PREDICTION OF FROSTING PROCESS ON COLD WALL SURFACE BASED ON ARTIFICIAL NEURAL NETWORK WITH BACK PROPAGATION ALGORITHM

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The artificial neural network with back propagation algorithm is a multi-layer feed-forward neural network, which is suitable to study unsteady frost formation with multiple factors. The back propagation artificial neural network algorithm is used to study frost layer growth on cold flat surface, where four feature variables including temperature of cold flat surface, the velocity, relative humidity and temperature of air are adopted. The frost growth experiment generates the database, which is good for training frost growth due to its fast speed and high precision based on Levenberg-Marquardt learning rule. The establishment of neural network model in this paper can quickly and accurately predict the frost layer height on cold flat surface of different control variables, which is helpful for the implementation of defrosting.

Keywords: *Artificial Neural Network; Back Propagation Algorithm; Frosting Process; Frosting Characteristics; Frost Height*

1. Introduction

Frost crystals formed in low temperature environment widely exist in the nature, refrigerator, heat pump, air-conditioning, aviation, etc. With the height and density of frost layer growing, the heat transfer resistance and flow resistance will increase, which will reduce the heat transfer efficiency, affect the normal operation of the system and cause energy consumption.

Over the past few decades, the growth and formation of frost crystals has been re-searched by experimental [1-2] and physical-mathematical methods [3]. Le Gall et al. [4] established a mathematic model of frosting on cold flat surface according to a local volume averaging technique. Gong et al. [5] established a lattice Boltzmann model for simulating the thermal transport and phase transformation of frost growth process on the cold surface. The frost formation is an unsteady state process of transient heat and mass transfer accompanying with phase transition as well as moving boundary. Despite several researches have been carried out, the influence of all the parameters on frosting cannot be obtained by the traditional methods. Thus, a new approach is introduced to study the growth mechanism of frost crystals.

Several methods are used for process modeling and prediction in the field of refrigeration and heat transfer [6]. Artificial neural network (ANN) is a new tool, which is applied to predict heat and mass transfer based on both experimental and computational data [7-8]. Zhang et al. [9-10] make a comprehensive summary and provide fundamental guidelines how to integrate and apply machine learning methods. Hemmat et al. [11] used an artificial neural network to optimize the dynamic viscosity of hybrid nano-lubricants. Tian et al. [12] studied the influence of temperature and volume fraction of nanoparticles on thermal conductivity using artificial neural network. He et al. [13] proposed a algorithm to calculate the best neuron number in the Artificial Neural Network. Ruhani et al. [14] predicted the thermal conductivity by Artificial Neural Network and fitting method. Esfe et al. [15] evaluated and predicted the viscosity of NF by ANN from a multilayer perceptron (MLP) ANN with the Levenberg-Marquardt (LM) learning algorithm. Kalogirou [16] presented various applications of neural networks in energy problems. Temeyer et al. [17] constructed an ANN model to estimate parameters for frost deposition. Tahavvor and Yaghoubi [18] developed an ANN model to predict natural cooling on a horizontal circular cylinder. This model was also used to predict frost formation on a flat plate by Tahavvor [19]. From the literature review, it can be seen that the ANN method has rarely used to predict the physical characteristics by multiple factors of frost formation process. However, ANN with back propagation (BP) algorithm is a multi-layer feed-forward neural network according to the error BP algorithm, which is suitable for establish a frosting relationship with multiple factors. Although the neural network training consumes a large amount of computation time, it is fast and precise to predict the frost layer height on cold flat surface of different control variables once the successful network model is obtained to provide technical support for the implementation of defrosting.

In this study, we develop a BP neural network model for simulating frosting process on cold wall surface and compare with experimental results. Section 2 discusses the numerical model and theory of artificial neural network with BP algorithm. A frost growth experiment to generate the database for BP algorithm is described in Section 3. In Section 4, the variations of frost properties under different cold wall surface temperature, the air velocity, air relative humidity and air temperature are acquired and the present ANN model is verified. Based on the former part, it makes a brief summary in Section 5.

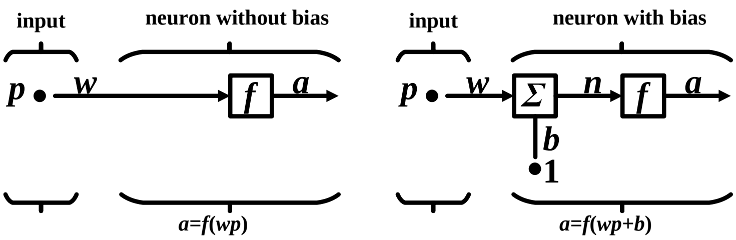
2. Numerical model and theory

As an adaptive nonlinear dynamic system, artificial neural network (ANN) is widely interconnected by a great many of simple processing units. Neural network system has many advantages, such as strong adaptability, large-scale parallel processing, self-organization and self-learning ability, distributed information storage, etc. BP algorithm is a kind of error back propagation algorithm, which is efficient nonlinear mapping. It is one of the most extensive application and mature artificial neural networks. Moreover, the parameters of the network with great flexibility can be set according to specific conditions. It has broad application prospects in many different domains. According to the basic principle and algorithm, the frost model based on BP algorithm is established.

2.1 Artificial neural network architecture

ANN consists of a set of single parallel processing elements, which can generate new experience from previous experience by learning, and can complete specific functions by changing the weight of connection points. In essence, ANN is a multi-variable nonlinear regression model. The specific input and corresponding output of neural network can be obtained by adjusting or training.

Fig. 1 shows a very simple model of artificial neurons with and without bias. The desired results can be obtained by continuously modifying weight w and bias b based on suitable learning rules in the artificial neural network model.



(a) Without bias **(b) With bias**

Fig. 1 - An artificial neuron model

2.2 Back Propagation algorithm

Fig. 2 shows that a multi-layer feed-forward neural network, and BP algorithm on the basis of LM training algorithm is the preferred choice owing to training accurately and rapidly.

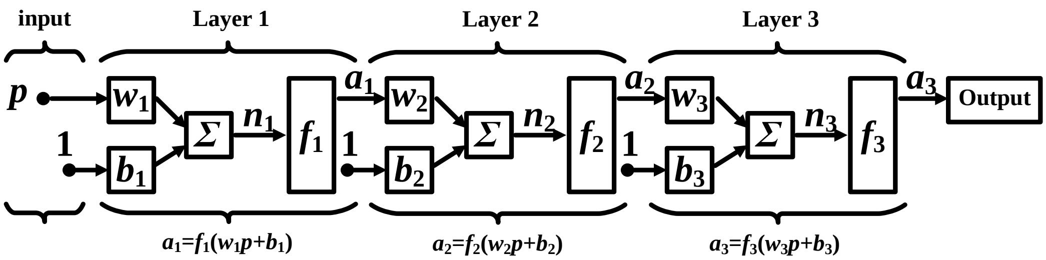


Fig. 2 - A multi-layer feed-forward neural network

BP algorithm is mainly applied to the learning of neural network weights and thresholds. Its learning process is composed of the signal forward propagation and the error back propagation. In the forward propagation, the input signal is from the input layer to output layer by the hidden layer, and the output is made at the output layer. If the signal of the output layer doesn't desire, the error is sent to the BP process. The error is from the output layer to front layer, and the actual output of network is closer to the expected output by optimizing the network weight through error feedback. Zhang et al [20] developed a general approach using the two machine learning methods where five feature variables are adopted. In this study, there are five inputs consisting of cold wall temperature, ambient temperature, air relative humidity, air flow rate, and frosting time. The output is the frost height reflecting the growth characteristics of frost crystal.

The mapping will be finished from n-dimensional to m-dimensional space vector. The excitation function is a logistic sigmoid

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

which has the characteristics of continuous derivation and

$$f^{'}(x) = f(x)(1-f(x)) \tag{2}$$

When training artificial neural networks, LM algorithm is adopted as a standard technique for the nonlinear least-squares problem extensively used under different fields. As an iterative technique, LM locates the minimum value of multivariate function, which is expressed as the squares sum of the nonlinear real valued function to solve the network weight and get accurate solutions by increasing the optimization parameters by adjusting the hidden nodes. BP algorithm solves the function optimization problem as follows:

$$\min_{a\le\omega\le b} E(\overline{\omega}) = \frac{1}{2}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2 \tag{3}$$

$$\hat{y}_k = f(\sum_{k=1}^{n} x_i w_i + \theta_i) \tag{4}$$

where $f(x)$ is the logistic sigmoid according to eq. (1), n is the number of samples, w is the weight of network, θ is the threshold of network, x_i is the input of samples, $\hat{y}_k$ and y_k represent the output values of actual and expected situation, respectively. The final output value of the network can be obtained from eq. (3).

BP algorithm based on the least-squares method is applied to simulate the average height of frost layer growth. Firstly, the selected data samples are fitted with a straight line, and then optimized by BP algorithm. Finally, a neural network sample training database is established to predict the amount of frosting. The fitting process of least-squares method is based on BP algorithm and least square method theory. The database samples are preprocessed including normalization, initial value setting, and error calculation. Among them, the original input data is normalized, and the data is transformed into [0, 1]. The normalization formula is expressed in the following form

$$\hat{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

where $\hat{x}_i$ is the dimensionless data of the samples, x_i is the raw input or output, $x_{\max}$ and $x_{\min}$ respectively represent the maximum and minimum values in raw data.

The excitation function of the training node is the sigmoid function. The sample data is calculated by BP algorithm to obtain the expected value. Three sets of frosting experimental data under different conditions are used to train the neural network. The reliability of the neural network is tested by the calculated amount of frosting compared with the test samples. If the error is within the given range, the trained neural network is proved to be reliable. For a detailed flowchart, see fig. 3.

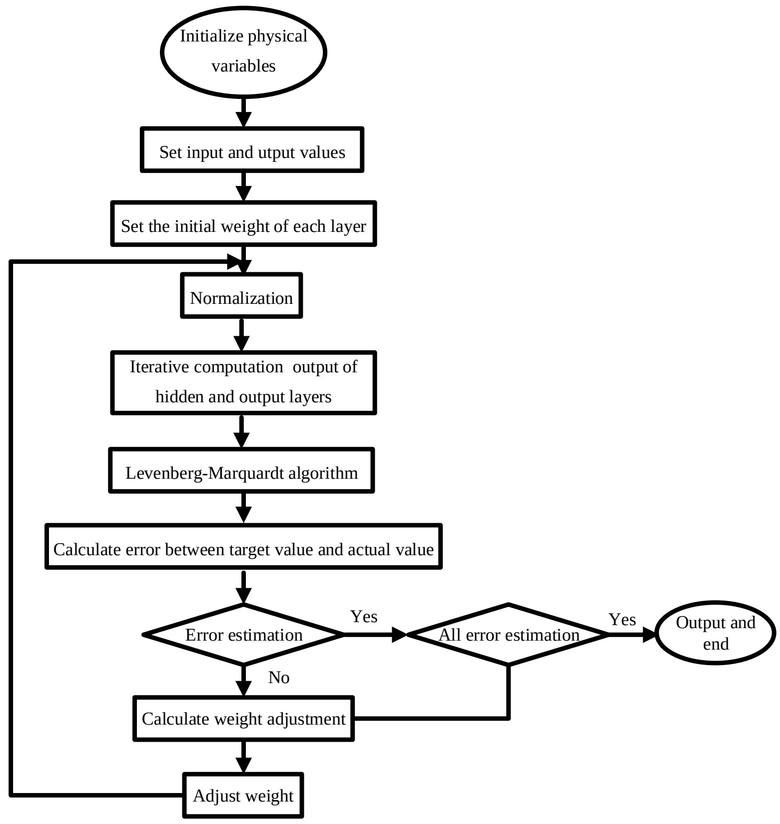


Fig. 3 - Flow chart of the present

3. Experimental methods

Fig. 4 shows the schematic representation of an experimental system established to research the frosting process on the cold wall surface, providing experimental data for artificial neural network. The experimental system consists of four parts: refrigeration system, wet air treatment system, micrography system and data acquisition system.

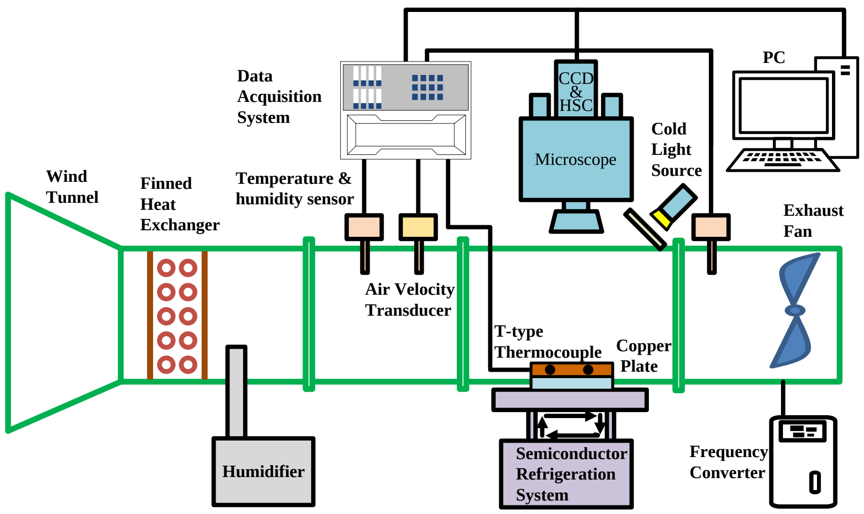


Fig. 4 - Schematic representation of experimental system

In the refrigeration system, the red copper wall (40×40×8 mm) is cooled by a semiconductor refrigeration chip (TEC1-12710). The circulating cooling water is delivered from a low temperature cabinet, which is used to cool the hot side of semiconductor refrigeration chip.

In the wet air treatment system, an isolated wind tunnel is made of plexiglass to eliminate environment interference and facilitate observation. On the both side and top there are two quartz glass observation ports in order to conveniently observe and analyze data by the micrography system. The air temperature is regulated through finned heat exchanger. An ultrasonic humidifier (YDH-806EB) is used to control the air humidity. In order to adjust air flow rate, a frequency converter is used to control the frequency to adjust the speed.

The micrography system includes stereomicroscope (SZX-ZB7, OLYMPUS), CCD microscope camera (Moticam2506) and cold light source (MLC-150C, MOTIC). Since the magnification of the stereomicroscope is 12 to 84, it can be used to observe the microscopic frost formation process. The CCD microscope camera connected with computer software can automatically capture and record the instant frosting dynamic process. The cold light source can compensate light for observation and avoid the interference of thermal radiation on frosting. The frost layer height can directly measure by using the image analysis system in the computer software.

All data in the frosting experiment system are collected through the data acquisition system (Agilent-34970A) for subsequent analysis and neural network training. An anemometer (EE65-VB5, ±0.2 $m \cdot s^{-1}$) is used to monitor and record data of air flow rate. The air temperature and humidity at the inlet and outlet are monitored and recorded by respectively installing two contact-type digital temperature-humidity sensor (JWSH-5VBDD, ±0.5 °C & ±3％ RH). Five holes are evenly punched at the same horizontal plane of 1 mm below the red copper plate. Then the T thermocouples (GBTS200, ±0.1 °C) are inserted for measuring the temperature of cold wall surface and obtain the average value.

4. Results and discussion

The frosting process on the cold wall surface under a variety of parameters is simulated by BP artificial neural network model from the experimental data.

Firstly, the experimental data of frost formation with three different surface temperatures T_s=−8.4, −16.5 and −28.6 °C are used for training the neural network. Secondly, the frost layer height are calculated by trained network model with surface temperatures T_s=−22.5 °C to evaluate its accuracy.

As shown in fig. 5, the training results through the BP algorithm are in accord with that of the experimental data under different cold wall temperatures (the air velocity u=0.16 $m \cdot s^{-1}$, the air temperature T_a=10.8 °C and the air relative humidity φ=41.2%). The relative mean errors between the training results and the experiment data are 3.99%, 2.60%, 4.04% and 1.95%, respectively. The comparison results show good consistency and it is evident that the artificial neural network ANN method can accurately determine frost growth height from the experiment data.

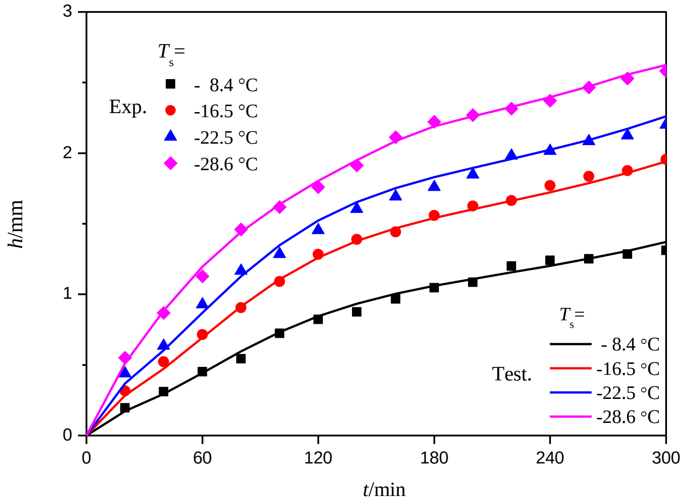


Fig. 5 - Frost growth height vs. time at different cold surface temperatures

According to the developed BP algorithm, new data of frost growth height under various conditions are calculated and plotted. Fig. 6 shows the frost height growth versus time and various cold wall temperatures. The higher frost layer is on the colder surface. The lower the cold wall temperature, the higher the supersaturation and nucleation rate, and so the more the frost crystals are formed. The growth rate at the beginning (<120 min) of frosting is relatively higher than that at the end period. This is because the moist air deposition leads to height rapid growth of frost layer in the beginning stage. The growth rate of frost layer gradually slows down with the height increase of frost layer, due to the nucleation rate decreases with the increase of temperature.

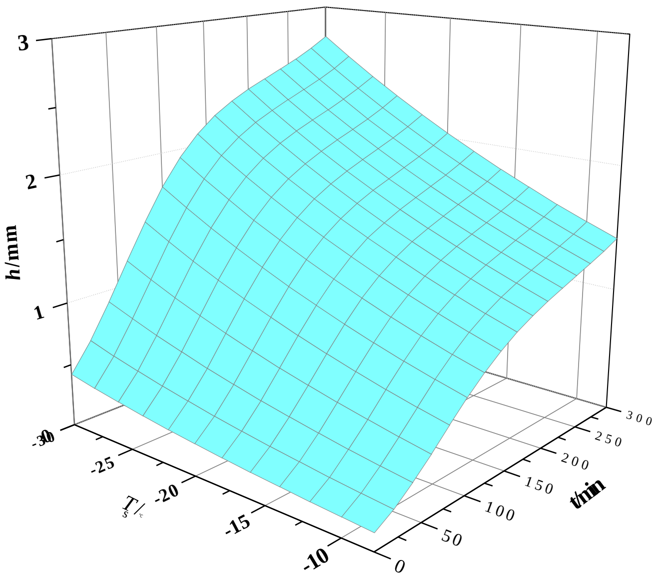


Fig. 6 - Frost growth height versus time and various cold surface temperatures for T_a=10.8 °C, φ =41.2% and u=0.16 m·s^{-1}

The air relative humidity is another main factor affecting the frost layer growth. The following study will focus on the variation of frost height layer with time under different air relative humidity.

The experimental data with air relative humidity RH=50.6% and 93.7% are used for training by BP algorithm (u=0.181 m·s^{-1}, T_a=24.5 °C, T_s=−14.7 °C), and the curve with RH=81.1% is calculated by trained network model to evaluate its accuracy. The relative mean errors between the training results and the experiment data are 2.08%, 1.56% and 2.73%, respectively. The results of ANN and experiments shown in fig. 7 are the relation curves of frost height change over time. The frost height increases rapidly as the crystals grows at the beginning of frosting, but the growth rate slows down with time. Increasing the air relative humidity leads to a significant increase in height. The greater the air relative humidity, the earlier the supercooled water drops freeze, the shorter the freezing time, the faster the frost formation, the thicker and denser the frost layer. On the basis of the phase transformation dynamics theory, the formulation φ [21] reveals the important relation that the driving force of phase transformation ΔG is not only related to temperature T, but also proportional to the logarithm of supersaturated pressure ratio p_v/p_{sa}. The partial pressure of supersaturated water vapor is related to the air moisture. The greater the moisture content, the greater the partial pressure of supersaturated water vapor. Therefore, the higher the air relative humidity, the greater the supersaturated pressure ratio, the greater the driving force of phase transformation, the easier the water vapor molecules are to undergo phase transformation, and the faster the formation and growth of frost crystal.

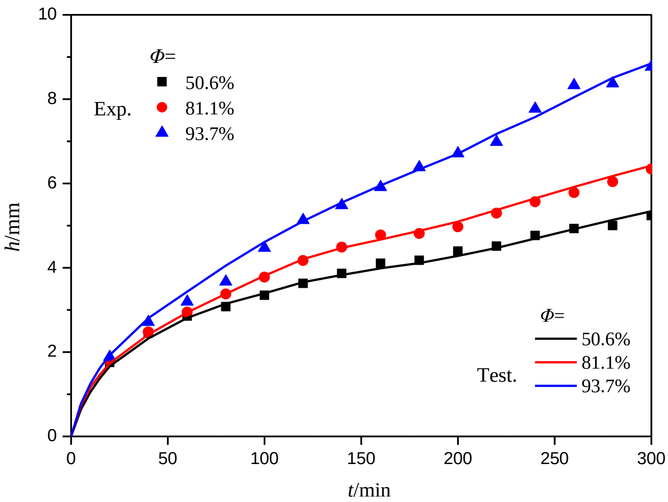


Fig. 7 - Frost height growth vs. time at different air relative humidity

Fig. 8 plots the frost height growth versus time and various air relative humidity by the developed BP algorithm. We can see that the frost layer gets higher with the increase of relative humidity. This is because the supersaturation degree of water vapor gets bigger with the increase of relative humidity, and the nucleation rate of frost crystal also increases to promote the frost height growth. It can be seen that the effect of air relative humidity on the frost formation is very obvious. Reducing air humidity can effectively inhibit the deposition of frost crystal.

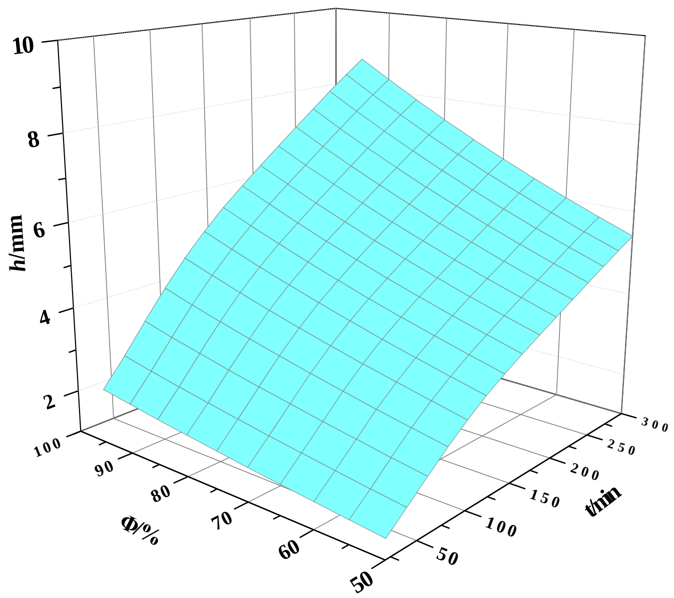


Fig. 8 - Frost height growth versus time and various air relative humidity for T_s=−14.7 °C, T_a=24.5 °C and u=0.181 m·s^{-1}

Fig. 9 illustrates the training results and the experimental data of the frost height with different air temperatures versus time. The experiment data in two cases of air temperatures T_a=11.6 and 23 °C are used for training by BP algorithm (T_s=−14.7 °C, φ=33.0% and u=0.584 m·s^{-1}), and the curve with T_a=−16.6 °C is calculated by trained network model to evaluate its accuracy. The relative mean errors between the training results and the experiment data are 3.40%, 2.55% and 2.27%, respectively.

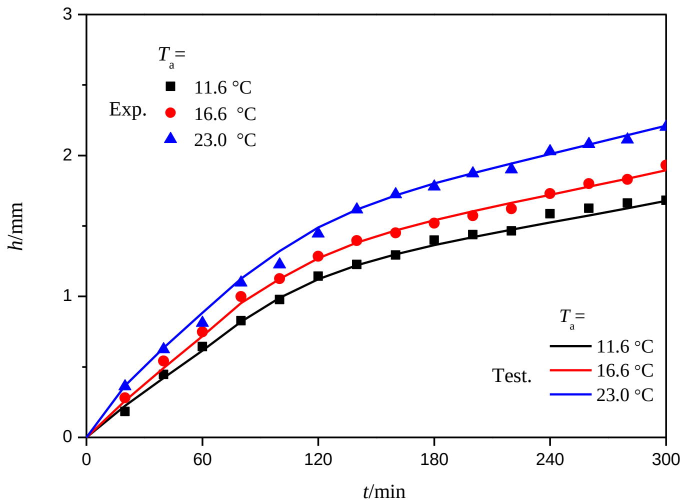


Fig. 9 - Frost height growth vs. time at different air temperatures

Fig. 10 shows frost height growth versus time and various air temperatures. We can see that the frost layer gets high with the increase of air temperature. When the air temperature is higher, the frost crystal grows faster and the frost layer is thicker. Based on the crystal growth theory, the growth rate of frost crystal depends on the supersaturation degree of water vapor near the growth point. When the air temperature increases, the temperature near the growth point also increases, which makes the crystal at the top of the frost layer easy to melt to restrain the frost layer growth. However, when the air relative humidity remains constant and the air temperature increases, the saturated water vapor concentration increases correspondingly, and the air moisture content increases. When the influence ratio of the moisture content is larger than that of the air temperature, more frost crystals will agglomerate. Therefore, the comprehensive effect of all these factors determines the speed of frost growth, and we should pay more attention to reducing the environment moisture content.

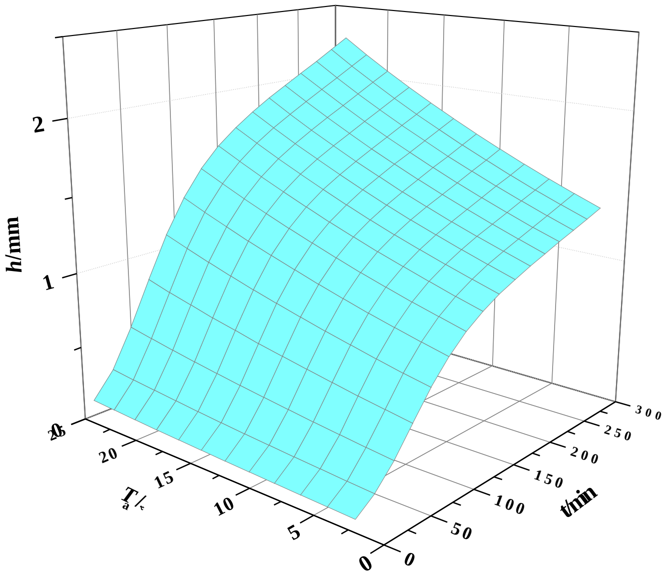


Fig. 10 - Frost height growth versus time and various air temperatures for T_s=−14.7 °C, φ =33.0% and u=0.584 m·s^{-1}

The establishment of neural network model in this paper can quickly and accurately predict the frost layer height on cold flat surface of different control variables. At present, there are many defrosting control methods. The frost sensor defrost control method uses photoelectric or capacitive detector to monitor the frosting of the evaporator. When the frost layer reaches a certain height, it sends a signal to defrost. However, this method needs high quality sensor, high frequency and stable efficiency gain amplifier, which is not suitable for mass production due to its high cost. Therefore, it is only in theoretical research and has no practical significance for the time being. Through the research of this paper, the frost height can be obtained under different conditions to provide technical support for the implementation of defrosting

5. Conclusion

By using artificial neural network with BP algorithm, the frosting process on cold flat surface under various conditions was studied compared with the results of the experiment. Results indicate that the results of artificial neural network agree well with the experimental results and the BP algorithm based on Levenberg-Marquardt learning rule is good for training frost growth due to its fast speed and high precision.

The new results of frost height growth can be easily determined by the artificial neural network method with the less calculation cost and time.

The frost height obtained under different conditions can be used as a technical support for the implementation of defrosting.

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Nomenclature

b	bias of neurons	Greek symbols	
h	frost height (mm)	θ	network threshold
G	driving force of phase transformation (J)	φ	relative humidity
m	number of neurons		
n	number of weight		
p	pressure (Pa)	Subscripts and superscripts	
T	temperature (°C)	a	air
t	time (min)	s	cold wall surface
u	velocity of air (m s^{-1})	sa	saturation
w	weight of network	v	vapour

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