Crop canopy temperature model of ditch-cultivated based on artificial neural network

Min Zhang[1], Qiang Fan[2], Fucang Zhang[3], Xia Li[1], Xuzhang Xue[4], Guodong Wang[1]*

[1]*College of Science, Northwest A&F University, Yangling 712100, Shaanxi, China*

[2]*College of Water Resources and Architectural, Northwest A&F University, Yangling 712100, Shaanxi, China*

[3]*Key laboratory of Agricultural Soil and Water Engineering in Arid and Semiarid Areas of Ministry of Education, Northwest A&F University, Yangling 712100, Shaanxi, China*

[4]*National Engineering Research Centre for Information Technology in Agriculture; Beijing 100097, China*

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Abstract

Aiming at the mechanism model are influenced by multiple random factors, this paper establishes canopy temperature models based on BP network and RBF network respectively. The models take the temperature, humidity, illumination, soil temperature and ditch depth in the closed greenhouse as input neurons and takes canopy temperature as the output neuron. The results show that both models can well predict ditch-cultivated crop canopy temperature. The mean error between the simulation value and measured value of BP network model is 0.8408℃, and root-mean-square error of 0.5789℃. Actual output and expected output of RBF network model differ little, mean error of 0.2236℃ and root-mean-square error of 0.3496℃. In contrast, RBF network model can more accurately predict crop canopy temperature of ditch-cultivated than BP network model.

Keywords: Ditch-cultivated, Canopy Temperature Model, Artificial Neural Network

1 Introduction

Crop canopy is important space for crops' photosynthesis and transpiration. The change in canopy temperature is influenced by growing environment of crops. It is significant basis to measure water status of crops and provides necessary data support for irrigation control and greenhouse management [1, 2]. So, study on the relationship between crop canopy temperature and each environmental factor and establishment of canopy temperature model are of great significance.

Currently, both Chinese and foreign experts establish multiple simulation models for plant canopy temperature focus on field [3, 4], multi-span greenhouse and Venlo greenhouse [2, 5-8] and study effects of plant canopy temperature under different environments on water status and plant growth conditions. Modeling approach for existing plant canopy temperature is mechanism method, i.e. energy balance method with environmental data as variables and multiple regression equation method. Microenvironment of ditch-cultivated in closed greenhouse is more complex than common greenhouse, and also influenced by multiple random factors. Besides, it is difficult to confirm soil parameters. Thus, modeling with mechanism method greatly influences prediction accuracy of ditch-cultivated crop canopy temperature. ANN has the self-learning ability to simulate human thinking and can realize self-adjustment according to environmental changes. In addition, it owns nonlinear adaptation information processing capability and very strong fault-tolerant capability and can overcome errors caused by parameter selection in mechanism method. ANN expresses dynamic modeling of complex environment through limited parameters and is thus applied widely in information processing, intelligent control and production. In addition, it opens up a new research approach for establishing crop canopy temperature model.

This paper takes potted Chinese cabbage under ditch-cultivated mode in closed greenhouse and adopts BP network and RBF network to establish crop canopy temperature models, respectively. Temperature, humidity, illumination, soil temperature and ditch depth in the closed greenhouse serve as the input of the network and crop canopy temperature in the ditch serve as the output of the network. Then, the relationship between crop canopy temperature under ditch cultivation environment and environmental factors is analysed to provide theoretical support for further optimizing structural design and optimum greenhouse control of ditch cultivation method and analysing plant irrigation and water status.

2 Introduction of artificial neural network

ANN was first put forward by Warren S McCulloch and Water H Pitts in 1943 and owns such advantages as parallel processing, distributed storage, self-learning and associative

*** *Corresponding author*** e-mail:Gdwang211@yahoo.com.cn

memory. It develops on the basis of multiple disciplines including biology, cognitive science, modern neurosciences and computer science and reflects fundamental characterristics of functions of human brain. It is widely applied and developed in artificial intellectual control and optimization, pattern recognition and graphic processing, prediction and intelligent information management, communication and complex system modeling.

2.1 NEURON MODEL

ANN is formed through widely interlinking large quantities of neurons and used to simulate the structure and functions of brain nervous system. Neuron as a basic unit of neural network abstracts and simulates biological neurons. Figure 1 shows a simplified neuron model. It is a nonlinear component with multi-input and single output.

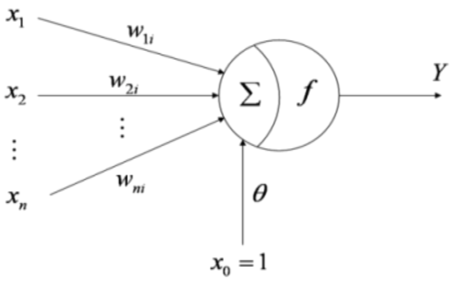

FIGURE 1 The model structure of single neuron

Its input-output relationship can be described as:

$$I_i = \sum_{j=1}^{n} w_{ji} x_j - \theta_i \,, \tag{1}$$

$$Y = f(I_i)\,, \tag{2}$$

where, w_{ji} is connection weight from cells j to cells i (for excited state, w_{ji} takes positive value; for inhibitory state, w_{ji} takes negative value); x_j refers to input signal from other cells $(j = 1, 2, \cdots\cdots, n)$; θ_i is the threshold value of neuron unit; n means the number of input signals; Y refers to neuron output; $f(.)$ is a transfer function. The transfer function can be a linear function, but it is usually the nonlinear function like the step function or *S* curve.

ANN explores human image thinking. It simplifies knowledge expression. After network structure is confirmed, ANN can carry out self-learning and self-correction of deviation according to sample data and imply "summarizing rules" gained through self-learning in weight matrix.

2.2 BP NEURAL NETWORK

Back-Propagation model is an error back propagation learning algorithm used for multilayer feed-forward neural network and was proposed by Rumelhart, Hinton and Williams in 1986. BP network contains input layer and output layer as well as one-layer or multi-layer hidden layers. Its structure is shown in Figure 2:

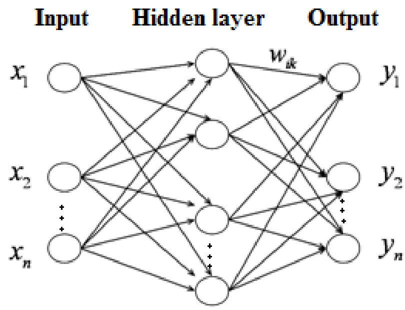

FIGURE 2 The structure of BP networks

When information is inputted in the network, the information is first transmitted to the hidden layer through the input layer, and then transmitted to the next hidden layer after the conversion by the transfer function until information is transmitted to the output layer to output. The information will go through the conversion by the transfer function whenever it passed one layer. The transfer function of BP network should be differentiable anywhere. Usually, *S* function is adopted. For example:

$$f(x) = \frac{1}{(1+e^{-x})}\,. \tag{3}$$

BP learning algorithm is a learning algorithm with the tutor. It adjusts network connection weight through the deviation between actual output and expected output of the network so that the network can gain expected output for any input. BP learning algorithm trains the network with a group of training samples. Each sample contains input and expected output. During the training, firstly, input information in the training samples is transmitted into the network; the network conducts calculation from the first hidden layer and transfers the calculation result to the next layer until the result is transmitted to the output layer. Every layer of neuron only influences the state of the next layer of neuron. If expected output is not gained in the output layer, calculate the error between the output value of the network and the expected output of the sample; then the network returns the error signal along the original connection passage layer by layer and adjusts connection weight of the nodes in each layer so as to gradually reduce the error until the error meets requirements.

BP network is composed of forward transfer of information and back propagation of the error. Forward transfer is used to calculate network and solve the output for an input. Back propagation is used to transmit the error layer by layer and modify the connection weight so that the network can calculate correctly. Once the network is used to solve practical problems after the training, only forward propagation is needed, without the need of back propagation.

2.3 RBF NEURAL NETWORK

Radial Basis Function is composed of input layer, hidden layer and output layer. Its structure is shown in Figure 3. The nodes in the input layer transmit input signal to the hidden layer. The nodes in the hidden layer are composed of radial functions like Gaussian function. The basis function in the nodes in the hidden layer influence input signal partially and have local approximation capability. When the input signal approaches the central scope of the basis function, nodes in the hidden layer will generate large output. The nodes in the output layer usually adopt linear function.

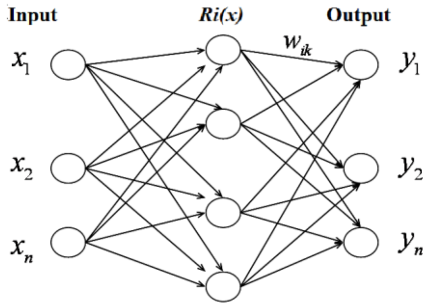

FIGURE 3 The structure of RBF networks

Common basis function in RBF neural network is Gaussian function:

$$R_i(x) = \exp[-\frac{\|x - c_i\|^2}{2\delta_i^2}] \quad i = 1, 2, ..., m \,, \tag{4}$$

where, c_i is the centre of the i^{th} basis function; δ_i refers to the variable of the i^{th} perception which decides the width of the basis function embracing the central point; $\|x - c_i\|$ is the norm of vector quantity $x - c_i$ and expresses the distance between x and c_i.

RBF neural network mainly adopts stochastic algorithm and self-organizing learning algorithm to select network centre. The two learning algorithms cannot be used for online learning in dynamic input mode. The foundation of valid algorithm is that all possible sample data must be gained in advance. Thus, they are only applicable to offline learning in static mode. Beside, the number of neurons in the hidden layer of RBF network based on above two learning algorithms should be confirmed artificially. Since it is necessary to consider the number of neurons in the hidden layer and a suitable norm, the difficult in solving problems increases.

Zhu Mingxing and Zhang Delong come up with RBF network model based on nearest neighbor-clustering learning algorithm. Nearest neighbor clustering learning algorithm is an online self-adaptation clustering learning algorithm. It is unnecessary to confirm the number of neurons in the hidden layer in advance. RBF network through clustering is optimal. Besides, the algorithm can be used for online learning [9].

According to nearest neighbour clustering learning algorithm, the output of RBF network should be:

$$f(x^k) = \frac{\sum_{i=1}^{M} w_i \exp(-\frac{|x^k - c_i|^2}{r^2})}{\sum_{i=1}^{M} \exp(-\frac{|x^k - c_i|^2}{r^2})} \,. \tag{5}$$

The radius r decides complexity of dynamic self-adaptation RBF network. If r is smaller, the number of clusters gained is more; the calculation amount is larger; the precision is higher. If r is larger, the number of clusters gained is less; the calculation amount is smaller; the precision is lower. Since r is a one-dimensional parameter, an appropriate r can be usually found through experiments and error information. It is much more convenient than confirming the number of hidden units and a suitable norm. Since each pair of input-output data may generate a new cluster, such dynamic self-adaptation RBF network actually carries out adaptive adjustment of the parameter and structure simultaneously.

3 Brief introduction to basic information

The experiment is conducted in a closed greenhouse in water-saving irrigation experiment station (east longitude 108°04'; northern latitude 34°17'; elevation 506m) of key laboratory of agricultural water-soil engineering in arid region of Northwest A&F University in Yangling, Shaanxi. The closed greenhouse is 3m wide and 12m long. The height of the ridge is 2.5m. It is covered by white polyethylene film. The tested cultivar is Chinese cabbage, which is cultivated with substrate. Substrate moisture in the pot is adequate during seeding. In the growing process, supplement water 2 times of water consumption caused by transpiration at the interval of 2 days.

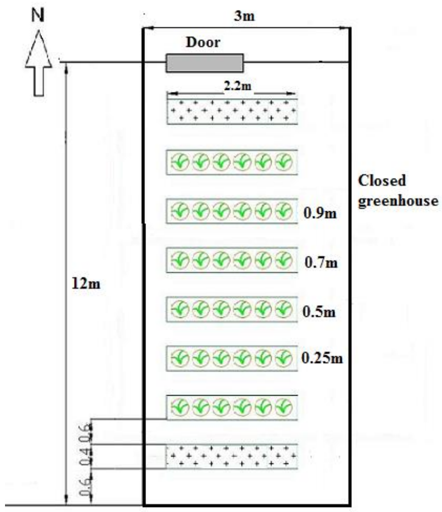

FIGURE 4 Layout of experience

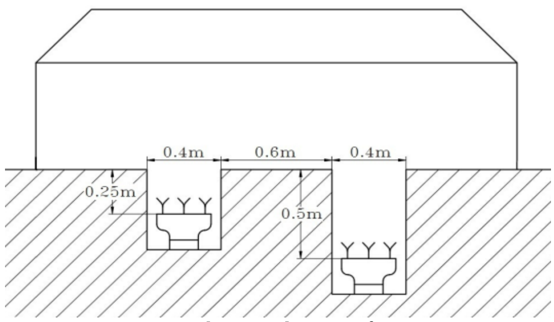

FIGURE 5 Schematic diagram of experience

Multiple rows of ditches with different depth are excavated along the east-west direction in the closed greenhouse. The length and width of each ditch are 2.2m and 0.4m respectively, at the interval of 0.6m, as shown in Figure 4 and Figure 5. Substance surface of the pot is placed in the ditches with the depth of 0.25m, 0.5m, 0.7m and 0.9m respectively. Repeat 5 times for each ditch. To prevent effects of ditch wall desquamation and soil moisture on air humidity, the plastic film is covered on the ditch wall and the bottom of the ditch.

Temperature and humidity in the greenhouse are collected with temperature and humidity collector. The probe is hung at 0.5m in the greenhouse. TES1339 professional illuminometer is used to measure the illumination. Intelligent agriculture controller is adapted to measure soil temperature. The sensor is buried underground at 0.25m in the ditch. The data are stored at the interval of 10min. The data measured at 7:00~20:00 on July 8-13, 2013 are selected as model training and verification data. The main measurement items and test instruments are shown in Table 1.

TABLE 1 List of experimental apparatus

Measurement items	Measuring instrument	Technical parameter
Temperature	Temperature and humidity collector	Measuring range: -30~70℃; Measuring accuracy: 0.01℃
Humidity	Temperature and humidity collector	Measuring range: 0~99.9; Measuring accuracy: 0.1
Illumination	TES 1339 Professional illuminometer	Measuring range: 0.1lux~200000lux; Measuring accuracy: 0.1lux
Soil Temperature	Temperature collector	Measuring range: -40~80℃; Measuring accuracy: 0.2℃
Depth Ditch	Meter	Measuring range: 0~2m; Measuring accuracy: 0.001m

4 Crop canopy temperature model based on ANN

According to the analysis of canopy temperature transmission mechanism, the temperature, humidity, soil temperature and illumination in the greenhouse as well as ditch depth and their change rate have certain mapping relation with crop canopy temperature in the greenhouse. The change of any parameter can impose direct influences on crop canopy temperature in the greenhouse. So, this model predicts crop canopy temperature through monitoring changes in the temperature, humidity, illumination, and soil temperature and ditch depth on July 8-13, 2013. Since the experiment mainly considers effects of high-temperature environment in the closed temperature on ditch-cultivated crop canopy temperature, the data at 7:00～20:00 on each measuring day are selected. 200 groups of data are gained after abnormal data and repeated data are eliminated. The data are divided into 2 sample sets. 170 groups of data as training sample set of the network are used to train the network established. 30 groups of data as inspection sample set of the network are used to inspect accuracy of model prediction after the training.

4.1 CROP CANOPY TEMPERATURE MODEL BASED ON BP

Crop canopy temperature model based on BP network is shown in Figure 6.

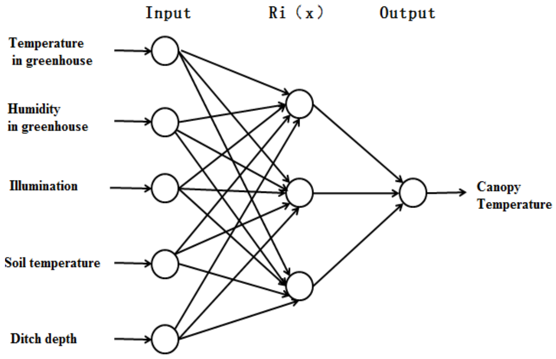

FIGURE 6 BP model of canopy temperature

The number of neurons in the input layer is 5, including the temperature, humidity, illumination, and soil temperature and ditch depth in the greenhouse. The number of neurons in the output layer is 1, indicate as crop canopy temperature. In BP network model, the hidden layer adopts *S* activation function. The output layer adopts linear activation function. It is known from empirical formula and actual training that the number of neurons in the hidden layer is 27.

$$(S_i+1)S_h+(S_h+1)S_o=n_pS_o\,, \tag{6}$$

S_i means the number of neurons in the input layer; S_h is the number of neurons in the hidden layer; S_o is the number of neurons in the output layer; n_p is the number of training samples.

Since the dimension of network input and output is different and the quantity differs greatly, normalization processing of sample data must be conducted before network training to prevent small numerical value information from being submerged by large numerical value information, i.e. normalize input signal to [0, 1]. The normalization equation is:

$$X^*=\frac{X-X_{\min}}{X_{\max}-X_{\min}}\,, \tag{7}$$

X^* refers to normalized data (the value is between 0 and 1); X is the actual value of network input data; $X_{\max}$ and $X_{\min}$ are the maximum value and the minimum value of input data.

To verify effectiveness and reliability of BP neural network model on canopy temperature prediction, MATLAB software is used to train and simulate BP neural network model. Since the length of the paper is limited, simulation results of only 12 groups of experimental data are provided, as shown in Table 2.

In accordance with the simulation results, actual output and expected output of BP network model differ little, with mean error of 0.8408°C and root-mean-square error of 0.5789°C. It thus can be seen that BP network has relatively accurate prediction result for ditch-cultivated crop canopy temperature.

TABLE 2 Simulation results of BP networks model

NO.	Input					Output	Measured
	Temperature /℃	*Humidity/%*	*Illumination/klx*	*Soil temperature /℃*	*Ditch depth/m*	*Canopy Temperature/℃*	*Canopy Temperature/℃*
1	36.84	41.56	16.27	14.1	0.25	35.478	35.1
2	44.17	32	42.02	14.2	0.25	41.62	42.48
3	48.94	31.78	47.06	14.21	0.25	44.773	45.23
4	36.84	36.44	11.01	13.55	0.5	33.397	32.96
5	44.17	29.78	41.09	13.6	0.5	39.03	41.6
6	48.94	29.11	44.46	13.67	0.5	42.868	45.31
7	44.17	27.78	19.88	12.2	0.7	35.927	34.94
8	48.94	28	41.76	12.22	0.7	38.655	38.61
9	46.35	27.56	32.26	12.25	0.7	37.089	36.88
10	36.84	66.67	5.628	10.9	0.9	29.796	29.44
11	44.17	64	12.61	10.9	0.9	33.226	32.19
12	48.94	57.11	36.58	10.9	0.9	34.523	34.21

4.2 CROP CANOPY TEMPERATURE MODEL BASED ON RBF

Negative gradient descent is adopted to adjust BP network weight. Such method has certain limitations. It has the shortcomings as follows: slow convergence rate; long training time; easy to be caught in local minimum. Radial basis function network is superior to BP network in terms of approximation capability, classification ability and learning rate. Thus, this paper adopts radial basis function network to establish crop network temperature model in order to improve prediction precision of canopy temperature.

In a bid to verify effectiveness and reliability of RBF neural network model on canopy temperature prediction, MATLAB software is used to train and simulate RBF neural network model. The same 200 groups of measured data serve as sample data of the neural network. The input of the neural network includes the temperature, humidity, illumination, soil temperature and ditch depth in the greenhouse. Expected output of the network is crop canopy temperature. The neural network model is as shown in Figure 7.

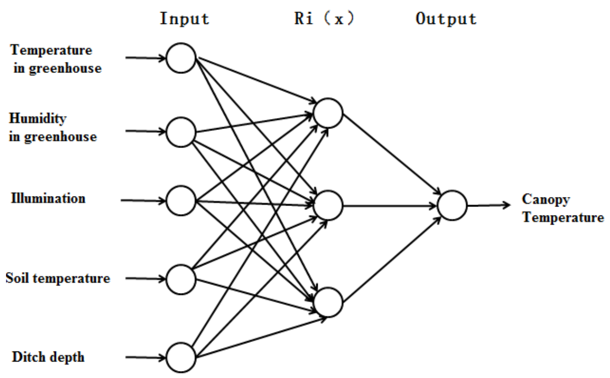

FIGURE 7 RBF model of canopy temperature

To prevent small numerical value information from being submerged by large numerical value information, normalization processing of sample data must be conducted before network training to normalize input signal to [0, 1]. 170 groups of experimental data are taken as the training samples of the network after normalization. During the training, the width of the basis function is 0.15. After the training, the number of neurons in the hidden layer is 92. 30 groups of data serve as inspection sample set of the network. It is known through network training that the model has fast convergence rate and short training time. Table 3 shows RBF network simulation results of 12 groups of experimental data.

TABLE 3 Simulation results of RBF networks model

NO.	Input					Output	Measured
	Temperature /℃	*Humidity/%*	*Illumination/klx*	*Soil temperature /℃*	*Ditch depth/m*	*Canopy Temperature/℃*	*Canopy Temperature/℃*
1	36.84	41.56	16.27	14.1	0.25	35.106	35.1
2	44.17	32	42.02	14.2	0.25	42.645	42.48
3	48.94	31.78	47.06	14.21	0.25	45.082	45.23
4	36.84	36.44	11.01	13.55	0.5	33.05	32.96
5	44.17	29.78	41.09	13.6	0.5	41.518	41.6
6	48.94	29.11	44.46	13.67	0.5	45.026	45.31
7	44.17	27.78	19.88	12.2	0.7	36.32	34.94
8	48.94	28	41.76	12.22	0.7	38.489	38.61
9	46.35	27.56	32.26	12.25	0.7	36.992	36.88
10	36.84	66.67	5.628	10.9	0.9	29.457	29.44
11	44.17	64	12.61	10.9	0.9	32.464	32.19
12	48.94	57.11	36.58	10.9	0.9	34.206	34.21

Based on the simulation results, RBF network model has fast computing speed. Besides, the simulation value and measured value differ little, mean error of 0.2236℃ and root-mean-square error of 0.3496℃. It thus can be seen that

RBF network has more accurate prediction result of ditch-cultivated crop canopy temperature than BP network.

5 Conclusions

Aiming at the mechanism model are influenced by multiple random factors and it is difficult to confirm soil parameters, this paper takes Chinese cabbage as the object of study and establishes canopy temperature simulation models based on BP network and RBF network respectively. The models take the temperature, humidity, illumination, soil temperature and ditch depth in the greenhouse as input neurons and takes canopy temperature as the output neuron. Moreover, experimental verification of the models is carried out through the measured data. The results show that both models can well predict ditch-cultivated crop canopy temperature. The mean error between the simulation value and measured value of BP network model is 0.8408℃, and root-mean-square error of 0.5789℃. Actual output and expected output of RBF network model differ little, mean error of 0.2236℃ and root-mean-square error of 0.3496℃. In contrast, RBF network model can more accurately predict crop canopy temperature than BP network model.

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Authors

Min Zhang, born on February 2, 1982, China

Current position, grades: candidate in College of Science, Northwest A&F University.
Scientific interests: environmental biophysics and model.

Qiang Fan, born on September 27, 1980, China

Current position, grades: doctor candidate in College of Mechanical and Electronic Engineering, Northwest A&F University
Scientific interests: wireless sensor network and compressed sensing.

Fucang Zhang, born in February, 1962, China

Current position, grades: professor, doctor candidate instructor.
Scientific interests: water saving irrigation theory and technique, agricultural soil and water environment, etc.

Xia Li, born in October, 1978, China

Current position, grades: associate professor.
Scientific interests: environmental biophysics and model.

Xuzhang Xue, born in October, 1967, China

Current position, grades: research fellow.
Scientific interests: water saving agriculture, precision agriculture, etc.

Guodong Wang, born in August, 1957, China

Current position, grades: professor, doctor candidate instructor.
Scientific interests: environmental biophysics, etc.