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The Prediction of Greenhouse Temperature and Humidity Based on LM-RBF Network

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***Abstract* – In order to improve the accuracy of prediction for the temperature and humidity of the northern greenhouse, this paper proposes a model to predict the temperature and humidity of a greenhouse based on improved LM-RBF. The input data of the model were measured in a greenhouse in Tianjin in March. This model uses the inside and outside meteorological data of the greenhouse as input, and the temperature and humidity in a greenhouse as output. The higher prediction accuracy is obtained by the experimental results, which proved the feasibility of this scheme. This model can be used to forecast the temperature and humidity of a greenhouse and guide the control of the temperature and humidity of a greenhouse.**

Index Terms* – *RBF network, LM algorithm, temperature and humidity prediction.

I. INTRODUCTION

With the rapid development of China's greenhouse industry in recent years, China's greenhouse area ranks first in the world. This makes the control of the greenhouse system environment more and more demanding[1]. However, due to the complexity of the greenhouse itself and the interaction between the environmental factors in the greenhouse, it is very difficult to model the greenhouse system. The literature[2]-[5] constructs a mathematical model of the greenhouse through the energy conservation equation and the material balance equation inside the greenhouse, thereby realizing the temperature and humidity prediction of the greenhouse. However, this type of model has a complex structure with many parameters , and many parameters are difficult to determine and can only be obtained through experience[6]. In order to further optimize the greenhouse prediction model, domestic and foreign scholars use Back Propagation neural network model to predict temperature and humidity in the greenhouse. The literature[7] proposed a prediction model using BP neural network in solar greenhouse humidity in 2012. The literature[8] proposed a neural network trained by the LM algorithm in 2016 to achieve smart frost control of greenhouses in central Mexico. In order to overcome the shortcomings of the BP neural network such as slow convergence speed, some scholars use the Radial Basis Function neural network to predict the temperature and humidity in the greenhouse and they also use some algorithm to optimize the network to further improve the prediction effect. The literature[9] proposed a long-term greenhouse temperature prediction model based on PSO-RBF neural network in 2017. Based on the RBF network, this paper uses the Levenberg-Marquardt (LM) algorithm to optimize the structural parameters of RBF neural network network weights with LM algorithm, and further improves the prediction accuracy of the RBF neural network model. The reason for this is that LM algorithm is insensitive to over-parameterization problems, can effectively deal with redundant parameters, and greatly reduces the chance that the cost function will fall into local minimums, which is suitable for optimizing network. The experimental results show that the maximum relative error predicted by the network does not exceed 0.5%, compared with previous methods, the prediction accuracy has been improved.

II. DATA COLLECTION AND PROCESSING

The data collection time was in March 2017. A greenhouse in Tianjin was used as the sampling target. The sampling period was 10 minutes. The interior of the greenhouse was equipped with a natural ventilation system, a sunshade system, an external insulation system and a supplemental lighting system, and the peripheral thermal insulation screen. There are thermal screens and air dehumidification fans outside the greenhouse. A total of 144 sets of data per day were collected for the greenhouse temperature, the greenhouse humidity, the state of the thermal screen, the state of the shading net, heating valve opening, outdoor temperature, illumination, and wind speed. The status of the shading net, thermal screen and heating valve was obtained through the data provided by the greenhouse system. The temperature, humidity, illuminance, and wind speed were measured by the air temperature sensors, the air humidity sensors, the optical sensors, and the wind direction and wind speed sensors, respectively. The shading net and the thermal screen use 0 and 1 respectively for closing and unfolding. The heating valve opening is the percentage of the current opening and the maximum opening, and the rest of the data is normalized according to the formula (1).

$$y_i = \frac{x_i - 0.95 \times x_{i\min}}{1.05 \times x_{i\max} - 0.95 \times x_{i\min}} \tag{1}$$

Where y_i are the normalized data in the range [0,1]. x_i is the measured input value. $x_{i\max}$ are the maximum value of the input value. $x_{i\min}$ are the minimum value of the input value.

III. GREENHOUSE MODELING METHOD

A. RBF Neural Network

The RBF network is a common three-layer forward neural network. The three layers are the input layer, the hidden layer, and the output layer[10]. RBF neural network can deal with the intractable laws in the system, has a good generalization ability, has the advantages of simple training, simple structure, fast convergence, etc. It has been successfully applied in the nonlinear shape function approximation, pattern recognition, system modeling and other fields[11]-[13]. The network structure shown in Figure 1.

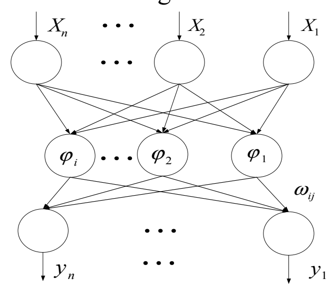

Fig.1 RBF network structure

The input vector of the neural network model is $X = (x_1, x_2, \cdots, x_m)^T$ .Where m is the number of input samples. The output y_1 and y_2 are the actual values of the temperature and humidity measured by the sensor, and i is the number of hidden layer nodes. The w_i is the weight between the hidden and the output neurons. Using gaussian kernel function as the network kernel function ϕ_i.

$$\phi_i(x) = e^{-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2}} \tag{2}$$

Where σ_i is the width of RBF. The c_i is the center of RBF. The formula for calculation is as follows:

$$\sigma_i^2 = \frac{1}{m}\sum_{x\in\sigma_i}(x-c_i)^T(x-c_i) \tag{3}$$

Where m is sample number. The output layer is weighted by hidden nodes, and the formula for calculation is as follows:

$$y(x) = w_i + \sum_{i=1}^{h} w_i e^{-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2}} \tag{4}$$

Where h is the number of hidden nodes.

B. LM Algorithm

The LM algorithm is an optimization algorithm that can optimize large-scale parameters[14]. This method is a combination of Gauss-Newton algorithm and gradient descent method, so this method has the local convergence of Gauss-Newton algorithm, and can use the gradient descent method to search global expansion. The LM algorithm uses an approximate second-order derivative, so it is faster than the gradient descent algorithm. The LM algorithm is based on the following principles:

$$\begin{cases} W_{(k+1)} = W_{(k)} + \Delta W_{(k)} \\ \Delta W = -(\cdot 2S_{(k)})^{-1} \cdot S_{(k)} \end{cases} \quad k = 0,1,2,\cdots,n \tag{5}$$

Where the W(k) is the solution vector consisting of the weights and thresholds of the k-th iteration. The S(k) is the error indicator function. The corresponding Hessian matrix and gradient vectors are ·S(k) and ·S(k) respectively.

The Gauss-Newton algorithm uses a least-squares method to estimate the function's solution, so its error indicator function can be expressed by:

$$S_{(k)} = 1/2\sum_{i=1}^{N} e_i^2(x) \tag{6}$$

Where $e_i(x)$ is the error, N is the vector dimension of the output. The ΔW calculated by the algorithm can be expressed as:

$$\Delta W = -\left[J^T J\right]^{-1} J^T e(x) \tag{7}$$

Where J is the Jacobian matrix of S.

The form of the LM algorithm can be expressed as:

$$\Delta W = -\left[J^T J + \mu I\right]^{-1} J^T e(x) \tag{8}$$

Where μ is the damping coefficient, which is usually the specified constant, and μ >0. Where I is the identity matrix.

As a combination of Gauss-Newton method and gradient descent method, when μ=0, the algorithm is transformed into Gauss-Newton method; when μ tends to a large value, the algorithm can be approximated as a gradient descent method. When the damping coefficient μ is large enough,it always guarantees $\left[JT(x)J(x)+\mu I\right]^{-1}$ reversible. In the actual solution process, μ is a dynamic parameter. The damping of the LM algorithm used in the experimental part of this paper is $\mu = J^T(x)e(x)$.

C. LM-RBF Network

The structural parameters that can be optimized in the RBF neural network include the center of the hidden layer nodes, the widths of the network, and the number of hidden layer nodes. Optimizing these parameters can significantly improve the prediction accuracy and generalization ability of the network. The hidden layer nodes optimal number can be dynamically adjusted by repeated experiments. The center of the hidden layer nodes can be learned by using gradient descend algorithm. Finally, the network optimization can be achieved by finding the width of the basis function that makes the error function the minimum.

The steps for optimizing the RBF neural network width using the LM algorithm are as follows:

Step1: Initialize the weights and thresholds of the RBF neural network, and set the training error ε and the LM algorithm's damping coefficient μ and the fine adjustment factor β, and let k = 0, $\mu=\mu_0$;

Step2: Calculate the output of the RBF neural network, and calculate the network error indices S(k) and ΔW, and use formula (5) to update the width and the weights and the thresholds of the RBF network;

Step3: If S(k) < ε then the algorithm stops, otherwise the algorithm further iterates to calculate X(k+1) and its error indicator S(k+1);

Step4: If S(k+1)<S(k), then let k=k+1, μ=μ/β, jump to step2, otherwise do no update μ,and let $\mu_{k+1}=\mu_k$, μ=μβ, the algorithm jumps to step3.

IV. GREENHOUSE MODEL AND SIMULATION

A. Greenhouse Modeling

The collected data are normalized using the formula (1) method. The data are collected every 10 minutes every day. The normalized data were used to bulid the forcasting model of the temperature inside greenhouse and humidity for the intelligent greenhouse by RBF neural network.

The neural network input is the state of the thermal screen, the state of the shading net, heating valve opening, outdoor temperature, illumination, and wind speed. The outputs were respectively the indoor temperature and humidity. In this paper, all 1440 data of the first 10 days of the month are selected as training data, and the 288 data of the two days of the month are randomly selected as test data. The RBF neural network is optimized according to the method mentioned in Chapter 3.Optimization is realized by optimizing the center of the hidden layer nodes of the network, the widths of the RBF, the number of hidden layer nodes, and the weight of the network. According to the number of inputs, The error target(ε) of the LM algorithm is set to 10^{-6}, the damping coefficient(μ) is 0.001, the adjustment factor(β) is 10, and the maximum number of iterations is 100, and the network training stops when the algorithm reaches the maximum number of iterations or the error reaches the target ε. The number of hidden nodes in the network was finally determined to be 3 through continuous experiments.

B. Greenhouse Model Simulation

All the normalized data were taken as the input and output of the neural network model, and the model was simulated by Matlab software. The RBF neural network, PSO-RBF neural network and the LM-RBF neural network were used to build the greenhouse temperature and humidity prediction model. The simulation results shown in Figure 2 and Figure 3.

In this paper, the accuracy of the model is evaluated by the RMS error, the absolute error of all test samples, and the relative error sum. The error values are shown in Table 1. The RMS error curve is generated by neural network training. The formulas for calculating the absolute error and relative error are as follows:

$$R_x = |Y - Y'| \tag{9}$$

$$R_y = \frac{|Y - Y'|}{Y'} \tag{10}$$

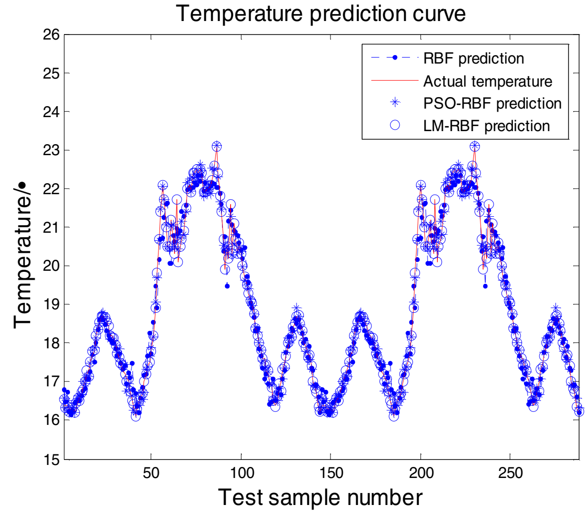

Fig.2 Temperature prediction curve

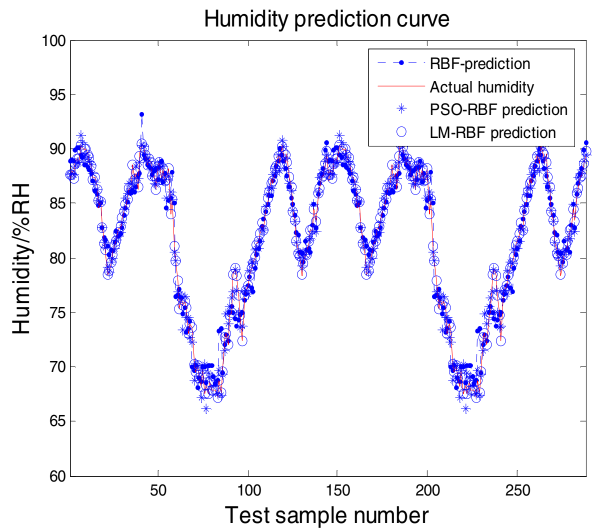

Fig.3 Humidity prediction curve

Through the simulation results in Figure 2 and Figure 3,combined with the error data of the test sample and the average operating time of the three models in Table 1, it can be seen that using PSO-RBF network modeling can effectively improve the prediction accuracy of the system, however, with the increase of data volume, particle swarm size and iterations, this system is liable to fall into local optimal problems[15]. To overcome this problem, this paper uses the LM-RBF network to further improve the system's prediction accuracy.

The relative error of the LM-RBF network is shown in Figure 4 and Figure 5. It can be seen from the figure that using the LM-RBF network model can better meet the requirements of temperature and humidity prediction and the maximum relative error of temperature and humidity prediction inside greenhouse does not exceed 0.5%. This indicates that the model can effectively predict the temperature and humidity inside greenhouse for the intelligent greenhouse, and also provide theoretical support for the controller design of greenhouse environment.

TABLE I

THE ERROR VALUE

Modeling method	temperature / Humidity RMS error	temperature/ Humidity absolute error sum	temperature/ Humidity relative error sum
RBF neural network	0.0019/ 0.0019	19.1767/ 69.3851	1.0792/ 0.8273
PSO-RBF neural network	0.0014/ 0.0011	10.9411/ 35.2101	0.6194/ 0.4138
LM-RBF neural network	9.99e-006/ 9.91e-006	5.9571/ 23.5929	0.3125/ 0.2763

The relative error of the LM-RBF network is shown in Figure 4 and Figure 5. It can be seen from the figure that using the LM-RBF network model can better meet the requirements of temperature and humidity prediction and the maximum relative error of temperature and humidity prediction inside greenhouse does not exceed 0.5%. This indicates that the model can effectively predict the temperature and humidity inside greenhouse for the intelligent greenhouse, and also provide theoretical support for the controller design of greenhouse environment.

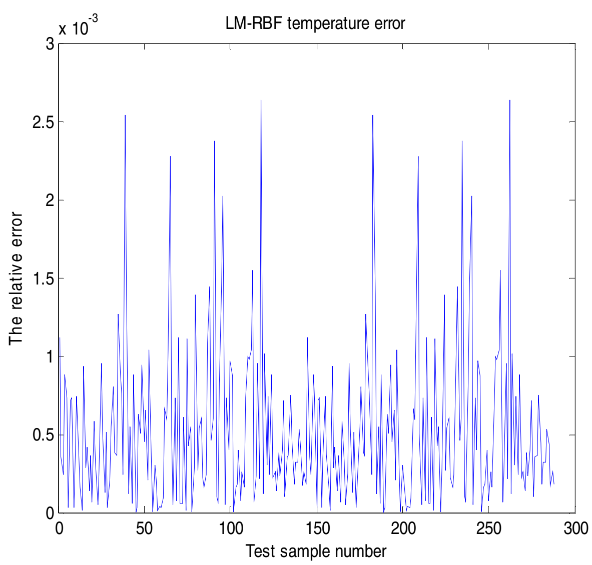

Fig.4 Temperature relative error curve

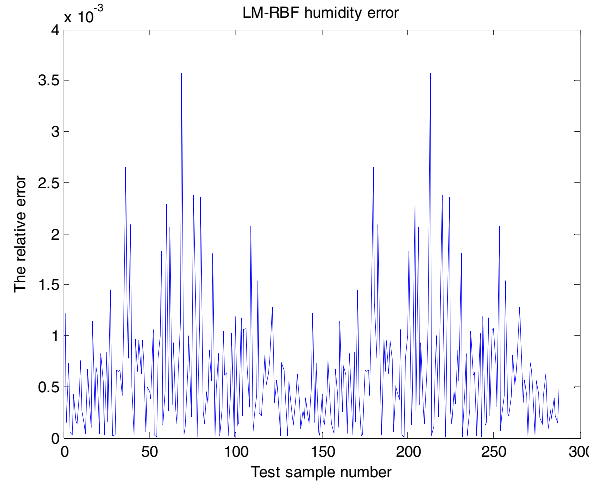

Fig.5 Humidity relative error curve

V. CONCLUSION

In this paper, we analyze the environmental factors affecting the temperature and humidity in the greenhouse, select the main factors affecting the temperature and humidity inside greenhouse as the input of the neural network prediction model, and use the indoor temperature and humidity as the output respectively to construct the greenhouse model based on LM-RBF network. By optimizing the structural parameters and the weights and the thresholds of the RBF network, the accuracy of the prediction model is improved, and the network structure and parameters obtained after the training of the neural network model are recorded. Based on these recorded parameters of the network, a neural network control model is built to realize the functions of regulating and controlling the environment required for the growth of greenhouse crops.

The temperature and humidity forecasting system proposed in this paper can predict the temperature and humidity in the greenhouse, and basically realizes the prediction of temperature and humidity inside greenhouse.

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