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Prediction of Indoor Temperature and Relative Humidity Based on Cloud Database by Using an Improved BP Neural Network in Chongqing

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ABSTRACT For continuous improvement of productivity, accurate, stable, and reliable control of temperature and humidity is important in industrial production. Accurate prediction of air temperature and humidity can improve the predictability and stability of air conditioning control systems. In this paper, based on the cloud database of industry settings, an improved prediction model based on backpropagation (BP) neural networks was established to forecast indoor air temperature (IT) and relative humidity (IH) every 10 min and 6–72 h in advance. The experimental building was in Chongqing, a typical humid, hot-summer, and cold-winter area in China. The test data were used to determine the optimal parameters of the neural network model. The experimental results showed that the IT and IH predictions by our model have strong correlations with the actual data, with the coefficients of determination being 0.9897 and 0.9778, respectively. Compared with other literature, our model was more effective in temperature prediction. The presented method can be used for the prediction and control of the indoor temperature and relative humidity in industrial production.

INDEX TERMS Back propagation neural networks, cloud database, indoor temperature prediction, indoor relative humidity prediction.

I. INTRODUCTION

The control of temperature and humidity plays an extremely important role in the production process of industries such as food production [1], [2], tobacco processing [3], [4], and biological product manufacturing [5], [6], which directly affects the quality of products. Sometimes it is even related to the safety of the equipment and human. Accurate indoor air temperature and humidity prediction in industrial buildings can reduce energy consumption and improve the stability of the air conditioning control system. An effective way to evaluate indoor temperature and humidity parameters is to use building energy simulation tool. Although the simulation tools can achieve accurate simulation requirements, it is based on the premise of collecting all kinds of detailed parameters of the building such as the change in weather conditions, structures of the building, geographic location, and energy produced by lights and equipment loadings [7], [8]. The collection of these parameters takes time and effort, and not all data are available. In addition, the establishment of these models often requires expert knowledge and the calculation is time-consuming, which becomes an obstacle when using mainstream building energy analysis software.

In terms of certain predictions, several techniques existing in the literature indicate that nonlinear models are better than linear ones [9]. Since the neural network can infinitely approximate any continuous function, it has been widely applied in various building predictions. Kreider [10] first introduced the method of artificial neural network into the prediction of energy consumption of HVAC equipment in building systems. Kwok *et al.* [11] and Leung *et al.* [12] used indoor occupant room rate and hourly usage area as input parameters to the artificial neural network prediction process. According to the relevant parameters of the experimental building and the meteorological data of the building area, the load of the building was predicted. Results showed that the building physical parameters and meteorological input parameters had a great influence on the accuracy of building load forecasting. Pandey *et al.* [13] used an artificial neural network to forecast indoor room temperature by using three different roof passive cooling methods.

Lu and Viljanen [14] designed four neural network models developed by nonlinear autoregressive with external input model and genetic algorithm to forecast indoor temperature (IT) and relative humidity (IH). The coefficients of determination are 0.996 for indoor air temperature and 0.994 for relative humidity. Yigit and Ertunc [15] developed a feed forward neural network to forecast the air temperature and humidity at the outlet of a wire-on-tube type heat exchanger. The experimental results showed that the average relative error of outlet air temperature was less than 1%, and the error of outlet humidity was less than 2%.

Although much research was carried out in this area, little studies have been done in the literature to predict both temperature and relative humidity simultaneously. Özbalta *et al.* [16] trained several neural network models to predict the average daily indoor air temperature and relative humidity values in an education building in Izmir, Turkey. The coefficients of determination between the simulated and experimental results of indoor temperature and relative humidity were calculated as 0.94 and 0.96, respectively. Mba *et al.* [17] used artificial neural networks for hourly prediction and forecasted indoor temperature and relative humidity 24 hours and one month ahead. However, predictions with shorter prediction time horizon (e.g., a few minutes) are needed to provide guidance for industrial production.

Accordingly, we used the indoor and outdoor air temperature and relative humidity as information in a tobacco factory warehouse in the humid, hot-summer, and cold-winter area in Chongqing. The data are collected every 10 minutes from the sensors and uploaded to the cloud. The data are stored, processed, and displayed in the cloud database. An improved prediction model based on BP neural networks is proposed to forecast indoor temperature and relative humidity 6 hours, 24 hours, and 72 hours in advance. The results are compared with other research work to verify the effectiveness of our model. This method can provide theoretical and technical support for indoor temperature and relative humidity prediction and control strategies for air conditioning systems.

II. METHODOLOGY

A. EXPERIMENTAL BUILDING AND DATA ACQUISITION

The study was conducted in a tobacco industrial building in Chongqing, a typical city in the hot-summer and cold-winter zone in China. The annual average relative humidity is between 70%-80%, which belongs to high humidity areas. The indoor air temperature and relative humidity were measured at the planned warehouse, shown in Fig. 1. The length and width of the building are 48.2 m and 34.4 m, respectively. The ceiling height is 2.8 m. The whole building is divided into two areas, which are connected by a door with 4.4 m × 3.2 m size.

The quality of tobacco is affected by the distribution of air flows, relative humidity and temperature [4]. If the building environment is unstable, such as the rapid changes of temperature and humidity, the quality of tobacco leaves will be greatly reduced. Thus it is essential to find the stable areas to store tobacco. Computational fluid dynamics (CFD) technology has become an important calculation method and is increasingly applied in the field of architecture [17]–[19]. We established the CFD model to obtain the temperature and humidity distribution characteristics of the indoor building environment. The KM algorithm was used to cluster and analyze the standardized data. Then the relatively stable environmental areas were obtained. Sensors used to obtain the experimental data were set in these areas.

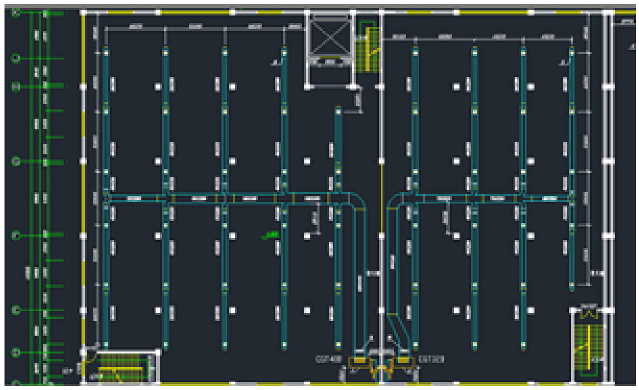

FIGURE 1. The plan of cigarettes factory NO.5 Warehouse.

In this work, the selected temperature and humidity sensor is SHT15, manufactured by the Sensirion. It is a composite single-chip sensor that integrates temperature and humidity measurement with calibrated digital signal output. It has the advantages of strong anti-interference and quick response. The characteristics of the sensor are presented in Table 1 below.

TABLE 1. Characteristics of temperature and relative humidity sensors.

Parameter	Range	Accuracy	Resolution
Temperature（℃）	-40~123.8	±0.3	0.01
Relative humidity（%RH）	0-100	±3	0.03

Fig. 2 shows the position of some sensors in the experimental space. According to the requirements of the tobacco factory, the installation height of the sensors are 1.6 m

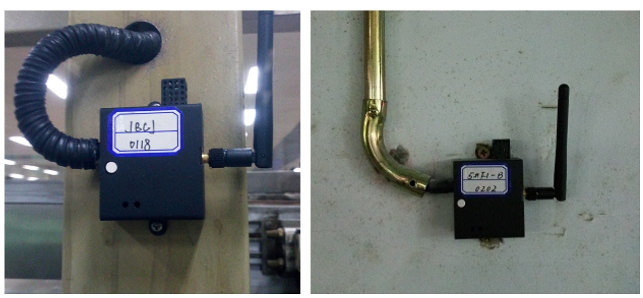

FIGURE 2. Data acquisition system.

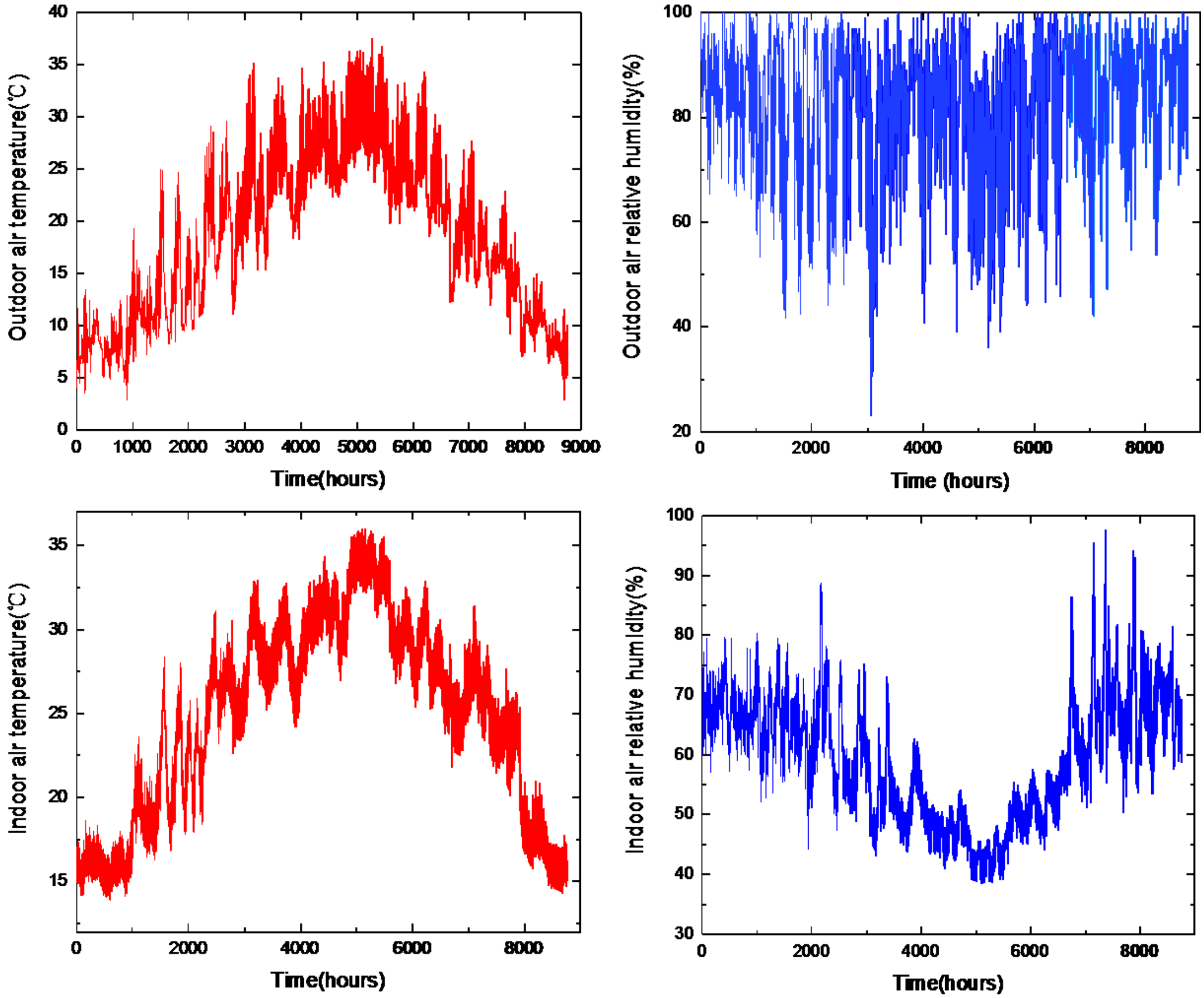

FIGURE 3. Experimental average data for one year.

from the ground and are fixed on the pillar or the wall. The indoor air temperature and relative humidity data are simultaneously recorded every 10 minutes. Since the cloud sever has higher computation capacity and storage [20], these data are uploaded to the cloud. The cloud database could aggregate, back up, and process the sensing data updated from different cloudlets [21]. The data are collected from January 2017 to January 2018 and are shown in Fig. 3 below.

B. ESTABLISHMENT OF THE PREDICTION MODEL

Some researchers proposed Back Propagation (BP) neural network to make predictions [22]–[24]. It is a multi-layer feed-forward neural network trained according to the error reverse propagation algorithm, which is widely applied in function approximation, classification, pattern recognition, as well as data compression and prediction. A three-layer BP neural network structure is displayed in Fig. 4.

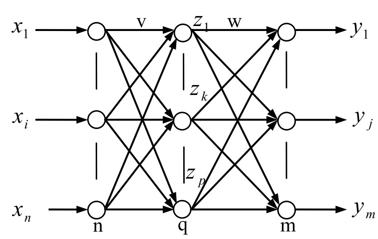

FIGURE 4. Three-layer BP neural network structure.

The original BP neural network model can accurately forecast the next data. However, in industrial production process, the phenomenon of large time lags in temperature and humidity is widespread, and one set of forecasted data is not enough to support the decision of the air-conditioning system. Therefore, we establish an improved prediction model based on BP neural networks by importing the predictive data into the training samples to extend the prediction time and the model can forecast more data.

In the improved prediction model, the indoor and outdoor temperature and relative humidity data collected in real-time are selected as input variables to the training samples. The output variables are the forecasted indoor temperature and relative humidity, which is obtainable by training the samples. As time goes on, new measurement data are collected, and they are updated into the training samples at the same time. With the increase of sample size, the prediction accuracy of neural network will increase, but it will increase the complexity of the network and the simulation time. For time series prediction, training time is an important parameter. When the training time is too long or even exceeds the predicted time horizon, the model is meaningless. Thus, in our model, the size of the training sample is fixed, as displayed in [25, Fig. 5]. The above improved model can predict indoor temperature and relative humidity accurately for a long period and update the training samples in real-time.

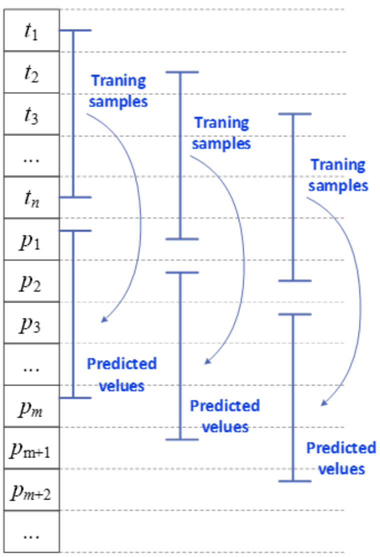

FIGURE 5. Improved prediction model.

C. MODEL EVALUATION CRITERIA

Various statistical indicators are put forward to check the predictive performance of the model [26]–[28]. In our study, the results of the model were analyzed by the coefficient of determination (R^2), the mean square error (MSE) and the mean absolute error (MAE). The coefficient of determination can well measure the degree of proximity between the actual data and the predicted values. R^2, MAE, and MSE can be evaluated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}[y_i - \frac{1}{n}\sum_{i=1}^{n} y_i]^2} \tag{1}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - p_i|}{n} \tag{2}$$

$$MSE = \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{n}(3) \tag{3}$$

Where y_i is the measured value, p_i is the predicted output. When the R^2 value equals to 1 and the MSE value verges on 0, the performance of this model is outstanding.

III. RESULTS AND DISCUSSION

Based on the data recorded by the cloud database in 2017, the indoor relative humidity and temperature can be predicted simultaneously every 10 minutes, 6 hours, and 24 hours in advance. Matlab was used to train the improved prediction model. As explained by Kapetanakis *et al.* [29], the selection of input variables will affect the accuracy and complexity of prediction models under different climate conditions. In order to obtain better results, we compared the prediction effect of several different input variables. Table 2 lists the different input variables in the established BP neural network, where OT(k), OH(k), IT(k), and IH(k) are the vector of values of outdoor temperature, outdoor relative humidity, indoor temperature and indoor relative humidity at time k, respectively. The training samples are the last 10000 data pairs. The number of network layers is 3 and the precision is set as 0.001.

TABLE 2. Input and output variables for each model.

Models	Inputs	Outputs	Description
M1	y(k),y(k-1),…,y(k-11) u(k),u(k-1),…,u(k-11)	y(k+1)	y(k)=[IT(k);IH(k)] u(k)=[OT(k);OH(k)]
M2	y(k),y(k-1),…,y(k-11) u(k),u(k-1),…,u(k-11)	y(k+1)	y(k)=[IT(k);IH(k)] u(k)= OH(k)
M3	y(k),y(k-1),…,y(k-11) u(k),u(k-1),…,u(k-11)	y(k+1)	y(k)=[IT(k);IH(k)] u(k)=OT(k)

A. DETERMINATION OF OPTIMAL PARAMETERS

So far, there is no justifiable method to identify hidden neurons in mathematics. It is generally started from the minimum number of the elements [30]. As the number of neurons continues to increase, retraining of BP neural network will continue until the satisfactory results appear, the number of hidden neurons at this time is considered to be optimal. In order to find the optimal parameters under different neural network structures, we conducted a set of tests. Table 3 shows the MSE of the testing data for different neural network structures.

From the table we see that when the number of hidden layer network nodes is 20, the model M1 has the minimum MSE, whereas for model M2 and M3, the values are 15. Analysis shows that the number of hidden layer network nodes drawn between 15 and 20 is more appropriate. The minimum

TABLE 3. Testing results for different models.

Hidden neurons	Mean square error (MSE) M1	M2	M3
5	0.29	0.25	0.47
10	0.40	0.38	0.42
15	0.34	0.22	0.33
20	0.17	0.30	0.36
25	0.22	0.41	0.48
30	0.24	0.43	0.50

MSE is 0.17 in M1. This model may be the optimal approximate model in industrial buildings. The training model was used to estimate the number of hidden network nodes, then the optimal parameter is selected for the actual test.

B. ANALYSIS OF PREDICTION EFFECT

Based on the analysis above, in order to test the short-term and long-term ability of the model to predict the IT and IH, we randomly selected some sets of data from the cloud database. These data are not in the training set. The prediction periods are 6 hours, 24 hours, and 72 hours, respectively. Fig. 6-8 displays the comparison of the predicted data and the actual values for indoor air temperature and indoor air relative humidity. The mean absolute error and mean square error of each experiment are listed in Table 4.

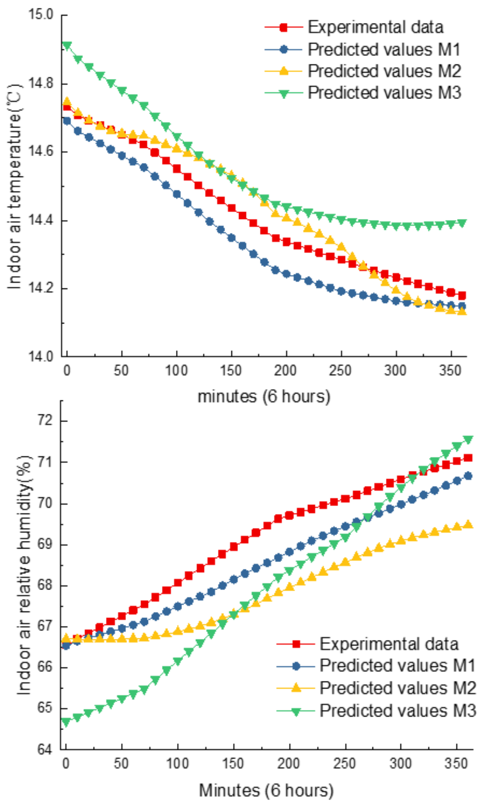

FIGURE 6. Comparison of experimental data and predicted values of IT and IH for 6 hours prediction.

TABLE 4. Mes and mae in different experiments.

Forecast time	Type of error	M1 IT	M1 IH	M2 IT	M2 IH	M3 IT	M3 IH
6h	MES	0.07	0.59	0.05	1.32	0.13	0.93
	MAE	0.01	0.40	0.01	1.98	0.02	2.11
24h	MES	0.22	2.27	0.23	2.60	0.16	2.79
	MAE	0.06	6.58	0.08	9.41	0.03	10.35
48h	MES	0.25	1.52	0.22	2.13	0.22	2.51
	MAE	0.09	3.89	0.11	6.90	0.07	9.47

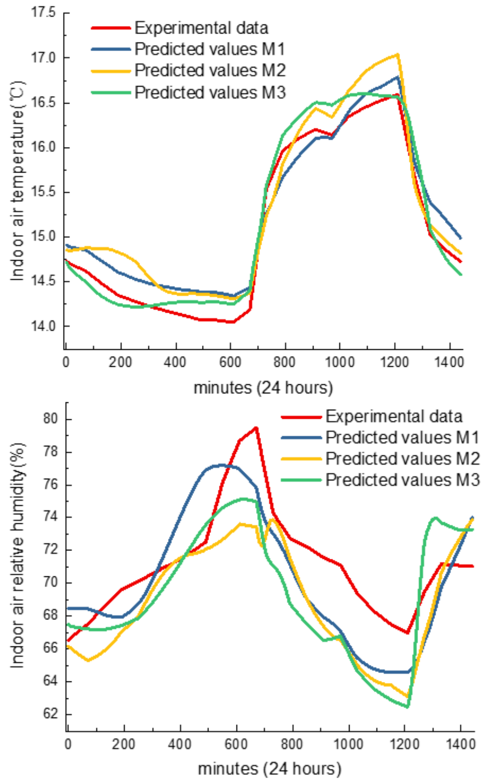

FIGURE 7. Comparison of experimental data and predicted values of IT and IH for 24 hours prediction.

Fig. 6 presents the evolution of the predicted values and experimental values of different model structures. The results show that there is a strong similarity between the model we proposed and the actual experiment. The MAE for M1, M2, and M3 are 0.07, 0.05, and 0.13 in temperature and 0.59, 1.32, and 0.93 in relative humidity, which supports that predicting 6 hours in advance is reliable. Compared with M2 and M3, M1 has a better prediction.

Fig. 7-8 displays the comparison between simulated values and predicted data of the three models. The average of MAE and MSE of the models are 0.217 and 0.074 respectively in temperature. This indicates that it is feasible and effective to predict the temperature 24 hours and 72 hours in advance. However, analysis of the figures shows a poor relationship between experimental date and predicted values in indoor air relative humidity. The deviation between experimental

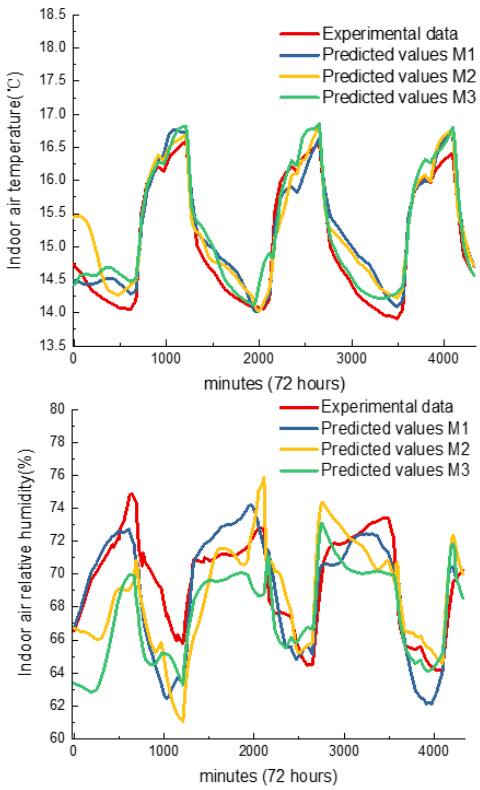

FIGURE 8. Comparison of experimental data and predicted values of IT and IH for 72 hours prediction.

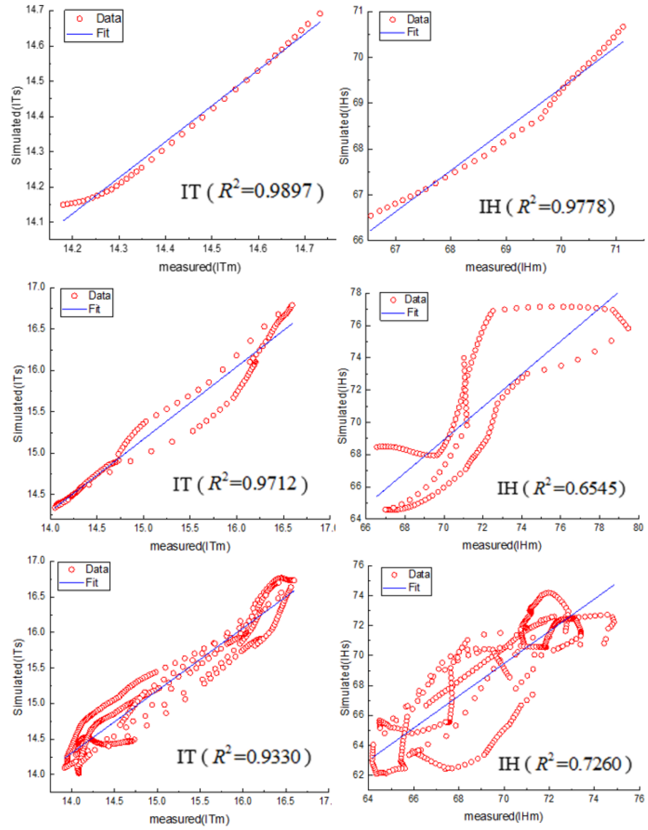

FIGURE 9. Regression lines between measured values and values predicted 6 h, 24 h, and 72 h ahead of M1.

data and neural network predictions is very high for relative humidity and cannot be ignored. This may be due to the fact that indoor relative humidity is affected by more factors than the indoor temperature, especially in this study, some important information, such as heating power and ventilation rate is not available, which makes the indoor relative humidity much more difficult to predict [14].

Based on the above experiments, the models obtained can accurately forecast indoor air temperature in an industrial building in Chongqing, 72 hours in advance. However, indoor relative humidity can only be predicted for several hours in advance. The accuracy for indoor relative humidity prediction needs to be improved.

Combining the data in Table 4, we find that M1 has the best predictive effect of the three models. It seems that more input variables can improve prediction accuracy. Although the experimental buildings are all in a humid region, the result is different from the experimental conclusion obtained by Mba *et al.* [17]. This may be due to the differences in neural network structures, building types, and climate environment, etc.

Fig. 9 displays the regression lines between actual and predicted values of M1 (The regression lines of M2 and M3 are presented in the Appendix). The ITm, ITs, IHm, and IHs are the measured and simulated values of indoor temperature and indoor relative humidity, respectively. The coefficient of determination R^2 is calculated so as to intuitively judge the degree of fit. As the R^2 value verges on 1, the model is more successful.

For 6 hours prediction, the coefficient of determination for model M1 is 0.9897 and 0.9778, respectively, which are both higher than M2 and M3. It shows that M1 can better predict indoor temperature and relative humidity simultaneously 6 hours later. When it comes to predict indoor temperature 24h and 72h in advance, the mean coefficients of determination are 0.9521, 0.942, and 0.9687 respectively. According to the results, M3 is the most effective model for predicting indoor air temperature. For 24 hours and 72 hours ahead prediction of relative humidity, the mean determination coefficients of the three models are 0.6902, 0.5566, and 0.4793 respectively. The results indicate that the best approximation of indoor relative humidity is given by M1, but the coefficient of determination is terrible compared to indoor air temperature. Thus, it should be improved in further work. Interestingly, we find that in all cases, the coefficient of determination of the indoor air temperature is higher than the relative humidity in model M1, which indicates that in comparison with the relative humidity, the predicted value of indoor temperature can better adapt to the actual measured value.

To conclude, for 6 hours ahead prediction, in the subtropical monsoon humid climate in Chongqing, the best

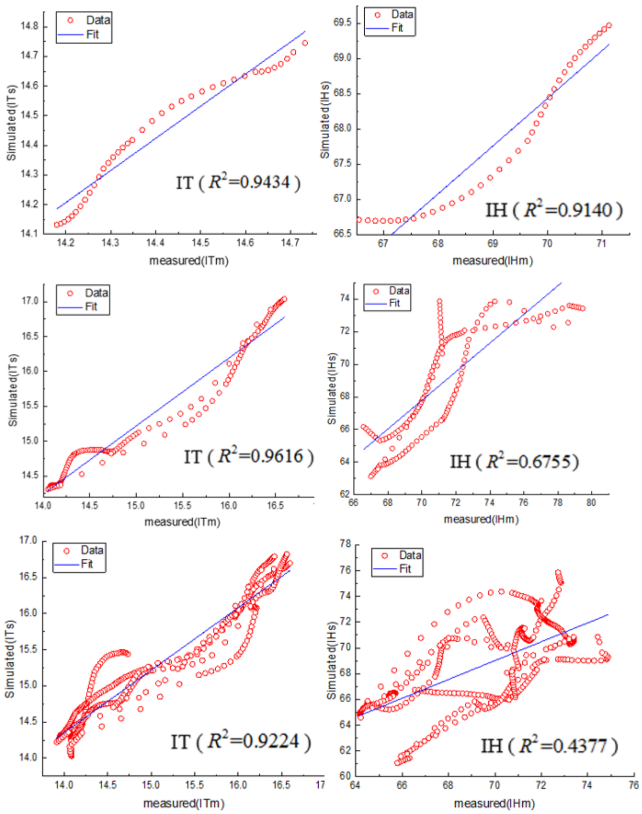

FIGURE 10. Regression lines between measured values and values predicted 6 h, 24 h, and 72 h ahead of M2.

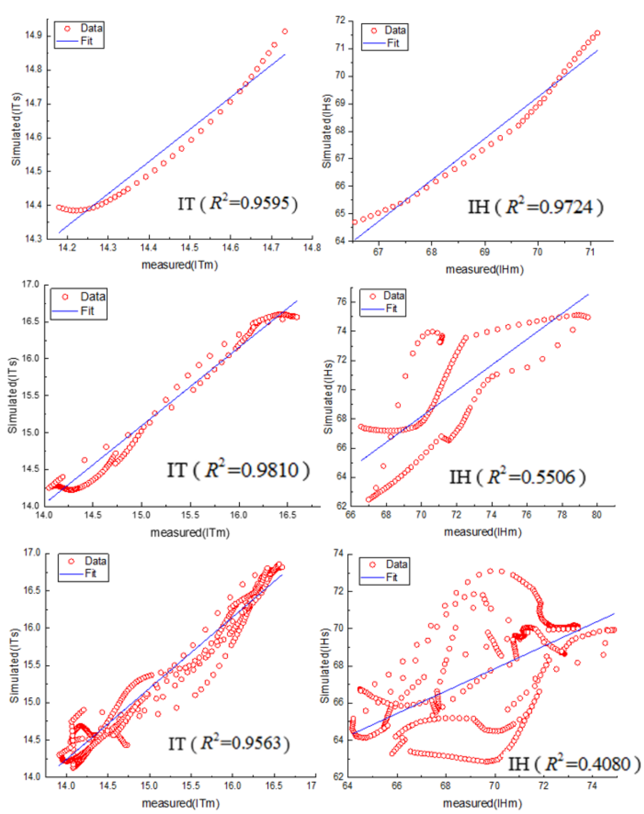

FIGURE 11. Regression lines between measured values and values predicted 6 h, 24 h, and 72 h ahead of M3.

TABLE 5. Average determining coefficient of different models.

Model	One day ahead prediction		One week ahead prediction	
	IT	IH	IT	IH
Mba L's model	0.970	0.694	0.970	0.764
Our model	0.974	0.917	0.862	0.714

approximate model to forecast indoor temperature and relative humidity in industrial buildings is M1. For 24 hours and 72 hours prediction in advance, M3 is the best approximate model for indoor air temperature. Besides, some other factors, such as the time efficiency [31], stability [32] and reliability guarantee [33] of the model, will also affect the choice of the optimal model.

C. COMPARISON WITH OTHER LITERATURE

In humid areas, the latest study was done by Mba *et al.* [17]. Authors used artificial neural networks for hourly prediction and forecasted indoor temperature and relative humidity 24 hours and one week ahead in a modern house. For comparison with their models, we also took hourly data form the cloud as a database and used our model to do the same experiment. The experimental results are shown in Table 5. Results show that our model is better at predicting temperature, but the relative humidity is not good.

IV. CONCLUSION

This paper proposes an improved model based on BP neural networks to simultaneously forecast indoor relative humidity and air temperature every 10 minutes, 6 hours, 24 hours, and 72 hours in advance in a tobacco factory warehouse in Chongqing. Compared with other studies, our models enable shorter prediction horizons and better temperature predictions. Compared with traditional temperature and humidity prediction models, the neural network prediction model based on cloud database does not require data such as wind speed, solar radiation, thermodynamic properties of building materials, window-wall ratio, etc. This greatly reduces the complexity of the model and avoids many constraints. Another advantage of the model is its fast calculation speed and continuous learning from actual data. The experimental results indicate that our model can predict indoor air temperature and relative humidity 6 hours ahead at the same time, and can accurately predict temperature 3 days in advance. The presented model was compared with other similar methods.

Potential future work includes further reducing the forecast interval and extending the forecast horizon. Also, the accuracy for indoor relative humidity predictions should be improved.

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