Application of BP Neural Network for Pre-Dehumidification Time Prediction of Capillary Ceiling Radiant Cooling Panel Air Conditioning System

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Abstract. Pre-dehumidifying the room is generally needed before the capillary ceiling radiant cooling panel (CCRCP) air conditioning system is turned on. Accurate pre-dehumidification time is critical for condensation prevention and energy usage. The pre-dehumidification time, which is related to multiple variables with complicated correlation relationship, is difficult to be calculated by conventional methods. Therefore, BP neural network is considered to be applied to predict the pre-dehumidification time. In this study, a dynamic model of CCRCP + displacement ventilation air conditioning system was built to simulate the pre-dehumidification process in TRANSYS. And then BP neural network was established, it takes the indoor and outdoor temperature and humidity conditions at 7:00 in every morning as the influencing factors and predict the optimal pre-dehumidification time for each day. The results show that the mean square error (MSE) of the BP neural network training process is $1.90958 \times 10^{-5}$, the correlation coefficient $R$ between the training data and the sample data reaches 0.99906, and the correlation coefficient $R$ between the predicted data and the sample data reaches 0.99897. The BP neural network can reflect the intrinsic relationship between optimal pre-dehumidification time and input variables, and has high accuracy in predicting optimal pre-dehumidification time of CCRCP air conditioning system.

1. Introduction
The capillary ceiling radiant cooling panel (CCRCP) air conditioning system has been successfully utilized in Europe for about 20 years in public buildings [1], such as libraries, hospitals, and schools. More and more Asian countries are also paying attention to this integrated system in recent years. As a new type of air conditioning system, CCRCP has many advantages such as energy saving and high comfort [2] [3]. However the promotion of the CCRCP system in hot and humid areas has been resisted because of the problem of condensation. There are usually two situations when condensation occurs. In situation 1, condensation occurs during the operation due to off-design conditions. A lot of research has been done on condensation prevention based on situation 1. Novoselac. A and Srebric. J [4], according to the research on the ambient air condition of cooling panel + displacement ventilation system, found the operating state of the system should be properly controlled in order to prevent condensation. Lim. J. H et al. [5] compared different control methods for radiant floor cooling systems and found the water
temperature control is better. In general, there are two approaches commonly adopted: regulating the temperature of the supply chilled water or cutting off the chilled water supply when the risk of condensation is noticed. In situation 2, the permeation of moist air during the night causes the condensation occurrence in the start-up stage. Scholars have proposed that supplying fresh air for pre-dehumidification in advance can effectively solve the problem, but a new matter—how long should the pre-dehumidification system start in advance is generated. Xia et al. [6] analysed the parameters of indoor air during the system operation period and proposed the concept of the optimal pre-dehumidification time. Gong et al. [7] advised to consider a ventilation device with multiple adjustment functions in the design period to cut down the pre-dehumidification time. Since the pre-dehumidification time has many related variables and the correlation is complicated, which is difficult to obtain by conventional calculation methods, it usually gives a fixed value based on experience, 1 hour or half an hour. Therefore, artificial intelligence algorithms are naturally considered to be adopted in the present study.

The neural network is a computer system developed on the basis of simulating human brain neural tissue, it has nonlinear mapping ability and is especially suitable for solving complex problems of internal mechanisms. In recent years, scholars have begun to apply neural networks in the field of HVAC to deal with complex problems. Chirag Deb et al. [8] used artificial neural network to forecast diurnal cooling energy load for institutional buildings. Radiša Ž. Jovanović et al. [9] adopted various neural networks for prediction of heating energy consumption. But it is rural to apply the neural network to predict pre-dehumidification time. In this study, an office in Shanghai is taken as the research object. The dynamic model of CCRCP + displacement ventilation air conditioning system is built in TRNSYS to simulate the pre-dehumidification process, and the BP neural network is used to predict the pre-dehumidification time. The feasibility and accuracy of BP neural network are also analysed below.

2. Pre-dehumidification model
In order to obtaining pre-dehumidification time samples, the most effective method is to establish a pre-dehumidification model in the simulation software. Building a pre-dehumidification model involves two steps: establishing an air conditioning system model and simulating a pre-dehumidification process in the software platform. Exact air conditioning system model and reasonable pre-dehumidification simulation are both essential to obtaining accurate time samples.

2.1. CCRCP+ displacement ventilation Air conditioning system model
A complete radiation air conditioning system consists of three parts: radiation terminal, fresh air system, and cooling and heat source [10]. Conventional capillary is utilized as radiation terminal, while a displacement ventilation system is adopted to supply fresh air. For the research is mainly based on the terminals in the room, with the cooling and heat sources not involved, the type of cooling and heat sources are not introduced in this paper. Taking a representative room of an office building in Shanghai as the research object, CCRCP + displacement ventilation air conditioning system model was built in the TRNSYS to simulate the indoor thermal environment, so as to analyse the condensation characteristics of the ceiling panels and obtain the pre-dehumidification time.

The summer interior design temperature is 26 °C of dry bulb temperature and the relative humidity is 50%. 6 people in mild activity state are assumed in the room. In order to meet the purpose of dehumidification and hygienic standard, the minimum fresh air volume sent into the room is 180m³/h, the air supply moisture content is 9.69g/kg. The maximum cooling load is 2.446 KW, while the cooling load of the fresh air isn’t included, the largest cooling load of fresh air is 0.816KW and the largest cooling load of the ceiling panel is 1.63 KW during entire cooling season. The variable water temperature control is adopted and proportional regulator and control annunciator are used to regulate the supply water temperature. In addition, the operating time of the air conditioning system is controlled by the dynamic control table, moreover the starting time is 8:00 in the morning of the working day. Based on the design of CCRCP systems and fresh air systems, a complete model is established in TRNSYS, as shown in figure 1.
2.2. Simulation of pre-dehumidification process

According to a simple simulation, it was found that in the high temperature and high humidity weather, the condensation will occur if the ceiling panels are not pre-dehumidified during the start-up stage, but the condensation will disappear after 1h pre-dehumidification. Therefore, the pre-dehumidification is necessary for condensation prevention. The optimal pre-dehumidification time, which means the least time for ventilation device to start to ensure the temperature of ceiling panels higher than the indoor air dew point temperature during the start-up stage, will be referenced as a new concept. According to the simulation, the ventilation device starting time is adjusted to avoid the condensation occurring, thereby the optimal pre-dehumidification time will be obtained. For example, selecting July 21 (Tuesday on the eighth week) as a simulation day, the ventilation device will be started 0.5h in advance. If the simulation results show that there is no risk of condensation, the pre-dehumidification time will be decreased at intervals of 0.1h until the condensation occurs and the pre-dehumidification time is locked in the interval of [0.5-0.1n, 0.5-0.1 (n-1)] (0≤n≤5). Then the steps above are proceed to repeat at intervals of 0.01h. The time at the boundary of condensation occurrence is the optimal pre-dehumidification time. The ventilation device does not need to be started in advance means the optimal pre-dehumidification time is 0 min. In this way, the optimal pre-dehumidification time under different temperature and humidity conditions throughout the cooling season is obtained.

3. The BP neural network models for pre-dehumidification time prediction

The BP neural network is a multi-layer feedforward neural network, and its algorithm training is reversed according to the error. The basic structure of BP neural network can be divided into three layers: the input layer, the hidden layer and the output layer (figure 2) [11]. A hidden layer can have several layers, which are consist of several nodes. The nonlinear mapping from the input layer to the output layer is realized by using connective weight matrixes from the input layer to the hidden layer and from the hidden layer to the output layer. The backpropagation learning algorithm is adopted for the learning procedure. The biggest advantage of BP neural network is that it can get some rules between input parameters and output values only through its own learning and training. Before that, it does not need to determine the mapping relationship between input and output in advance, which means it has excellent nonlinear mapping capability. At the same time, the number of layers of the hidden layer in the BP neural network and the number of neurons in each hidden layer can be arbitrarily set according to the
needs of the user, and the network training result will vary with the setting parameters, which shows it has a flexible network structure. Based on the above advantages, BP neural network mainly applied to four aspects: function approximation, relationship recognition, data classification and data compression. In the above introduction part, the reasons for choosing BP neural network have been given. This part explains the inputs, outputs and the structure of BP neural network model developed in this study.

The structure of BP neural network models for predicting pre-dehumidification time is 3-10-1. The output of neural network is the predicted pre-dehumidification time. In the input layer, factors affecting pre-dehumidification time can be broadly divided into two categories: indoor factors and outdoor factors. The outdoor factors are mainly the temperature and humidity of the outdoor air that affects the indoor dew point temperature through the osmosis; the indoor factors include the temperature of the panel surface at the system start-up stage and the parameters of supplied air. Since parameters of supplied air are commonly fixed for a room at the period of dehumidification and the temperature of the panel surface is obviously related to indoor air, the indoor air temperature and humidity are automatically taken considered.

Because the pre-dehumidification time is generally less than 1h, four variables, indoor temperature, indoor relative humidity, outdoor temperature and outdoor relative humidity, at 7:00 in the morning, are set as the input nodes. The relationship between the optimal pre-dehumidification time and the indoor /outdoor dry bulb temperature at 7:00 in the morning is shown in figure 3, and the relationship between the optimal pre-dehumidification time and the indoor/outdoor relative humidity at 7:00 in the morning is shown in figure 4.
Figure 4. The relationship between the optimal pre-dehumidification time and relative humidity

85% of the data is randomly selected as training samples, and the BP neural network, which is trained by the train function, will be saved as a sample to make the next prediction.

4. Result and discussion
The performance analysis of pre-dehumidification time prediction is evaluated by mean square error (MSE) and correlation coefficient R.

The mean square error (MSE) is a measure that reflects the degree of difference between the estimator and the estimated amount. The following is the formula for calculating the MSE:

\[
MSE(\hat{\theta}) = E(\hat{\theta} - \theta)^2
\]

Where \(\theta\) represents the target value (in the present model, the pre-dehumidification time in the sample is represented), \(\hat{\theta}\) represents an estimated value of \(\theta\) determined from the sample, and \(E\) represents a mathematical expectation.

The MSE is the most basic criterion used to evaluate the point estimate. The smaller the mean square error is, the more accurate the estimate of the estimated point is, or the smaller the difference between the estimated value \(\hat{\theta}\) and the parameter \(\theta\) is.

The correlation coefficient R is the quantity used to measure the degree of linear correlation between two research variables, also known as the linear correlation coefficient.

\[
R(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var[X]Var[Y]}}
\]

Where \(Cov(X, Y)\) represents the covariance of X and Y, \(Var[X]\) represents the variance of X, and \(Var[Y]\) represents the variance of Y.

The correlation coefficient characterizes the degree of correlation between X and Y. When R is larger, the correlation between X and Y is greater. When R=0, it is generally considered that there is no linear relationship between X and Y.

The results show that the best MSE during training is \(1.90958 \times 10^{-4}\), as showed in figure 5. The correlation coefficient R between BP neural network training data and TRNSYS simulated sample data reaches 0.99906, the correlation coefficient R between BP neural network predicting data and TRNSYS simulated sample data reaches 0.99897.

Taking the parameters of indoor and outdoor air in the whole cooling season as input nodes, and the results of prediction are compared with the results of TRNSYS simulation (figure 6). The predicted value of the BP neural network is highly fitted to the TRNSYS simulation value and almost completely coincides.
5. Conclusion
In this study, a capillary ceiling radiation cooling panel + displacement ventilation air conditioning system is built in the dynamic simulation software TRNSYS, and the pre-dehumidification process is simulated to obtain the value of the optimal pre-dehumidification time in different indoor and outdoor conditions. The BP neural network model of pre-dehumidification time prediction is also established in MATLAB which takes the simulated value from TRNSYS as samples for training and predicting. The results show that the best MSE during training is $1.90958 \times 10^{-4}$, and the correlation coefficient R between BP neural network training data and TRNSYS simulated sample data reaches 0.99906, the correlation coefficient R between BP neural network predicting data and TRNSYS simulated sample data reaches 0.99897. The BP neural network can reflect the intrinsic relationship between the optimal pre-dehumidification time and the indoor/outdoor air conditions, and has strong nonlinear mapping ability and high prediction accuracy. Therefore, in the future practical application, the optimal pre-dehumidification time can be accurately predicted by BP neural network based on the indoor/outdoor temperature and humidity conditions, and then converted into a start-up signal and transmitted to the ventilation device to achieve fresh air pre-dehumidification for preventing condensation.

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