Study of frosting diagnosis with Back Propagation network and Elman network

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Abstract: Frosting diagnosis is important in refrigeration system control. This paper focuses on frosting diagnosis in a single-stage vapor compression refrigeration system. According to the reduction of refrigerating capacity, the experimental data of frosting can be divided into three categories: light, moderate and severe frosting. Then, two frosting prediction models are established with Back Propagation neural network (BPNN) model and Elman neural network (ENN) model. The simulation results illustrate that the overall diagnostic performance of the ENN is better than that of BPNN. The mean squared error (MSE) should be paid more attention for affecting the accuracy of models. The presented method in this paper can provide technical reference for frosting prediction.

1. Introduction
When the temperature of heat exchanger is lower than dew point temperature and 0°C, frost will form on the surface of heat exchanger. Frost not only increases the thermal resistance, but also increases the evaporator pressure drop. As a result, the cooling capacity and heat transfer efficiency are reduced[1,2]. Especially in the low temperature and high humidity environment, the frost on the surface of the evaporator affects the safe and stable operation of the evaporator and the system directly[3]. Therefore, research on frost fault diagnosis of evaporator in refrigeration system is of great importance and has been paid more attention to in the recent years.

Various artificial neural network (ANN) models have been used in fault detection and diagnosis (FDD) of HVAC&R and power plant systems in recent years[4-5]. Bin et al.[6] proposed a new model to predict the frosting weight and refrigerating capacity of fin evaporator. It combines the ridgelet neural network and random finite element method. Simulation analysis indicates that the new prediction model has highest prediction precision and efficiency. Datta et al.[7] established a three-layer neural network model with a single hidden layer, took the operating time, relative humidity and environmental temperature of the refrigeration unit as input variables of the neural network, and took the weight of defrosting water as output variables, to predict the amount of frost in the evaporator of the display cabinet in the supermarket. Hosseini et al.[8] took the environmental temperature and humidity, plate temperature, wind speed, and running time as the input parameters of the model, and established a MLP-
BR(multi-layer perceptor and Bayesian regularization rule) neural network model with or without self-organization feature map to predict the frosting amount of the vertical plate under natural convection.

In previous studies, there are few studies on neural network identification that takes the excessive frosting amount on the surface of the evaporator in refrigeration system as the fault type. In this paper, the frosting experiment of finned tube exchanger is carried out, and BPNN and ENN are used to diagnose the frosting degree. Different hidden layer nodes of BPNN/ENN model are investigated. Moreover, key parameters are studied to optimize model. This work provides an effective way to diagnose and predict the frosting formation.

2. Experimental system

2.1. Experimental apparatus and procedure
The refrigeration system of the low-temperature wind tunnel test bench consists of two parts: one is the temperature and humidity regulation system that regulates the air in the wind tunnel, and the other is the test system that connects the test specimens. Fig.1 presents the schematic diagram of the temperature and humidity regulation system. The temperature regulation part consists of the refrigeration system and the electric heating wire. The two parts regulate the temperature of the airflow in the wind tunnel together.

Close the shut-off valves 3, 4, 15, 25 and 26 to conduct frost experiments on the finned evaporator. The low pressure steam of the refrigerant in the gas-liquid separator is sucked into the compressor and compressed to a high pressure steam back to the condenser. The condensed liquid passes through the shut-off valve 8, the subcooler, the shut-off 12, the sight glass and the electromagnetic flow meter and then is throttled and depressurized in the electronic expansion valve 16. The expanded gas-liquid mixed refrigerant enters the evaporator to absorb heat and evaporate, and then flows into the gas-liquid separator. The steam of the refrigerant is sucked into the compressor to start the next refrigeration cycle.

Frost experiments on finned evaporator at different ambient temperature (-10°C, -18°C, -25°C), relative humidity (65%, 70%, 75%, 80%) and air velocity (2m/s, 2.5 m/s, 3 m/s, 4 m/s), That is to simulate the frosting process of the finned evaporator under different working conditions.

During the experiment, the heat transfer temperature difference between the air and the heat exchanger is 7°C, and the degree of subcooling and the degree of superheating of the testing system are 5°C. The data are tested and saved every 5s. When the wind speed drops to 0.2m/s, the frosting experiment stops and the system begins to defrost. A total of 127620 sets of frosting data under different working conditions were obtained through the frosting experiment. Each set of experimental data contains 12 features. According to the reduction of refrigerating capacity, the experimental data of frost formation can be divided into three levels: light, moderate and severe frosting.
2.2. Data preprocessing and model parameters selection
Before the neural network is trained, the experimental data should be preprocessed. That is the characteristic parameters normalization. Since the temperature value in the experimental data is negative, the preprocessing function ‘mapminmax’ is used to normalize the data to [-1,1]. The output parameters are processed from one dimension to three dimensions. That is, the output parameters are: light frosting [1 0 0], moderate frosting [0 1 0], and severe frosting [0 0 1].

BPNN and ENN of single hidden layer are constructed according to Table 1. Data feature of original measurement data are listed in Table 2. They are inlet dry bulb temperature (Ti), outlet dry bulb temperature (To), inlet relative humidity (hi), outlet relative humidity (ho), inlet air volume flow (Qi), outlet air volume flow (Qo), the temperature of the evaporator outlet (Tevao), the pressure of the evaporator outlet (Pevao), evaporation temperature (Te), superheat of evaporator outlet (Tsupe), Vapor pressure difference between the inlet and outlet of wind tunnel (PD), mass flow of refrigerant (M).

Table 1. Model parameters

| Ni | No | Nh | transfer function | learning function | training function |
|----|----|----|-------------------|-------------------|------------------|
| 12 | 4-13 | 1 | logsig | learnngdm | trainngdx |

Table 2. Data feature of original measurement data

| Parameter | Maximum value | Minimum value | Average value | Standard deviation |
|-----------|---------------|---------------|---------------|--------------------|
| Ti °C     | -8.74         | -26.83        | -15.81        | 6.03               |
| To °C     | -11.41        | -31.48        | -19.49        | 5.75               |
| hi %      | 87.59         | 54.68         | 71.03         | 5.19               |
| ho %      | 86            | 29.54         | 74.55         | 4.86               |
| Qi m³/h   | 14247.55      | 18.74         | 5177.27       | 2684.19            |
| Qo m³/h   | 14172.41      | 18.3          | 5112.65       | 2670.56            |
3. Results and discussion

First, take the number of neuron nodes in the hidden layer is 10, the number of iterations is 100,000, the MSE is 0.01, the initial learning rate is 0.01 for simulation. The model gradually converges over the course of training. The minimum mean squared error of the validation set is 0.037698. The R values of training set, validation set, small test set and overall set are 0.9153, 0.91124, 0.9121, 0.91421, respectively. Predicted value and actual value are highly correlated and the model performs well. In addition, in order to test the generalization ability of the model, samples that are not in the original sample set are input to the trained BP neural network for simulation testing. Its accuracy rate is 89.120%.

When the number of iterations is 100,000, the model takes too long to train. Moreover, the model has largely converged when the number of iterations is 40,000. Therefore, the maximum number of iterations is adjusted to 40,000. In addition, adjusting the MSE to 0.03-0.04 can meet the diagnostic requirements. Adjust the parameters and change the Nh for simulation.

3.1. Simulation results of BP neural network

In this section, MSE is simulated for 0.034 and 0.04. Look at the curves with MSE of 0.034 in Fig.2 and Fig.3, it can be seen that the training time of the model is shorter and the MSE of the validation set is lower when the Nh is 5, 6, 7, 10, or 12. The accuracy of the training set and validation set is still increasing gradually with the increase of the Nh. A comprehensive comparison of the training time and generalization ability of this model shows that the model performs better when the Nh is 12. The accuracy of the training set, validation set, and test set are 95.287%, 95.285%, and 93.426%, respectively. The training time is 1480.845598s.

Compare the model with MSE of 0.034 and the model with MSE of 0.04. The neural network model with larger MSE converges faster when the Nh is higher. In the optimal situation, although the model with MSE of 0.034 consumes 953 seconds more training time than the model with MSE of 0.04, it obtains higher accuracy of the training set, validation set and test set. Moreover, under different numbers of hidden layer nodes, the accuracy of the training set and the validation set of the model with MSE of 0.034 is almost higher than that of the model with MSE of 0.04. Therefore, in order to make the accuracy higher, the model will set a smaller MSE.
3.2. Simulation results of Elman neural network

Elman neural network model is used to model and simulate the frost experimental data. The mean squared error is 0.034.

3.3. Simulation results of Elman neural network

The relationship between Nh, running time, and accuracy are given in Fig.4 and Fig.5, respectively. The optimal Nh of this model is 11. In this situation, the accuracy of the validation set, training set, and test set are 94.234%, 94.449%, and 91.917%, respectively. The training time of the model is 1147.59s.

Compare the BPNN and ENN. For the training set and the validation set, there is little difference in the accuracy of the two models. However, the accuracy of the test set of the BP neural network fluctuates widely at different hidden layer nodes, whereas the accuracy of the test set of the ENN is almost the same when the Nh is 8 to 12. ENN is more stable.

4. Conclusion

In this paper, the frosting of evaporator in refrigeration system is studied as a type of failure. The BPNN and ENN model are established to analyze the frosting data. The conclusion can be summarized as below:

Using the neural network, it is effective to diagnose the degree of evaporation frosting directly by the operating parameters of the refrigeration system. The evaporator can realize "defrost on demand" and improve system efficiency.

Compare the diagnostic performance of neural networks with MSE of 0.04 and 0.034. The results show that, with the same Nh, the accuracy of the training set and the validation set of the neural network
with MSE of 0.034 is higher than that of the neural network with MSE of 0.04, and the training time is shorter in most cases. Therefore, a smaller reasonable MSE can make the model more effective.

Compare the diagnostic performance of BPNN and ENN. The results illustrate that the accuracy of the training set and the verification set of the two models are not much different, but the accuracy of the test set of the ENN is more stable. In addition, the running time of ENN is less than that of BPNN at the optimal Nh.

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