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Determining heating pipe temperature in greenhouse using proportional integral plus feedforward control and radial basic function neural-networks*

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Abstract: Proportional integral plus feedforward (PI+FF) control was proposed for identifying the pipe temperature in hot water heating greenhouse. To get satisfying control result, ten coefficients must be adjusted properly. The data for training and testing the radial basic function (RBF) neural-networks model of greenhouse were collected in a 1028 m^2 multi-span glasshouse. Based on this model, a method of coefficients adjustment is described in this article.

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INTRODUCTION

The objective of greenhouse environment control is to create an ideal climatic condition for plant growth. The interior air temperature is the most important control factor. Generally, heating facilities must be installed in the greenhouse in order to make the interior air meet the need of the crop in cold days. Hot water heating is the prevailing method. In order to save energy, precise temperature control is necessary (Chalabi *et al*., 1996). For precise control of interior air temperature, it is better to adjust the electric valve of the hot water heating pipe according to the desirable temperature of the hot water pipe instead of adjusting the air temperature directly. Cai (2000) described a method to use proportional integral plus feedforward (PI+FF) to calculate the pipe temperature. Many coefficients must be identified in this method. Although the coefficients are the key factors for achieving satisfactory result, most greenhouse operators set the coefficients based on their experience and skill and constantly face the challenge of determining proper coefficients. The reason is that the interaction among the factors affecting air temperature in a greenhouse and the complexities of the phenomena (multivariable, nonlinear, nonstationary) are such that it is often difficult to develop a practical prediction model of greenhouse air temperature (Frausto and Pieters, 2004; Seginer, 1997). Neural networks can act as a curve approximator and the design process can be viewed as a curve-fitting problem. Hence, a greenhouse temperature prediction model using neural networks can be effective. Some such models presented (Linker and Seginer, 2004; Ferreira *et al*., 2002; Seginer, 1997) stimulated an interest in tuning the PI+FF coefficient using a neural network model.

This paper presents a PI+FF controller, a satisfactory neural network temperature prediction model and proposes a way to tune the PI+FF coefficients.

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PROPORTIONAL INTEGRAL CONTROL

The climatic conditions in a greenhouse comprise a complicated dynamic system. Taking into account the factors influencing the temperature, five minutes was selected as the time increment in analyzing the energy transfer from the hot water heating pipe to the air in a greenhouse (Davis and Hooper, 1991).

When $|t_2(n)-t_2(n-1)|\geq\sigma$, the proportional method is applied by using the following formula to calculate the desirable pipe temperature at 5 min from now,

$$T(n+1) = T_0 + k_p \times [t_1(n+2) - t_2(n)]$$

where $t_2(n)$ is the measured current temperature in the greenhouse; $t_2(n-1)$ is the temperature in the greenhouse measured 5 min ago; σ is a given threshold value; $T(n+1)$ is the desirable pipe temperature 5 min later; T_0 is the set point temperature; $t_1(n+2)$ is the anticipated temperature in the greenhouse 10 min later; and k_p is the proportional coefficient.

The changes of external climatic condition strongly influence the inside air temperature. For example, the decrease of the temperature outside the greenhouse or the increase of the wind speed will lead to the decrease of the temperature inside the greenhouse. When the environment-controlling computer predicts the inside air temperature based on the outside climate, the control method is defined as "feed-forward control" whose computational formulas can be represented as

$$T(n+1) = T_0 + k_p \times [t_1(n+2) - t_2(n)] + T_o + T_f + T_l,$$
$$T_o = k_1 \times (t - t_0),\ T_f = k_2 \times v_f,\ T_l = k_3 \times (l - l_0)$$

where T_o, T_f, and T_l represent the respective influences of the outside temperature, wind speed and solar radiation considered in determining the future pipe temperature value; k_1, k_2 and k_3 are the corresponding coefficients; t is the outside temperature; t_0 is the reference outside temperature (for zero correction); v_f is the wind speed; l is the solar radiation intensity and l_0 is the reference radiation.

When $|t_2(n)-t_2(n-1)|<\sigma$, the integral process begins in order to remove the steady offset caused by the proportional control, with the formula for calculating the pipe temperature being:

$$T(n+1) = T(n) + T_i$$

When $|t_2(n)-t_1(n+2)|>\sigma_1$

$$T_i = \begin{cases} \delta_i & t_1(n) > t_2(n) \\ -\delta_i & t_1(n) < t_2(n) \end{cases}$$

When $|t_2(n)-t_1(n+2)|\leq\sigma_1$

$$T_i=0$$

where $t_2(n)$ is the practical temperature in the greenhouse; $t_1(n+2)$ is the expected temperature in the greenhouse 10 min later; σ_1 is the threshold value; δ_i is the integral intensity; and $t_1(n)$ is the desired temperature at the present time.

The parameters which must be confirmed in the above computational process are T_0, k_p, k_1, k_2, k_3, t_0, l_0, δ_i, σ and σ_1. Each parameter has a specific physical meaning and can influence the control results significantly. They all can be adjusted by taking into account the expected air temperature, greenhouse air temperature, pipe temperature, wind speed, intensity of solar radiation and the external temperature in an effort to obtain a better control effect. By means of a neural network model, the control results can be simulated on a computer to provide an effective way to adjust the parameters.

RBF NEURAL-NETWORK MODEL

Radial basic function (RBF) neural-networks proposed by Moody and Darken (1988) in the 1980's were feedforward networks with a singular hidden layer and belong to the group of partly approximating networks with advantages of good function approximating capability and training rate, and were shown to be able to approximate any multivariate continuous function relatively well.

An RBF network with several inputs and single output was established to deal with the change of the greenhouse air temperature which depends on many factors. The topological structure is shown in Fig.1. The network consists of three layers, namely the input layer, radial basic function hidden layer and output layer. The input part does not transform the signals but only dispatches the input vector to the radial basic layer. The function in a hidden layer node (also called nucleus function) responds partly to the input signals, i.e. when the input function is close to the center range of the nucleus function, the hidden layer will produce a larger output. Under these conditions, Goss function was chosen as the RBF for this study. It was decided by the following two parameters: the field center c_j and the field width α_j. The output layer is a set of linear combiners with weights.

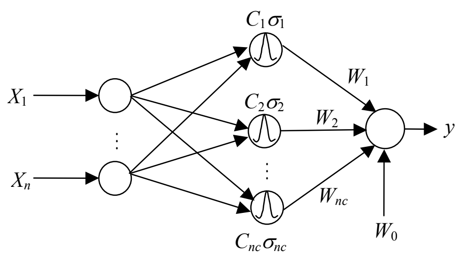

Fig.1 RBF network topological structure

Orthogonal least squares (OLS) proposed by Chen *et al.*(1991; 1992) has been widely used in training RFB networks; and can be used to calculate the connection weight, number of the hidden layer nodes, field centers of the hidden layer nodes, and the offset (W_0) at the same time.

Experimental data were collected in a commercial multi-span glass greenhouse built by the Shanghai Dushi Green Engineering Corporation for the Zhejiang University Research Center of Vegetable Science (Hangzhou, China). The floor area is 1028 m^2. Natural ventilation windows, curtains, wet pad, hot-water heating system etc. were installed in the greenhouse. Priva in Holland supplied the electric system and the computer control system. The sensors included a dry bulb and wet bulb thermometer placed in the greenhouse center to measure the inside air temperature and humidity, a temperature sensor attached to the exterior surface of the water pipe, and an angle sensor to measure the degree of roof window opening. An outdoor weather station was installed to gather outdoor radiation, temperature, wind speed, and wind direction data.

Data were collected and saved in the computer every 5 min during running period of the control system. The greenhouse is almost empty except for several basins of paddy in it. The 1240 sets of data, obtained from 00:00 on April 1 to 07:10 on April 5 in 2003, included the outside temperature, wind speed, solar radiation, opening-angle of roof window, cover ratio of the inside curtain, hot-water pipe temperature, inside temperature and inside humidity, and were selected for study. For each training step, the input to the neural network included the current values of the above variables plus the values of the inside air temperature from one interval and two intervals ago. The input data were normalized before they were entered into the neural network. The formula used for the normalization process is as follows:

$$y_i = \frac{1}{2}\frac{x_i - \overline{x}}{x_{\max} - x_{\min}}$$

where x_i is the measured value; $\overline{x}$ is the mean of all measured values; $x_{\max}$ is the maximum; and $x_{\min}$ is the minimum. All DC terms were subtracted from signals, which were then scaled to amplitude one, [−0.5, 0.5] interval. The temperature one interval ahead was selected as the output of the neural network. The first 500 datasets were used as the training set and the remaining as testing set. The air temperature prediction model was developed in MATLAB environment. A satisfactory result was obtained when the hidden nodes width was chosen as 30, the energy error specified as 0.02 (the root mean square error was 0.0073). The test result is shown in Fig.2, with the errors arranged from –0.55 °C to 0.64 °C.

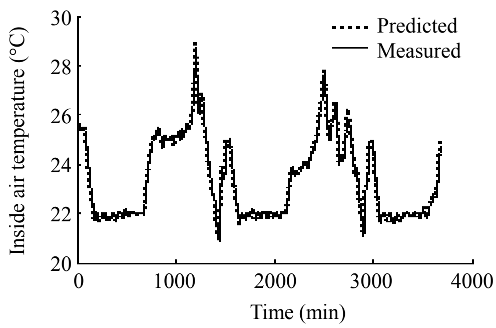

Fig.2 Predicted and observed inside air temperature

SETTING OF COEFFICIENTS

The coefficients setting program was also designed in MATLAB. It included 8 parts: inputting the data, training neural network, initializing control coefficients and the state of the greenhouse, calculating the temperature inside the greenhouse by means of the neural network model after entering the loop, calculating the pipe temperature of the next state through PI+FF, saving data, updating the greenhouse's state, exiting the loop when the specified number of loops was met and outputting the results by diagram. The input data included the measured values of all factors affecting the air temperature in the greenhouse as described above (temperature value and their normalized values expected). The environmental state at 00:00 and the expected inside air temperature at 00:10 on April 4th, 2003 were initialized. Then the pipe temperature at 00:05 was calculated using PI+FF. In the first loop, taking the environmental factors at 00:05 as the input vector, the neural network calculated inside air temperature at 00:10. In the process of saving data and updating state variables, the output of neural network was first saved into the data table, then the pipe temperature at 00:10 was calculated; finally the states of the greenhouse and weather at 00:10 were brought in. These data would be used in the next loop as the input vector to the neural network.

Throughout an entire day, 288 sets of data were collected (at 5 min intervals). Fig.3 shows the external climatic conditions and the simulated control results based on the coefficients shown in Table 1. In Fig.3a, the dashed line represents the anticipated inside air temperature from 00:10 to 24:10 and the solid line shows the inside air temperature simulated by the neural-network model. The coefficients shown in Table 1 were obtained by tuning them to "best" match the solid line with the dashed line. Fig.3b illustrates the hot-water pipe temperature from 00:05 to 24:00, which was derived by PI+FF. Figs.3c~3e show the external wind speed, external air temperature and solar radiation intensity respectively, from 00:05 April 4th to 00:00 April 5th, 2003.

The neural-networks greenhouse model refers to only existing structure and depends on special data, so, it is important to avoid extrapolations. But the coefficients identified by the model can be used in calculating the hot water pipe temperature in different climate.

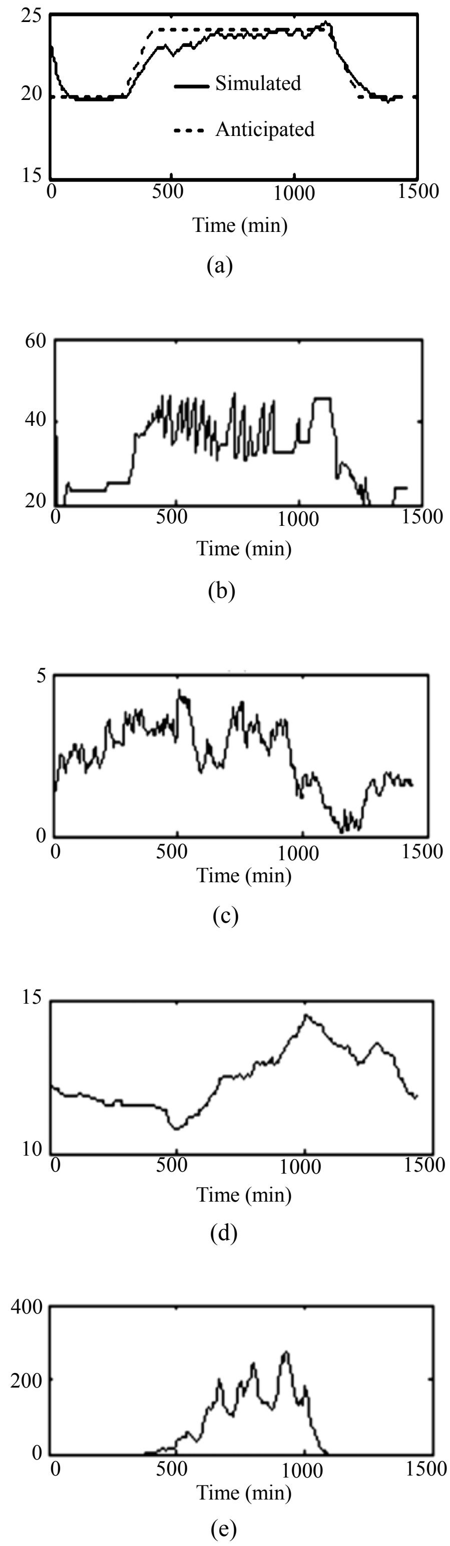

Fig.3 Outside climate and simulated control result
(a) Inside air temperature (°C); (b) Pipe temperature (°C); (c) Wind speed (m/s); (d) Outside temperature (°C); (e) Radiation intensity (W/m)

Table 1 The coefficients set from the model

Coefficient	Value	Unit
Pipe basic temperature T_0	20	°C
Proportional coefficient k_p	8	–
Outside temperature adjusting k_1	3	–
Wind speed adjusting k_2	1	°C/(m·s^1)
Solar radiation adjust k_3	–0.01	°C/(W·s^2)
Outside temperature adjusting threshold t_0	8	°C
Solar radiation adjusting threshold l_0	50	W/m^2
Integral intensity δ_i	2	°C
Inside air steady threshold σ	0.1	°C
Error threshold σ_1	0.3	°C

CONCLUSION

1. Temperature control in a greenhouse is challenging due to the influence of many factors. In this article, PI+FF control methods were used to calculate the pipe temperature in the hot-water heating system. They have been proven to be effective.

2. RBF, used in conjunction with properly chosen input vector, can be used to establish a prediction model of temperature in a greenhouse. The model can be used for setting parameters.

3. The parameters-setting method proposed in this article can provide a basis for studying intelligent control strategies. For example, the genetic algorithm can be used to set parameters on-line.

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