of nonlinear systems [6]. It has become a research hotspot due to its remarkable advantages. Jee-Heon Kim et al. [7] used the machine learning algorithm of ANN to establish the energy consumption model of the chiller for HVAC systems. By increasing the number of input variables and adjusting the proportion of training data, the prediction accuracy of chiller energy consumption is improved. In contrast, the number of neurons has no significant effect on the prediction accuracy. Based on 8 input variables, 60% training data and 12 neurons, the developed chiller model is able to predict the energy consumption with an accuracy of 99.07%. M. Kawashina et al. [8] applied the neural network prediction model to forecast the load in the ice storage air conditioner. Compared with the refrigerator scheme, the ice storage air conditioner using neural network consumes 7% more electricity than the refrigerator, but the operating cost is 13.5% lower. Albert T.P. So [9] studied the system identification and control of the back propagation (BP) ANN controller in the central air conditioning system. Compared with the proportion integration differentiation controller, the study found that the former has a better control effect. Gerald L. Gibson [10] developed a neural network building air conditioning system manager and studied the peak load of the air conditioning system in a middle school. The results showed that the prediction error using this model is less than 0.04%, and the established ANN building air conditioning system energy manager has high precision. D.B. Jani [11] developed a neural network model using a neural network with feed forward BP method by the experimental results for rotary solid desiccant dehumidifier fitted in a solid desiccant-vapor compression hybrid air conditioning system. The proposed ANN model can efficiently predict multiple parameters, including the outlet temperature, humidity ratio, moisture removal rate and effectiveness of desiccant dehumidifier.

Based on three different computing tools—ANN, adaptive neuro-fuzzy inference system (ANFIS) and fuzzy inference system (FIS) approach—T. Ravikiran and S.P.S. Rajput [12] studied the performance prediction of evaporative cooling air conditioning units. The result shows that the ANN method is the best. The statistical value r^2 and root mean square (RMS) of the primary air outlet temperature predicted by the neural network are 0.9999 and 0.1830, respectively, indicating that this method is accurate in predicting the performance of indirect evaporative cooling air conditioners. It is better than ANFIS and FIS in modeling evaporative cooling units. Hosoz M et al. [13] established a three-layer feedforward neural network (FNN) prediction model based on the error-based BP algorithm. The correlation coefficients R of the measured value and the predicted value are 0.969–0.993, and the average relative error is within the range of 0.66–4.04, and the root mean square error (RMSE) is very low. It shows that, as an alternative to classical modeling techniques, the ANN approach can be effectively used for predicting the performance of direct evaporative coolers.

From the literature review, the ANN has a good application and development prospect. It mainly focuses on the load forecasting, system control and performance forecasting of various of air conditioning systems in the field of HVAC and is mainly used for the prediction of filler performance and the performance prediction of indirect evaporative coolers in the field of evaporative cooling technology. However, there lacks research on ANN methods for predicting the performance of a DPIE cooler. Therefore, this study focuses on the performance prediction and analysis of a DPIE cooler using ANN. The BP ANN model is adopted due to its universality, strong nonlinear mapping, self-learning and adaptive [12,14]. The particle swarm optimization (PSO) algorithm is used to optimize the established BP model. Furthermore, there are many factors that can affect the evaporation efficiency, mainly including air dry-bulb temperature, relative humidity, total air volume, head wind speed, primary air volume, secondary air volume and secondary/primary air volume ratio. The Grey Relational Analysis (GRA) method is used to analyze the

influence of multiple factors on the evaporation efficiency, aiming to develop a performance prediction model of DPIE cooler with fast running and high accuracy.

The objectives of the current study are: (1) to collect basic data for analysis and application through practical tests of DPIE cooling air conditioning units; (2) to optimize and improve the accuracy of the BP ANN models; and (3) to explore the effects of multiple factors on performance prediction of DPIE cooler by using GRA.

2. Preparing for BP ANN

2.1. Cooler Overview

Compound DPIE cooler is used for all cases in this study as illustrated in Figure 1. It consists of a dry air channel and wet air channel. As for the wet channel, the heat and mass transfer between the air and spray water occurs. Air in the dry channel is cooled by the evaporation in the wet channel and is sent to the indoors by the fan for cooling.

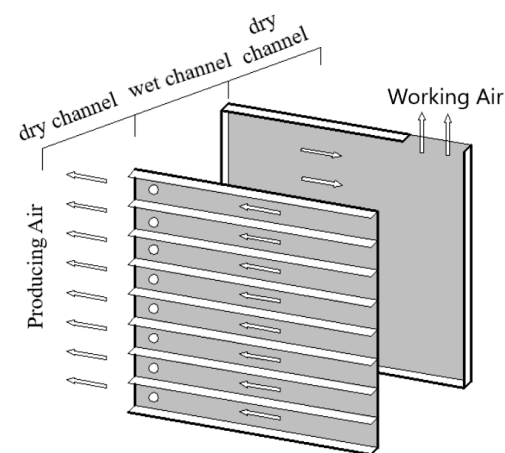


Figure 1. Structure of compound DPIE cooler.

2.2. Sample Data Collection

The schematic diagram of the measuring points of the DPIE cooler is shown in Figure 2. Positions 1, 2 and 3 in Figure 2a denote the air inlet, exhaust outlet and supply outlet, respectively. Temperature and humidity of positions 1, 2 and 3 are measured in the way of combining automatic recorder (Testo 174H) and manual records (Testo 869 Infrared Detector). An anemometer (Testo 410-1) is used to measure the average air speed of each section to further calculate the air volume. The air speed measuring points are illustrated in Figure 2b. The Yulin City of Shaanxi Province is selected to represent the climatic characteristics of moderate humidity; see Table 1 for the detailed data.

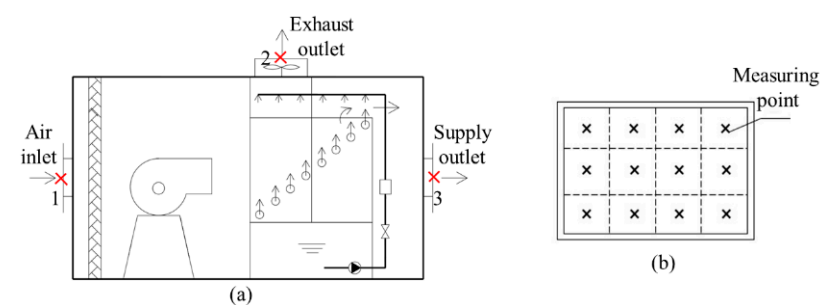


Figure 2. Schematic diagram of the measuring points: (a) unit measuring points; (b) air speed measuring points.

Table 1. Instrumental and environmental parameters for data collection.

Description	Operating Parameters and Environmental Parameters
Yulin City, Shaanxi Province, China (moderate humidity)	1. Unit Type, AJL120-MFH200A
	2. Air volume, 20,000 m ³ /h
	3. Actual air supply volume, 11,403 m ³ /h
	4. Exhaust air volume, 6620 m ³ /h
	5. Secondary/primary air volume ratio, 0.58
	6. Outdoor environment: temperature, 28.1~29.1 °C relative humidity, 27.8~28.4%
Automatic recorder (Testo 174H)	Range, 0~100 °C/%; Sensor accuracy, ±0.5 °C/±3%
Infrared Detector (Testo 869)	Range, −20~280 °C; Sensor accuracy, <0.12 °C
Anemometer (Testo 410-1)	Range, 0.4~20.0 m/s; Sensor accuracy, ±(0.2 m/s + 2%)

2.3. Processing of Sample Data

To train the network more effectively, the training data are normalized, namely converting all data to 0~1.

$$x = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

$$y = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (2)$$

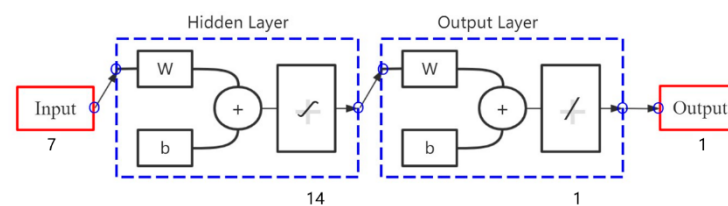
where x is the normalized input value. x_i is the original input value. $x_{\min}$ and $x_{\max}$ are the minimum and maximum value of original input, respectively. y is the normalized target value. y_i is the original value target value. $y_{\min}$ and $y_{\max}$ are the minimum and maximum value of the original target value, respectively.

Then, denormalizing the network output data is a necessary step by using the following formula.

$$y_i = y_{\min} + y \times (y_{\max} - y_{\min}) \quad (3)$$

2.4. Design of BP ANN

BP ANN consists of three important layers: input layer, output layer and hidden layer(s). Generally, a single hidden layer is able to implement the basic function of ANN and more hidden layers can improve the accuracy but a higher cost in training time. Therefore, a single hidden layer is selected in current study. The model structure is shown in Figure 3. It shows the 7-14-1-1 network structure with 7 input parameters and 1 output parameter. Random parameters W and b are the weight and the threshold of the network, respectively, and will change after each training in BP neural network's algorithm. Therefore, an initial value for the number of hidden layer nodes is necessary, then the performance of neural network with different number of hidden layer nodes is analyzed using trial-and-error method. Finally, the number of optimal network performance is selected. The batch gradient descent method is implemented to reduce the difference between the desired and actual result of the network.

**Figure 3.** The model structure of BP neural network.

To start the training, the number of important air inlet parameters (m), including dry bulb temperature, relative humidity, total air volume, head wind speed, primary air volume, secondary air volume and secondary/primary air volume ratio are selected as

the number of input layer. Evaporative efficiency (n) is selected as the output layer. The number of neurons in the single hidden layer (l) can be estimated by empirical formula, its initial value is 16 in this study, and then it is modified as needed. The final number of neurons is determined by trial-and-error method, as shown in Table 2, and the transfer function is tansig. Purelin function is used for output layer. The trainlm function of LM algorithm is used to avoid local optimal solution. Meanwhile, training time is set to 1000, relative error is 10^{-9} and learning rate is fixed at 0.1.

To evaluate the accuracy of the prediction model, r^2 , RMSE, relative error (η), average absolute error (AAE) and average bias error (ABE) [15,16] are discussed below. The square of the correlation coefficient r^2 represents the fitting of the predicted value curve and the actual value curve of the evaporation efficiency. The correlation between the two curves becomes higher as the value of r^2 increases to 1. The smaller the values of RMSE and η , the higher their accuracies are.

$$r^2 = \frac{\left[n \sum_{k=1}^n Y_P(k) Y_T(k) - \sum_{k=1}^n Y_P(k) \sum_{k=1}^n Y_T(k) \right]^2}{\left[\sum_{k=1}^n Y_P(k)^2 - \left[n \sum_{k=1}^n Y_P(k) \right]^2 \right] \left[\sum_{k=1}^n Y_T(k)^2 - \left[n \sum_{k=1}^n Y_T(k) \right]^2 \right]} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=k}^n (Y_P(k) - Y_T(k))^2}{n}} \quad (5)$$

$$\eta = \frac{Y_P - Y_T}{Y_T} \times 100\% \quad (6)$$

where k is the i th time. $Y_T(k)$ is the actual evaporation efficiency at the current time. $Y_P(k)$ is the predicted evaporation efficiency at the current time.

To reduce the relative error, the performance of ANN with different number of hidden layer nodes is analyzed, see Table 2 for the detailed data. Comprehensive analysis on three indicators shows that the performance of BP ANN is optimal with the nodes of 14.

Table 2. Analysis on performance of neural network with different number of hidden layer nodes.

Number of Nodes	r^2	RMSE	Relative Error η (%)
10	0.9567	4.7312	3.0357
11	0.9552	4.8981	3.1943
12	0.9537	5.0528	3.5273
13	0.9561	4.7929	3.2475
14	0.9581	4.6170	2.9422
15	0.9474	5.7428	3.8813
16	0.9480	5.6769	3.9655
17	0.9412	4.9289	4.0346
18	0.9542	5.0018	3.7074

2.5. Analysis of the Influencing Degree of Input Variables on the Output Variables

In this study, the GRA method is used to analyze the influencing degree of multiple input factors on the output results. GRA is a multi-factor statistical method suitable for dynamic process analysis, which measures the degree of correlation between various factors [17]. This method can make up for the deficiencies of mathematical statistics methods and the results of grey relational analysis does not conflict with the qualitative results with strong applicability. By quantifying the data, reducing the range of variables, the method requires less computation. Firstly, the correlation coefficient (ζ_i) can be calculated by Equation (7), and it reflects the correlation between parent sequence and sub sequence. Then, the correlation degree (r_i) is obtained by calculating the average value of various correlation coefficients described as Equation (8). The larger the number, the stronger the relevance.

$$\zeta_i(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \cdot \min_i \min_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \cdot \min_i \min_k |x_0(k) - x_i(k)|} \quad (7)$$

$$r_i = \frac{1}{n} \sum_{k=1}^n \zeta_i(k) \quad (8)$$

Table 3 shows the partial calculation results of the correlation coefficients of seven input variables. The correlation degree is shown in Table 4 by calculating the average value of seven input variables. By comparing the correlation degree of seven input variables and output variables, the following order can be found: secondary/primary air volume ratio > head wind speed > air inlet dry bulb temperature > total air volume > relative humidity > secondary air volume > primary air volume. Although the influence of secondary air volume is the smallest, its correlation degree of 0.5657 is larger than 0.5, and it is also considered as an important parameter.

Table 3. Partial calculation results of the correlation coefficients of seven input variables.

Number	Air Inlet Dry Bulb Temperature/°C	Relative Humidity/%	Total Air Volume/m ³ /h	Head Wind Speed/m/s	Primary Air Volume/m ³ /h	Secondary Air Volume/m ³ /h	Secondary/Primary Air Volume Ratio
1	0.8068	0.4895	0.8459	0.9495	0.6706	0.6778	0.8755
2	0.7238	0.5706	0.7086	0.8519	0.5814	0.5867	0.7293
3	0.6675	0.6581	0.6193	0.7260	0.5198	0.5241	0.6350
4	0.8403	0.6471	0.7216	0.8708	0.5901	0.5956	0.7431
5	0.9230	0.5838	0.9479	0.8471	0.7332	0.7417	0.9853
6	0.8589	0.5958	0.9714	0.8293	0.7471	0.7560	0.9915
7	0.9783	0.7253	0.7946	0.9793	0.6380	0.6444	0.8207
8	0.8666	0.7140	0.8459	0.9495	0.6706	0.6778	0.8755
9	0.8355	0.6907	0.8840	0.9057	0.6943	0.7020	0.9164
10	0.9505	0.7263	0.7788	0.9555	0.6278	0.6340	0.8039

Table 4. Summary calculation results of the correlation degree of seven input variables.

Type	Air Inlet Dry Bulb Temperature/°C	Relative Humidity/%	Total Air Volume/m ³ /h	Head Wind Speed/m/s	Primary Air Volume/m ³ /h	Secondary Air Volume/m ³ /h	Secondary/Primary Air Volume Ratio
<i>r</i>	0.7687	0.5885	0.6879	0.7717	0.5605	0.5657	0.8258

3. BP ANN for Performance Prediction

Yulin City of Shaanxi Province in China was selected as a test site, the test time continued from 1 August 2019 to 6 August 2019 with 10 sample data per day. In total, 60 sets of data are divided into two groups taking the data from 1 August 2019 to 5 August 2019 as the training data, and the data on 6 August 2019 as the validating data.

3.1. Analysis of BP ANN Training Results

Figure 4 shows the training error curve. It can be seen that the convergence speed of the first three training sessions is very fast. When the training time reaches to the 12th session, the standard deviation between the actual value and the predicted value of the unit evaporation efficiency meets the set requirements. Figure 5 shows the variation curve of network error. The ordinate is the MSE, and the abscissa is the number of iterations. When the BP ANN is trained for the 12th time, the performance of the network is the best, and the verification error is the smallest at the 6th iteration, which converges rapidly to 0.0013.

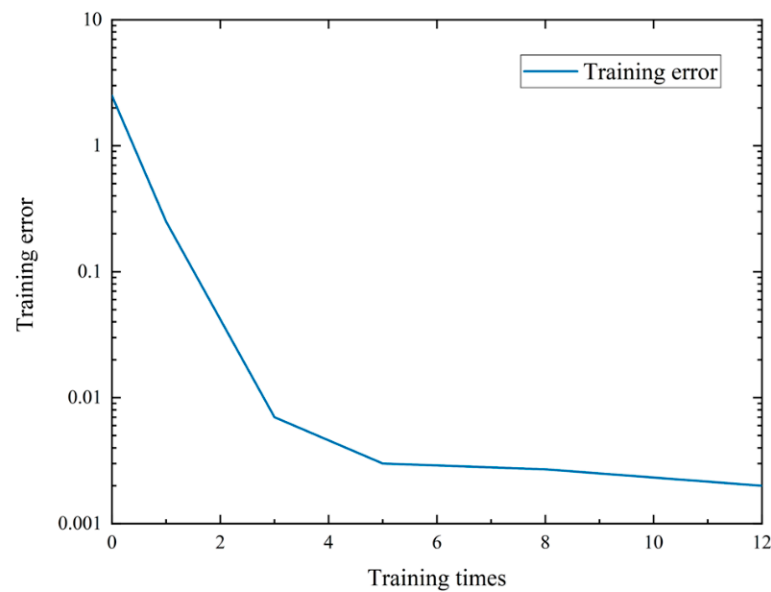


Figure 4. Training error curve of network.

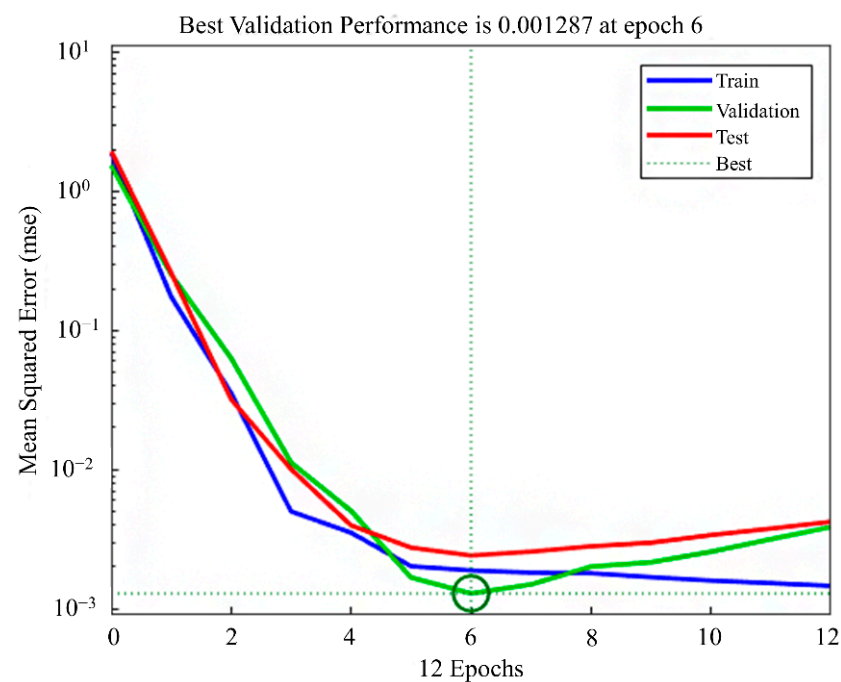


Figure 5. Variation curve of network error.

Figure 6 shows the change curve of the LM algorithm training process, the abscissa is the number of iterations, and the abscissa of the top graph is the gradient. It can be seen that the overall gradient shows a downward trend, and the gradient is only 0.0031 at the 12th iteration. The ordinate of the middle graph is the learning rate, and the learning rate is fixed at 10^{-5} from the start of the second iteration to the 12th iteration. The ordinate of the bottom figure is the verification. From the 7th to the 12th iteration, the mean square error keeps rising, and the MSE is the smallest in the first two times. The results show that the algorithm has a fast convergence speed and avoids the occurrence of local minimum value, so it can achieve good results for multi-sample and multi-variable training.

The fitting effect of the BP ANN training process is shown in Figure 7. It shows the training, verification, testing, and overall fitting effect of the training data. The abscissa is the expected output, and the ordinate is the actual output. R is the correlation coefficient

after linear regression. A better prediction result is obtained when the R is close to 1. It can be seen that the overall fitting effect of all the data during the training process is good, which is 0.9918.

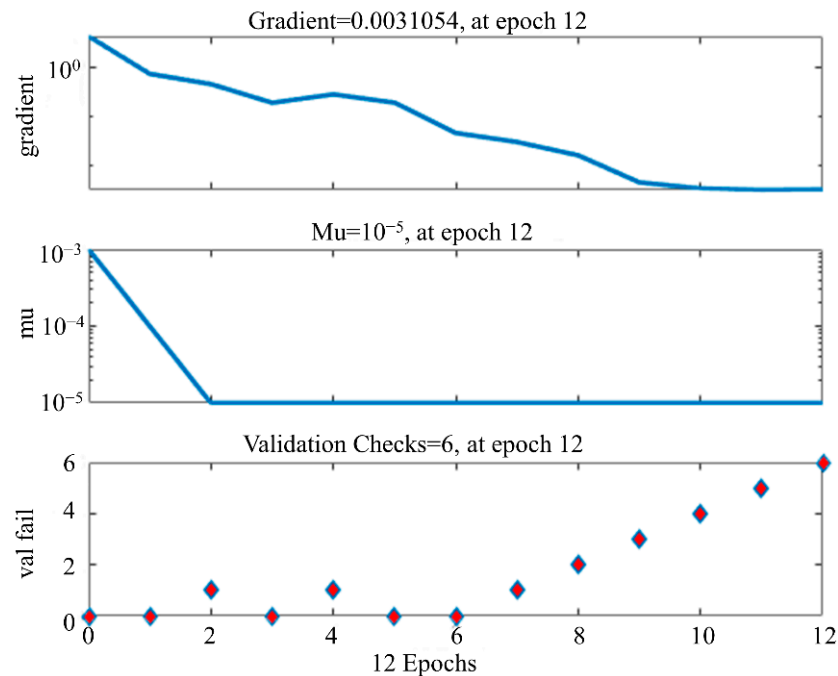


Figure 6. LM algorithm training process.

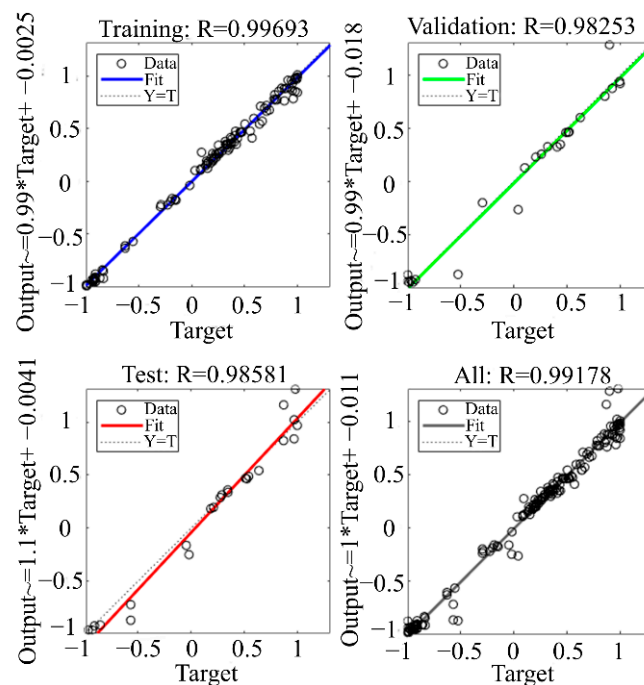


Figure 7. Fitting effect of network.

3.2. Analysis of the Predicted Results of BP ANN

Figure 8 shows the predicted and measured value of 10 samples on 6 August 2019. Figure 9 shows the relative error between the predicted and measured value of the 10 samples. The result of BP ANN for evaporation efficiency is consistent with the measured value. However, there is a problem that the errors of individual data are a little bit large. Among

them, the relative error of the test sample 7 is relatively large, which is close to 10%. The predicted results are verified by the formula described in Section 2.4, and the RMSE of the evaporation efficiency of the predicted model is 3.1367, and the r^2 is 0.9659.

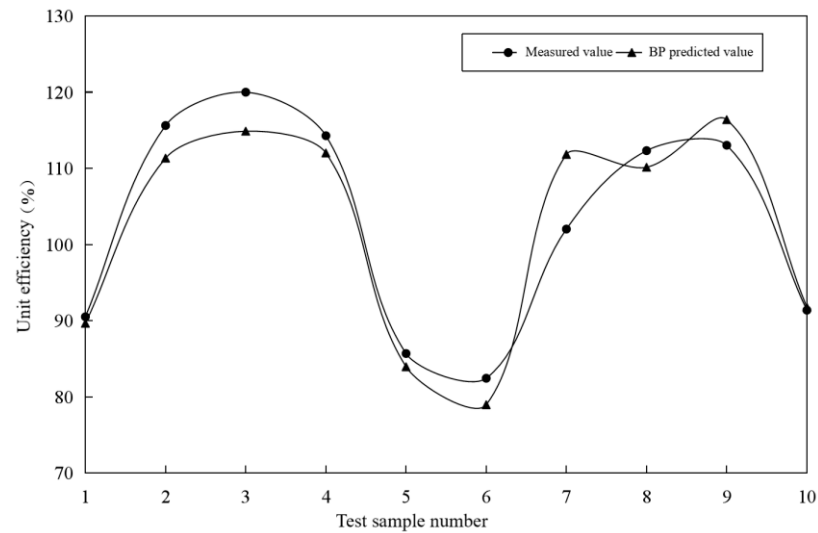


Figure 8. The predicted value of BP ANN on the unit efficiency.

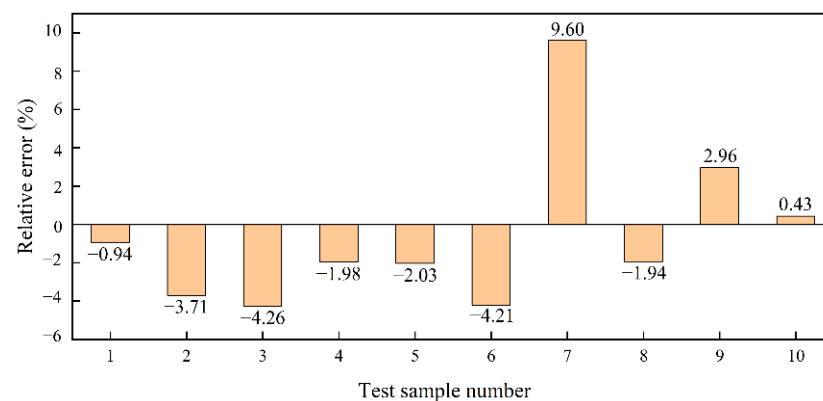


Figure 9. Relative error between predicted and measured values.

4. PSO-BP ANN for Performance Prediction

According to the analysis of the predicted results by BP ANN in Section 3, the predicted values are all within an acceptable range, but the errors of individual cases are a little bit large, and therefore it is necessary to improve the model. Currently, there are many available training algorithms, in which PSO is an optimization algorithm with the advantages of fast data convergence and easy programming. However, it also tends to come into the local minimum value [18,19]. The PSO-BP method is used to optimize the established BP model, which mainly optimizes and updates the thresholds and weights that affect the prediction accuracy of the network. After the optimization of PSO algorithm, the initial value of the thresholds and weights of BP ANN are updated iteratively. Finally, the optimized particle value is assigned to BP ANN which can improve the learning and predicting performance of the model. The flowchart of the PSO-BP ANN algorithm is shown in Figure 10.

PSO consists of two vectors of velocity and position as described below. The two vectors of velocity represent the displacement of particles, and the position determines the particle position.

$$v_i = (v_{i1}, v_{i2}, \dots, v_{iD}) \quad (9)$$

$$x_i = (x_{i1}, x_{i2}, \dots, x_{iD}) \quad (10)$$

where $i = 1, 2, \dots, n$.

Equations (11) and (12) are the updated formulas for particle velocity and position, respectively.

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{iD} - x_{id}) + c_2 r_2 (p_{gD} - x_{id}) \quad (11)$$

$$x_{id} = x_{id} + v_{id} \quad (12)$$

where $i = 1, 2, \dots, n$. v_{id} and x_{id} denote the velocity and position vector of D-dimensional component of the i th particle, respectively. ω is the inertia weight. p_i denotes the optimal position of the particles. P_g denotes the optimal position of the particles swarm. c_1, c_2 are the learning factors and non-negative constants, respectively. r_1, r_2 are the random numbers which are between 0 and 1.

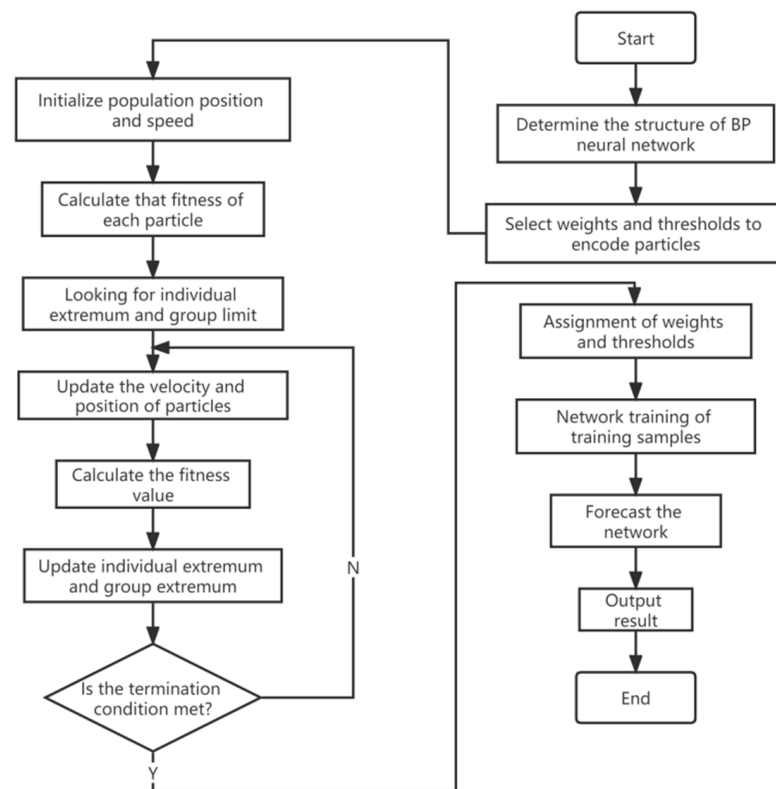


Figure 10. Flowchart of the PSO-BP ANN algorithm.

The PSO-BP algorithm has the advantages of short training time and high training efficiency [19,20]. The following parameters determine the training effect of PSO-BP ANN: the dimension of particles (D); the size of particle swarm (N); the learning factors c_1, c_2 ; Inertia weight ω ; Search range and speed range; the input parameters of the model.

The dimension of particles can be calculated by the expression described as $m \times n + n \times 1 + n + 1$. The value of D is 127 in the current study. N has a great influence on the calculation amount and global optimization ability of the algorithm. The larger the N is, more particles participate in the search, and therefore the algorithm has stronger ability of global optimization. Too large N will also lead to an exponential increase in its computing time. If N is too small, the global information will be reduced, and it is easy to fall into the local optimum. The growth of N is not proportional to the search ability. Therefore, N is taken as 50. The empirical values of learning factors within the range of 0~4. It is appropriate when c_1 and c_2 are both 2 in this study. Inertia weight ω represents the inertia of the particle before each iteration. The larger the ω is, the faster the particle moves and the faster the search speed is, and the stronger the global optimization ability is. However, it may make the algorithm unable to converge, so a reasonable value of the inertia weight is required. Therefore, the value of ω is set to 1. To limit the trajectory of

particles, the search range and speed range of PSO are set to 0 to 1. The parameters of PSO-BP ANN input layer and output layer are consistent with those of the BP network.

4.1. Predicted Results of PSO-BP ANN Model

The same samples described in Section 3 are used for the optimized model. The specific methods of normalizing and denormalizing data are the same as those in Section 2.3. Figure 11 shows the predicted results of PSO-BP ANN model when compared with actual measured results. Figure 12 shows the relative error between predicted and measured results. It can be seen that the changing trend between the predicted value for evaporation efficiency of the PSO-BP ANN and the measured value is similar, and the results of the two models are relatively close with a maximum relative error of -2.48% . For sample 7, the relative error of the BP ANN is 9.6% , while it is 2.21% after optimization, and the accuracy is effectively improved by 7.39% . The problem of large errors for individual sample has been effectively solved.

The predicted results of the PSO-BP ANN are tested and verified, and the RMSE of the evaporation efficiency of the prediction model is 1.102 , and r^2 is 0.9745 . The optimized model accords with reality, the predicted result is more accurate. Therefore, the PSO-BP ANN can accurately predict the evaporation efficiency and its changing trend.

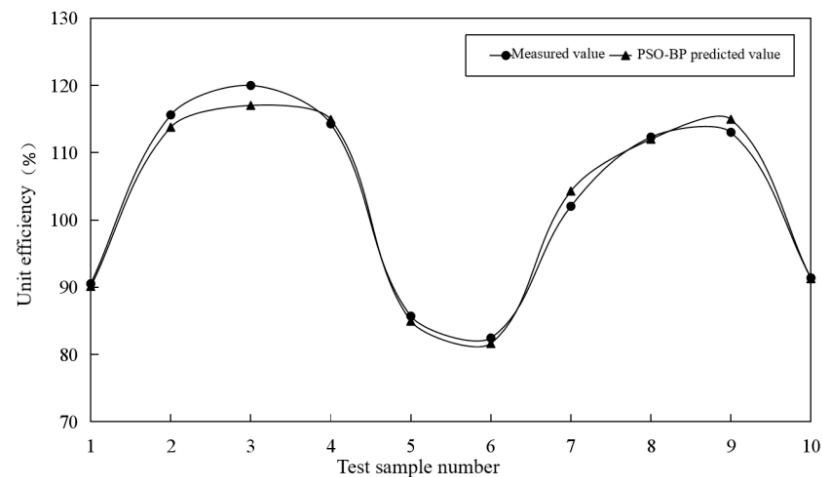


Figure 11. The predicted value of PSO-BP ANN on the unit efficiency.

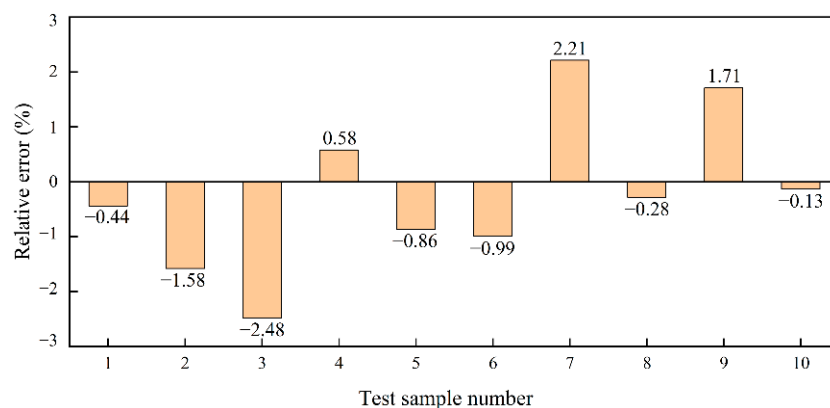


Figure 12. Relative errors between predicted and measured results.

4.2. Comparative Analysis of BP and PSO-BP ANN Models

Table 5 shows the comparison between the BP ANN and the PSO-BP ANN for predicting the evaporation efficiency of the DPIE cooling air conditioning unit. The AAE and ABE of the PSO-BP ANN model is generally smaller than that of the BP ANN. Lower AAE

and ABE infer that the PSO-BP ANN is more suitable for solving performance prediction problem of DPIE cooling air conditioning unit.

Table 5. Comparison between the BP ANN and the optimized PSO-BP ANN.

Sample Number	Test Moment/h	Measured Values/%	Value of BP/%	Value of PSO-BP/%	AAE of BP/%	ABE of BP/%	AAE of PSO-BP/%	ABE of PSO-BP/%
1	9:00	90.53	89.68	90.13				
2	10:00	115.63	111.34	113.8				
3	11:00	120	114.89	117.03				
4	12:00	114.29	112.03	114.95				
5	13:00	85.71	83.97	84.97				
6	14:00	82.46	78.99	81.64	3.21	−0.61	1.13	−0.23
7	15:00	102.04	111.84	104.3				
8	16:00	112.33	110.15	112.01				
9	17:00	113.04	116.39	114.97				
10	18:00	91.4	91.79	91.28				

5. Conclusions

This study presents the application of ANN for the performance prediction of DPIE cooler. A higher reliability and accuracy method of performance prediction was developed by PSO-BP ANN. The following conclusions are obtained:

- (1) The BP ANN results of evaporation efficiency are basically consistent with the measured values. The RMSE of the evaporation efficiency of the BP ANN is 3.1367, and the r^2 is 0.9659. However, the relative error of sample 7 is close to 10% which is a little bit large.
- (2) A PSO-BP ANN was established to improve the accuracy of the BP ANN. The relative error of the PSO-BP model is generally smaller than that of the BP ANN. For sample 7, the relative error of the PSO-BP ANN is 2.21% with an improvement of 7.39% when compared with the BP ANN.
- (3) The influencing degrees of seven input parameters on evaporation efficiency were discussed, among which the secondary/primary air volume ratio has the biggest impact.

The obtained results are within the acceptable range. However, the data available for analysis were limited by the weather conditions, i.e., the weather data and unit working conditions within six-day period were used during analysis. Future work will use more advantageous Long Short Time Memory Network under distinct weather conditions.

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Nomenclature

Nomenclature

b	threshold scalar
c_1, c_2	learning factors
D	dimension of particles
k	i th time
l	number of neurons in the output layer
m	number of neurons in the input layer
n	number of neurons in the hidden layer
N	size of particle swarm
P_g	optimal position of the particles swarm
p_i	optimal position of the particles
r_1, r_2	random numbers between 0 and 1
r^2	square of the correlation coefficient
r_i	correlation degree
v_{id}	velocity vector of D-dimensional component of the i th particle
W	weight matrix
x	normalized input value
x_i	original input value
x_{id}	position vector of D-dimensional component of the i th particle
$x_{\max}$	maximum value of original input
$x_{\min}$	minimum value of original input
y	normalized target value
y_i	original value Target value
$y_{\max}$	maximum value of original target
$y_{\min}$	minimum value of original target
$Y_p(k)$	predicted evaporation efficiency at the current time
$Y_T(k)$	actual evaporation efficiency at the current time
Greek symbols	
ζ	correlation coefficient
ω	inertia weight
η	relative error
Abbreviations	
AAE	average absolute error
ABE	average biased error
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
BP	back propagation
DPIE	Dew point indirect evaporative
FIS	fuzzy inference system
FNN	feedforward neural network
GA	genetic algorithms
GRA	grey relational analysis
HVAC	heating, ventilation, and air conditioning
MSE	mean square error
PSO	particle swarm optimization
R&D	research and development
RMS	root mean square
RMSE	root mean square error

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