Relative humidity prediction of northern greenhouse environmental factors on the basis of a radial basis function neural network

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Abstract

With its advantages of abundant resource, popularity, and efficiency, solar greenhouse is the only type of greenhouse that is widely used in Northern China. This study proposes a simulation prediction model that is based on a radial basis function artificial neural network. This model is suitable for dealing with humidity in northern solar greenhouses. We select 600 groups of training data to establish the network model and to verify its accuracy. We then randomly select 80 groups for validation. With a 7.35% average error rate, the prediction model shows satisfactory performance. Thus, the results can be used to predict the relative humidity curve in a greenhouse, as well as provide a scientific basis for reasonable regulation and control of a greenhouse environment.

Keywords: solar greenhouse, relative humidity, predict model, radial basis function neural network

1 Introduction

Daily food is important for Chinese people. In Liaoning Province, people traditionally preserve a sufficient amount of Chinese cabbage and radish before winter. Solar greenhouses enable people in Liaoning to buy various vegetables during winter. A solar greenhouse is the only type of greenhouse that is widely used in Northern China. Given their large area, low cost, simple structure, high light transmittance, thermal insulation, and heat storage capacity, solar greenhouses have become suitable for the cold weather in Northern China. Almost 30% of solar greenhouses in China are built in Liaoning Province, and these greenhouses have already improved the production capability of main fruits under the northern weather conditions. Furthermore, solar greenhouses guarantee the supply of winter vegetables in China. The production efficiency of solar greenhouses is also the largest agricultural planting benefit industry in more than 20 years [1].

Air humidity is an important environmental factor affecting greenhouses. High and low-humidity environments are unsuitable for crop growth [16]. To improve crop growth and prevent diseases, people must understand indoor humidity changing rules, as well as appropriate forecasting and reasonable measurements for adjustment. Considerable research has focused on greenhouse humidity forecasting models. Guo Zhenghao [2] established the solar greenhouse humidity of the air dynamic prediction model for Northern China on the basis of the heat balance equation and the water quality dynamic balance relationship. According to the moisture balance inside the greenhouse, He Fen et al.[3] established the greenhouse dynamic prediction model under indoor and outdoor meteorological conditions and greenhouse structure. Guo Qingchun et al. [4] introduced a relative humidity prediction model on the basis of a back propagation (BP) artificial neural network. Xue Xiaoping established the soil moisture forecast model on the basis of the support vector machine method.

This study proposes a prediction model of greenhouse relative humidity on the basis of a radial basis function (RBF) artificial neural network and previous research in Northern China. The remainder of this paper is organized as follows: Section 1 introduces the prediction model. Section 2 presents the test data analysis of prediction results. Section 3 discusses the model testing and validation. Finally, the discussion and conclusion are presented.

2 Selection of neural network

An artificial neural network [5] imitates the structure and function of a biological neural network on the basis of nonlinear mathematical models. This network contains a set of input and output units that are connected with weight. A neural network can be divided into a forward neural network, a feedback neural network, a self-organizing neural network, and so on. A neural network can be used for prediction, classification, and pattern recognition. BP and RBF neural networks are the most popular network models.

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2.1 BP NEURAL NETWORK

A BP neural network is a network model of the error BP algorithm. Such network is a one-way transmission of a multi-layer forward neural network, which has high non-linear mapping capability, self-learning and adaptive capability, generalization capability, and fault tolerance. The structure of the network is shown in Figure 1.

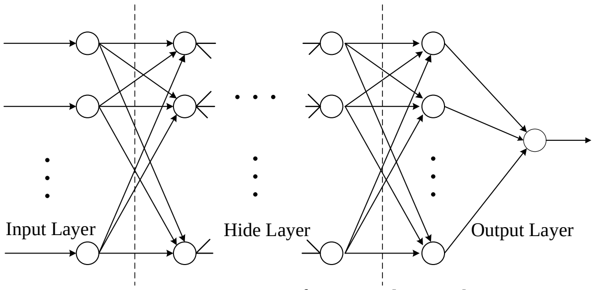

FIGURE 1 Structure of BP neural network

The BP algorithm, which is based on the gradient descent algorithm, is an instructor learning algorithm. The main idea is that the learning process is divided into two stages. The first stage (mode propagation) is input information flow through the input, hidden, and output layers through a layer-upon-layer transfer process. The second stage (error BP) obtains the desired output value and the error signal along the original path layer BP, as well as adjusts the weights and threshold. The BP algorithm has a slow convergence speed, local minimum, predictive capability, and training capability of contradiction.

2.2 RBF NEURAL NETWORK

An RBF neural network is a feed-forward network with satisfactory performance. With the use of traditional techniques of interpolation in multidimensional space, this network can perform identification and modelling on almost all systems. An RBF neural network is based on the RBF with a hidden layer unit base, hidden layer, hidden layer to the input vector transform, and pattern of low-dimensional transform input data into a high-dimensional space. Hence, this network enables the linear low-dimensional space, non-separable problem to be separated in a linear high-dimensional space.

An RBF network is a three-layer feed forward network. The mapping from input to output is nonlinear, whereas the mapping from the hidden layer space to the output space is linear. The structure of the RBF network is shown in Figure 2.

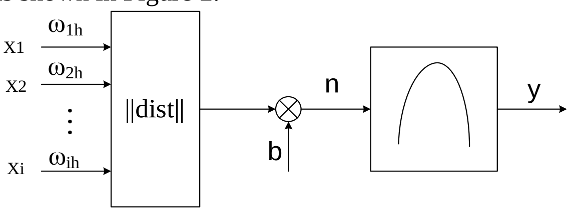

FIGURE 2 Structure of RBF neural network

2.3 COMPARISON AND SELECTION

Poggio and Girosi proved that the RBF network is the best approximation of continuous functions. With local activation function, RBF networks have more advantages than BP networks in terms of convergence speed. The learning method of RBF avoids the local optimal solution. Thus, an RBF network can approximate any nonlinear function with arbitrary precision after a full study of a sufficient number of hidden layer nodes. In addition, this network has the approximation capability for fast convergence rate and strong capability to resist noise, aside from its repair capacity.

After comparing the advantages and limitations of the two networks, we set the RBF neural network as the predictive network and the network activation function as the Gauss RBF. This relationship can be expressed as:

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right). \tag{1}$$

3 Test data selection of prediction

3.1 OUTLINE OF EXPERIMENTAL GREENHOUSE

The typical northern greenhouse (123.57°E, 41.83°N) has the following dimensions: shoulder height, 1.2 m; ridge height, 2.8 m; span, 8 m; and length, 50 m. The greenhouse has no indoor heating or ventilation equipment.

Data acquisition was performed on 22 to 24 May 2014. The sampling frequency was 1 time/min. The acquisition parameters were as follows: indoor temperature, indoor relative humidity, greenhouse light intensity, greenhouse soil temperature, dew point temperature, CO_2 concentration, outdoor temperature, and humidity. Acquisition equipment was as follows: WEMS-RHT-3/780 wireless temperature and humidity sensor, WEMS-CO_2/780 wireless CO_2 concentration sensor, WEMS-L2/780 wireless outdoor light sensor, and WEMS-ST/780 wireless soil temperature sensor.

3.2 DATA SELECTION

A greenhouse environment has multi-factors that can interact with one another. Indoor relative humidity is related to crop photosynthesis, crop transpiration, irrigation condition, indoor temperature, ventilation, and other processes.

Principal component analyses focus on condensing large original variables into a few factors with minimal information loss and on enabling the factor to obtain a certain explanatory method of multivariate statistical analysis. Principal component analysis is a mathematical method of data dimensionality reduction. The basic idea is to recombine the numerous relevant indicators X_1, X_2,…, X_P (such as p indicators) to a group with a lesser number of unrelated composite indicators Fm than the original target. He Fen [6] measured greenhouse environmental factors that affect the air humidity of data samples. Principal component analysis was conducted on the sample data. Results showed that the important factors include indoor temperature, outdoor humidity, outdoor temperature insulation, outdoor sun shade on degree, outdoor wind speed, skylight window angle, and side window opening angle.

External weather conditions influence greenhouse temperature and humidity. Xin Zhihong et al. [8] analyzed the influence of different sky conditions and different external weather conditions on the temperature and humidity inside the greenhouse. Results showed that the greenhouse thermal insulation performance is satisfactory and that the outdoor greenhouse temperature and humidity are related to the sky conditions and the variations in meteorological elements. They concluded that internal and external greenhouse humidity values possess a good positive correlation. During the closed period, relative humidity is less affected by the external factors and remains stable. The indoor and outdoor humidity difference tends to decrease during the ventilation period, indicating a positive correlation.

In sum, in cold weather, no heating and humidifying equipment are required, and greenhouses are mainly characterized by a sealed insulating state and relatively less ventilation time, while indoor water is mainly sourced for crop physiological function and irrigation. Thus, we select the indoor temperature, indoor light intensity, and dew point temperature prediction as the input factors. We select 600 groups of training data to establish the network model and to verify model accuracy. We then randomly select 80 groups for validation.

3.3 PRELIMINARY ANALYSIS OF DATA

An analysis of 22 to 24 monitoring records within 4 d revealed that indoor temperature reached the maximum at 4 p.m. to 5 p.m. The average maximum temperature was 38.41°C. The indoor temperature reached the lowest value of 10°C to 12°C. The average minimum temperature was 15.77°C. The greenhouse temperature curve is shown in Figure 3.

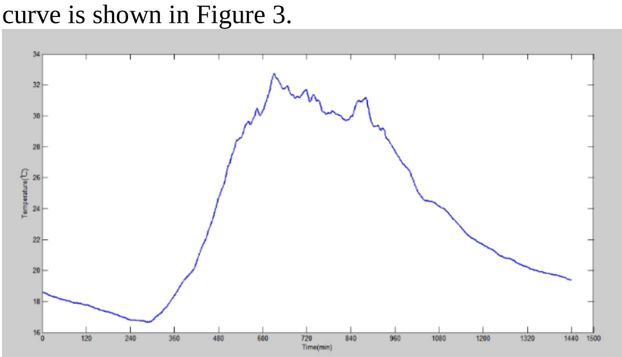

FIGURE 3 Greenhouse temperature curve

The greenhouse indoor relative humidity reached the highest value at 4 p.m. to 6 p.m. The average maximum humidity was 88.22%. The indoor relative humidity reached the lowest value of 10°C to 15°C. The minimum average humidity was 36.44%. The greenhouse indoor humidity curve is shown in Figure 4.

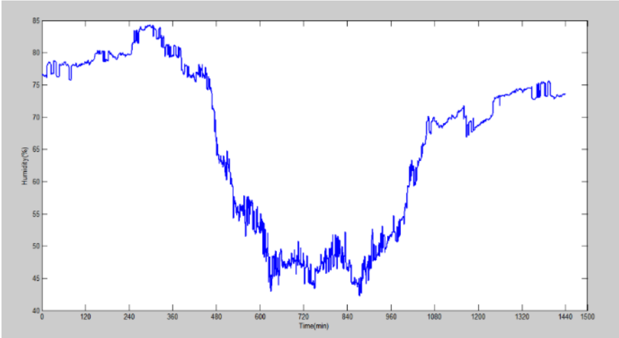

FIGURE4 Curve of humidity in greenhouse

The greenhouse light intensity reached the maximum at 9 to 11. The average maximum light intensity was 45559.375 lux. The greenhouse light curve is shown in Figure 5.

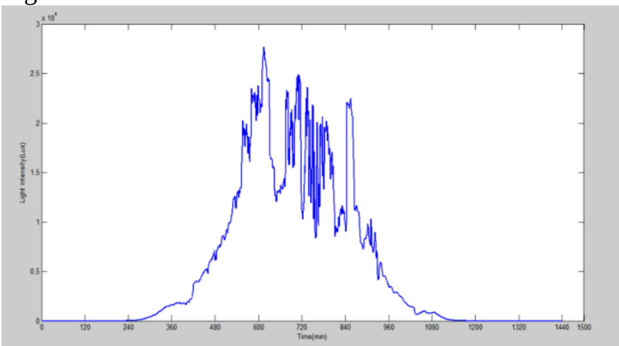

FIGURE 5 Curve of light intensity in greenhouse

By comparing the greenhouse temperature, relative humidity, and light intensity, the indoor temperature was found to correlate negatively with humidity. The indoor relative humidity and light intensity were also negatively correlated with each other. A comparison of the greenhouse indoor temperature, relative humidity, and light intensity curves is shown in Figure 6.

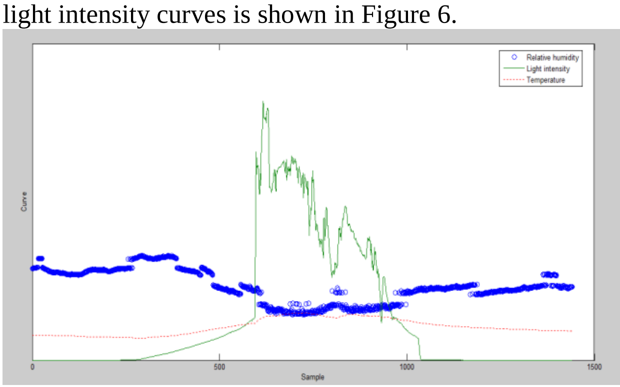

FIGURE 6 Comparison of humidity and temperature or light intensity

4 Model testing and validation

By using MATLAB program with 0.01 mean square error and 0.8 propagation velocity of RBF, we input the sample and set up the network. We then simulate and test the model. The simulation and actual values of the average relative error were both 0.19%, and the predictive and actual values of the average relative error were both 7.35%. The fitting contrast diagram of the network simulation value and actual value is shown in Figure 7. The fitting contrast diagram of the network forecasting value and actual value is shown in Figure 8. These results show that the network output can simulate the indoor relative humidity and predict its trend.

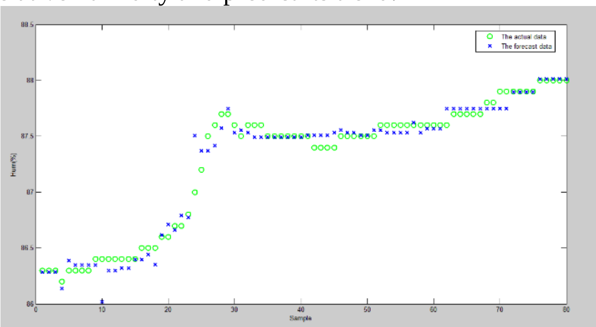

FIGURE 7 Simulation curve

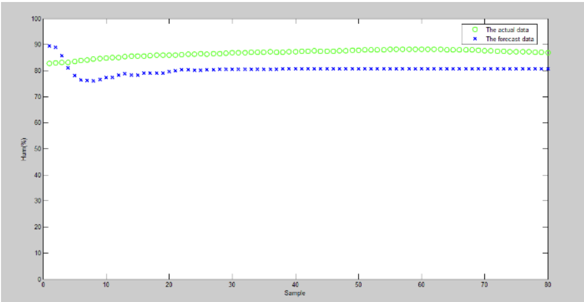

FIGURE 8 Prediction curve

5 Conclusions

Neural networks have been used to establish the prediction model of greenhouse environmental factors. In study, we used an RBF artificial neural network to establish the forecast simulation model for predicting and analysing the humidity of environmental factors in a greenhouse in Northern China. After testing, verification, and offline prediction research by the RBF neural network, results showed that the network convergence speed is significantly faster, the network set-up time is relatively shorter, and the function approximation capability is significantly higher than previous values. Therefore, the simulation model can simulate the basic trend with satisfactory prediction effect. This prediction can be used to control feed-forward greenhouse environments and to provide a scientific basis for the reasonable regulation and control of greenhouse environments.

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