Load forecasting and operation optimization of residential fresh air system based on artificial neural network

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Abstract. Radiant cooling and heating and fresh air system is more and more widely used in residential buildings as a high-comfort, energy-saving and efficient air-conditioning system. The fresh air system handles all the moisture load and part of the cooling load of the building. In actual operation, there are some problems, such as high proportion of energy consumption and mismatch between load and operation characteristics. In this paper, a zone-level artificial neural network (ANN) model is established to predict the moisture load of residential building fresh air system. Compared with the measured data, the zone-level ANN model is established and verified. The total data used for training and testing are 13260 and 864 respectively. This paper also introduces a system control optimization model, and optimizes the operation of the fresh air system combined with the load forecasting results of the zone-level ANN model. Under the scenario of potential energy storage and time of use price, the optimization control strategy is formulated to improve the flexibility of the system. The results show that the zone-level ANN model has high prediction accuracy. The root mean square error variation coefficients corresponding to the prediction results of moisture load is 8.72%. The optimization results can reduce the operation energy consumption and cost of the system by 27.2% and 29.2% respectively in the whole air conditioning season.

1 Introduction

About 40% of the global energy is consumed by buildings every year, and more than half of the building energy consumption is consumed by HVAC systems [1]. Therefore, it is urgent to provide comprehensive energy conservation and emission reduction measures for building air conditioning systems.

Radiation cooling, heating and fresh air system as an integrated air-conditioning system with integrated cooling, heating, dehumidification and fresh air has certain complexity. In practical application, solving dehumidification problem is the key to avoid condensation and improve comfort [2]. Generally, independent fresh air system is used to solve dehumidification problem of radiation air conditioning and fresh air system is used to deal with building moisture load. As a universal and energy-saving humidification equipment, heat pump solution humidification fresh air unit has better humidification effect in fresh air system. However, in engineering application, it is uncertain whether the unit can maintain a high energy efficiency level and good operating characteristics.

In order to reduce building energy consumption and operating costs, and to formulate operating strategies of fresh air system that more closely match building characteristics and load characteristics, it is necessary to forecast load demand and energy consumption of fresh air system accurately and quickly. As a typical black box model, artificial neural network (ANN) [3-5] has been widely used and studied in load forecasting.

In this paper, taking the fresh air system of radiant air conditioning in a residential area as the research object, an ANN model is established to predict the moisture load of fresh air units. The prediction accuracy of the model is improved by zoning and input optimization. Based on the load forecasting results, we provide an effective solution for cost reduction and energy efficiency improvement in actual operation and maintenance.

2 Zone-level ANN model load forecasting

2.1 System description

This paper takes a residential area in Suzhou, China as an example, which uses centralized radiant cooling and heating and fresh air conditioning system. The cold and heat sources of the system are ground source heat pump and heat pump solution conditioning fresh air unit.

The fresh air is pre-cooled before dehumidification in summer, as shown in Fig. 1. Outdoor fresh air is pre-cooled to 2 points by the surface cooler and then processed to 3 points by the solution humidifier unit to enter the room. This paper mainly aims at the prediction and analysis of the moisture load (2-3) of the solution humidity control unit. The wet load is determined by the difference of moisture content between 2 and 3 points and the fresh air volume.

A typical building in this residential area is selected as the research object in this paper, which has 33 floors

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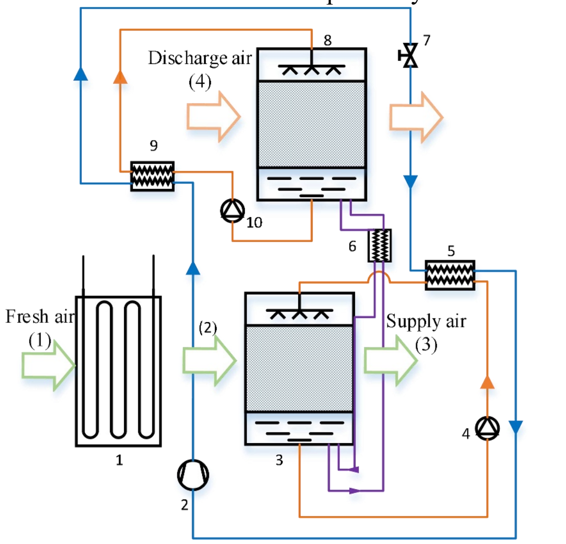
https://doi.org/10.1051/e3sconf/202235601016

and 14843.54m2 cold and warm areas. Four solution-conditioned fresh air units are used in the building, which are arranged on the East and west sides of the top floor and the bottom floor respectively.



1 Pre-cooling coil 2 Compressor 3 Dehumidifier 4 Pump 5 Evaporator 6 heat exchanger 7 Expansion valve 8 Regenerator 9 Condensor 10 Pump

Fig. 1. Flow Chart of Fresh Air System

2.2 Inputs, outputs and parameters of ANN model

The correlation of input parameters of ANN model plays an important role in the prediction accuracy of the model. In addition, the input should be easy to measure in engineering practice [8]. The influencing factors of HVAC load forecasting usually include outdoor meteorological parameters, indoor environmental parameters and HVAC system operation parameters. Specifically, it includes outdoor temperature, outdoor relative humidity, solar irradiance, occupancy rate, orientation, indoor temperature and external wall insulation coefficient of the building [9-10].

In order to improve the prediction accuracy of ANN model, the building is divided into thermal zones, and the indoor temperature in different areas is taken as the independent inputs of the model. Entering indoor temperature parameters in different zones can reflect the influence of orientation, occupancy rate and thermal control on load in different areas of the building. To verify that the partitioned ANN model has higher prediction accuracy, the whole building is divided into one thermal zone, two thermal zones and four thermal zones, which correspond to the models ANN1, ANN2 and ANN3 respectively. Thermal zones division is important to investigate the impact of occupant behavior on prediction accuracy. Furthermore, thermal zones division has a strong impact on the energy consumption and energy flexibility of a building.

In this paper, the inputs of ANN model are selected as outdoor temperature, outdoor relative humidity, indoor temperature and time according to the target of fresh air unit load forecast in the next 24 hours. The outputs of ANN model is the moisture load of fresh air system. The moisture load is expressed by the dehumidification capacity (kg/h) of the system.The number of hot zones in ANN1, ANN2 and ANN3 models is one, two and four respectively, and the zones are divided according to the orientation and floors.

The parameters of ANN model mainly include: the number of hidden layers, the number of hidden neurons, learning rate, etc. In this paper, a single hidden layer ANN model is adopted. The training results show that the ANN model has the highest accuracy when the number of hidden neurons is 12. The structure of ANN model is shown in Fig.2. Other parameters are set as follows: the maximum number of training times is 1000, the performance function is mean square error (MSE), the training performance target is 10-3, the training function is trainlm, and the maximum number of verification failures is 6.

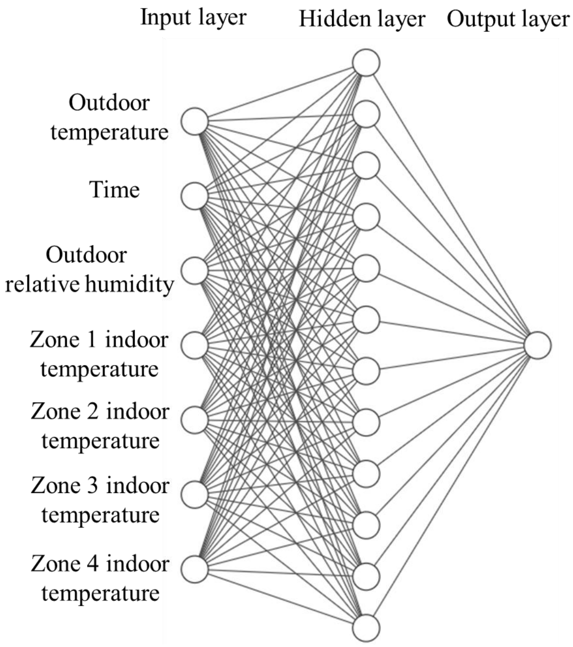


Fig. 2. Structure of ANN model

2.3 Training of ANN model

In this paper, the hourly measured data of the system in the air-conditioning season of 2020 (June 11th-September 10th) are used to train the ANN model, and the typical daily data are used to test the prediction accuracy of the model. The total number of training data and test data are 13260 and 864 respectively. Considering the different dimensions of different types of data, the data set should be normalized between 0 and 1 to improve the accuracy and convergence speed. The formula is as follows:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \#(1)$$

The training process of ANN model is a process of constantly adjusting the deviation to minimize the error between the output and the target. The mean square error (MSE) is used as the performance function, and four statistical indicators, namely correlation coefficient (R), root mean square error (RMSE), coefficient of variation of root mean square error (CV-RMSE) and mean absolute error (Mae), are introduced to comprehensively evaluate the prediction accuracy of the ANN model.The calculation formula of each index is as follows:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(p_i - t_i)^2 \#(2)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{m}(p_i - t_i)^2}{\sum_{i=1}^{m}(p_i - t_i)^2 + \sum_{i=1}^{m}(t_i - \bar{t})^2}} \#(3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(p_i - t_i)^2}{m}} \#(4)$$

$$CV - RMSE = \frac{RMSE}{\bar{t}} \#(5)$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|p_i - t_i| \#(6)$$

Where p represents the predicted value, t represents the measured value and m represents the total number of samples.

2.4 Prediction result and analysis of ANN model

The prediction accuracy evaluation results of ANN model considering partition are shown in Table 1. According to ASHRAE guidelines, CV-RMSE should be below 30%. The prediction results of ANN model in this study can meet the standard well. From the evaluation results, the prediction accuracy of ANN2 model and ANN3 model is obviously improved compared with ANN1 model. The CV-RMSE of ANN3 moisture load prediction result is 8.72%, which is reduced by 14.27% compared with ANN1 model. It shows that thermal zones division has a significant effect on improving the accuracy of neural network load prediction.

Table 1. Prediction accuracy evaluation of ANN model

Model	MSE	R	RMSE	CV-RMSE	MAE
ANN1	0.04	0.72	22.69	22.99%	20.84
ANN2	0.03	0.87	12.81	12.98%	11.32
ANN3	0.02	0.87	8.60	8.72%	6.86

In order to visually represent the predicted results of the model, the predicted values are compared with the actual values, and the comparison of moisture load predicted results is shown in Fig. 3-5. It can be seen that the predicted value is in good agreement with the actual value, especially for the ANN3 model.

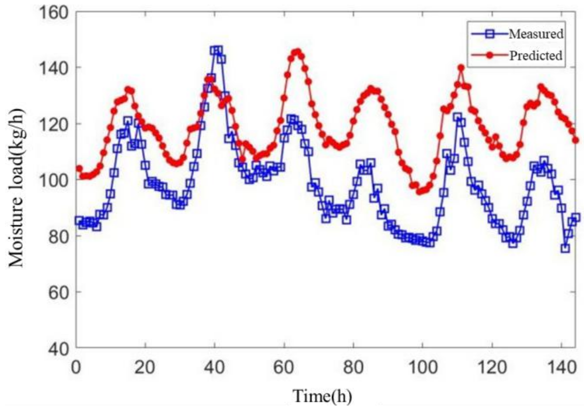


Fig. 3. Comparison between predicted results of ANN1 wet load and measured values

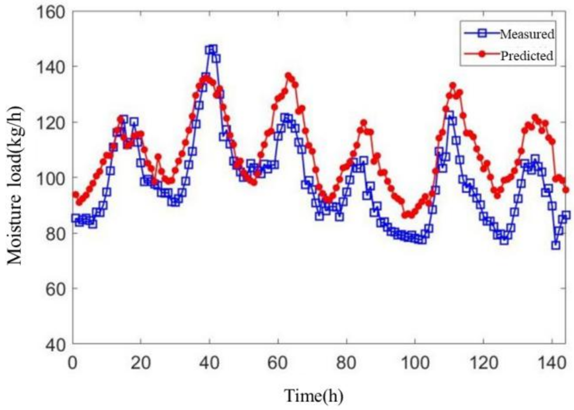


Fig. 4. Comparison between predicted results of ANN2 wet load and measured values

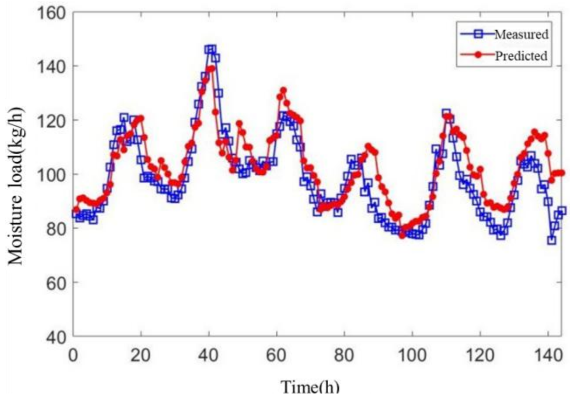


Fig. 5. Comparison between predicted results of ANN3 wet load and measured values

3 Control optimization strategy

3.1 Control optimization strategy based on load forecasting

In order to improve the comprehensive efficiency of fresh air system and reduce the operating cost, it is necessary to optimize its operation. Based on the potential energy storage method, an optimization model is established, and the control strategy is formulated according to the prediction results of ANN model. In this paper, the optimal operation of the fresh air system adopts the potential energy storage method, and the solution storage tank is configured in the system. Energy storage is carried out by storing concentrated solution, that is, storing dehumidification potential. At the same time, combined with the local time-of-use electricity price, the operation strategy is optimized according to the load forecast results in the next day.

Based on the operation goal of energy saving and efficiency improvement, the energy storage control strategy of fresh air system is formulated, in which the variables to be judged and decided are shown in Table 2, and the energy storage and release are expressed by the dehumidification potential (moisture load) of the solution. In order to ensure the feasibility of the operation strategy, the corresponding boundary conditions are given as follows:

$$0 \leq u_{c,n} \leq u_{c,max} \# (7)$$

$$0 \leq u_{d,n} \leq u_{d,max} \# (8)$$

$$\sum u_{d,n} \leq SW_{total} \# (9)$$

$$u_{d,n} + w_n = W_n \# (10)$$

As shown in Fig. 6, the optimal control flow of the system is as follows. It runs at full load during the off-peak period. After the hourly load is met, the concentrated solution is stored in the liquid storage tank at the energy storage rate $u_{c,n}$ to accumulate dehumidification capacity until the maximum energy storage capacity SW_{total}. After the liquid storage tank is full, shut down the unit, calculate the hourly energy efficiency of the unit according to the load prediction result of ANN model, and when the energy efficiency is low, give priority to release the energy storage at the energy release rate $u_{d,n}$. When the energy efficiency is high, use the cooling and dehumidification provided by the unit to match the hourly load.

Table 2 Optimization variables

Variables		Unit
SC_{max}	Energy storage capacity	kg
W_d W_n	All-day wet load Hourly wet load	kg kg/h
SW_{total} SW_n	Total energy storage Hourly energy storage	kg kg
u_c	Energy storage rate	kg/h
u_d	Energy release rate	kg/h
n	time	h
w_n	Hourly dehumidification capacity	kg/h

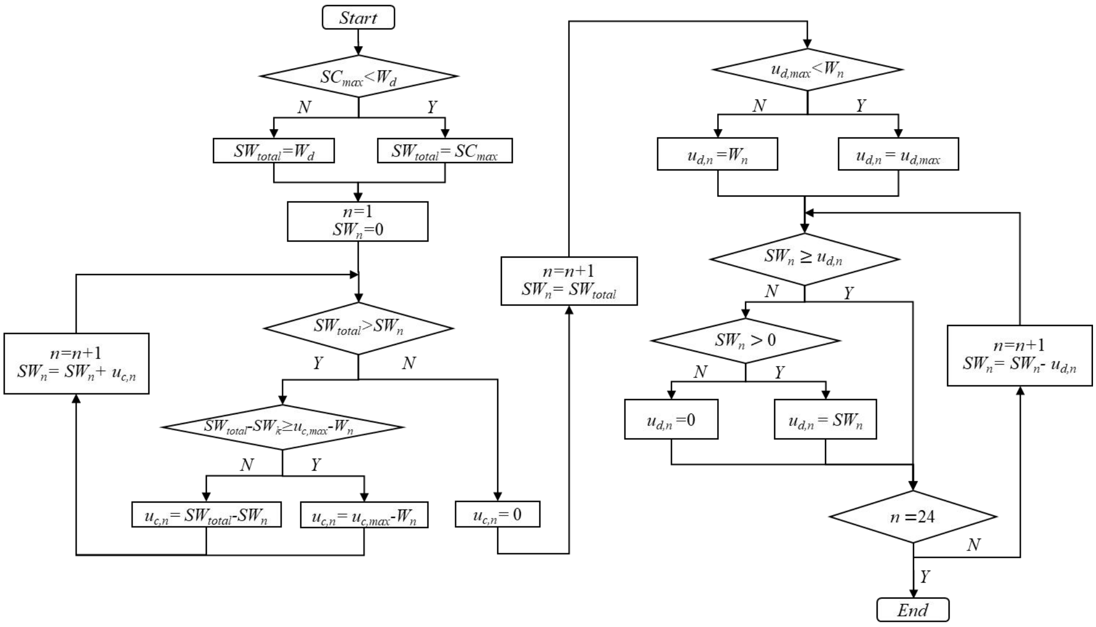


Fig. 6 Optimization procedure

3.2 Load mode and optimization results

According to the load forecasting results of ANN model, typical load days are selected for analysis and optimization. In the time-of-use electricity price scenario, based on the fresh air system without energy storage, the effect of energy storage optimization operation strategy on operating cost saving is analyzed.

According to the prediction results of the ANN model, the optimization model is applied to improve the operation strategy of fresh air units, and a typical day with high load is selected as a case study. The optimized daily load distribution is shown in Fig. 7. The load distribution after optimized operation can fully reflect the energy storage effect based on load prediction. During the off-peak period, except for meeting the hourly demand, the unit will store energy in the liquid storage tank to reach SC_{max}. All energy storage will be released when the load the COP of the unit operation are low.

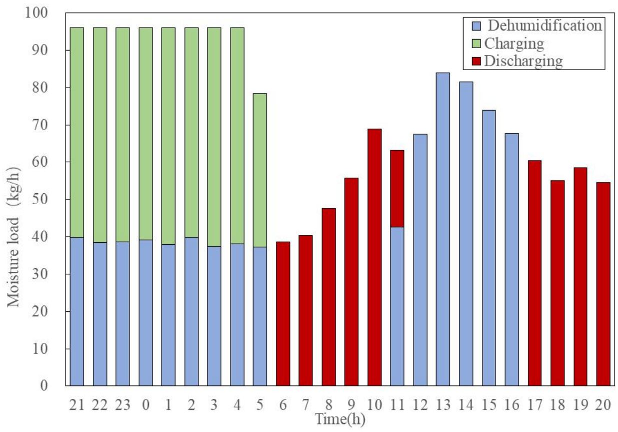


Fig. 7 Optimal load distribution of typical daily operation

Based on historical data, the load-energy efficiency level of fresh air system is fitted. The optimized energy consumption level based on control strategy can be obtained by using the optimized load distribution, and then the economic benefits of the strategy applied to the whole air-conditioning season can be calculated by the results of time-of-use electricity price. Table 3 lists the comparison between the theoretical optimization results of air conditioning season and the original results. The theoretical optimization results can reduce the operating energy consumption and operating cost of building air-conditioning system by 27.2% and 29.2% respectively in the whole air-conditioning season.

Table 3 Comparison between theoretical optimization results of air conditioning season and original results

Period		Energy consumption（kW/h）	Electricity cost (Yuan)
Original result	Off-peak period	134593	48225
	On-peak period	188428	105199
	Total	323021	153424
Optimization result	Off-peak period	133037	47667
	On-peak period	109289	61016
	Total	235126	108683
Energy/Cost saving		**27.2%**	**29.2%**

4. Conclusion

Taking a residential building as the research object, this study analyzes the energy efficiency characteristics of independent fresh air system in radiant air conditioning. The ANN modei is established to predict the moisture load of the system, and the accuracy of load prediction is improved by thermal zones division. At the same time, based on the load forecasting results, the optimal control strategy of fresh air system is formulated. It provides reference and guidance for the operation optimization of independent fresh air humidity control system in residential buildings. The main research results are as follow:

1)The partition ANN model is established to predict the moisture load of fresh air system, and the prediction accuracy of ANN model is improved by thermal zones division and optimizing the inputs. The results show that the CV-RMSE of the predicted moisture load of ANN3 model with four zones is 8.72%, which is 14.27% lower than that of ANN1 model.

2)Based on the load forecasting results and potential energy storage method, the optimal control strategy of energy storage of fresh air system is formulated. The optimal control strategy is applied to typical load days and the whole air conditioning season, and the optimized load distribution is analyzed. The theoretical optimization results of applying the control strategy in the whole air conditioning season are calculated. Compared with the original results, the operation energy consumption and operation cost are reduced by 27.2% and 29.2% respectively.

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