Management of CO_2 in a tomato greenhouse using WSN and BPNN techniques

Li Ting, Zhang Man*, Ji Yuhan, Sha Sha, Jiang Yiqiong, Li Minzan

(*Key Laboratory of Modern Precision Agriculture System Integration Research, Ministry of Education, College of Information and Electrical Engineering, China Agriculture University, Beijing 100083, China*)

Abstract: Rational management of CO_2 can improve the net photosynthetic rate of plants, thereby improving crop yield and quality. In order to precisely manage CO_2 in a greenhouse, a wireless sensor network (WSN) system was developed to monitor greenhouse environmental parameters in real time, including air temperature, humidity, CO_2 concentration, soil temperature, soil moisture, and light intensity. The WSN system includes several sensor nodes, a gateway node, and remote management software. The sensor nodes can collect 0-5 V and 4-20 mA analog signals and universal asynchronous receiver/transmitter (UART) data. The gateway node can process and transmit the data and commands between sensor nodes and remote management software. The remote management software provides a friendly interface between user and machine. Users can inquire about real-time data, and set the parameters of the WSN. The photosynthetic rate of tomato plants were studied in the flowering stage. A LI-6400XT portable photosynthesis analyzer was used to measure the photosynthetic rates of the tomato plants, and the environmental parameters of leaves were controlled according to the presetting rule. The photosynthetic rate prediction model of a single leaf was established based on a back propagation neural network (BPNN). The environmental parameters were used as input neurons after being processed by principal component analysis (PCA), and the photosynthetic rate was taken as the output neuron. The performance of the prediction model was evaluated, and the results showed that the correlation coefficient between the simulated and observed data sets was 0.9899, and root-mean-square error (RMSE) was 1.4686. Furthermore, when different CO_2 concentrations were selected as the input to predict the photosynthetic rate, the simulated and observed data showed the same trend. According to the above analysis, it was concluded that the model can be used for quantitative regulation of CO_2 for tomato plants in greenhouses.

Keywords: WSN, ZigBee, greenhouse information, photosynthetic rate, CO_2 fertilization

DOI: 10.3965/j.ijabe.20150804.1572

Citation: Li T, Zhang M, Ji Y H, Sha S, Jiang Y Q, Li M Z. Management of CO_2 in a tomato greenhouse using WSN and BPNN techniques. Int J Agric & Biol Eng, 2015; 8(4): 43－51.

1 Introduction

Greenhouse production systems are originally implemented in cold regions at northern latitudes in order to extend the production season of plants. In the last several decades, systems for greenhouse management have been greatly developed and many kinds of sensors have been used to measure various information about the environment. Park et al.[1] mentioned that most of the systems have been wired systems, which are more difficult to install and extend and cost more to maintain than wireless systems.

The wireless sensor network (WSN) is one of the most significant technologies of the 21st century. It has become an important tool for environmental monitoring. The relatively low cost of WSN devices allows a sufficiently dense population of nodes to be installed to adequately represent the variability of the environment. WSNs are also used in greenhouses. At present, a crucial issue is to automate and improve the efficiency of

Received date: 2014-11-17 **Accepted date:** 2015-04-14

Biographies: Li Ting, Master, Research interests: Agricultural informatization, Email: 15201423238@163.com; **Ji Yuhan**, Master, Research interests: Agricultural informatization, Email: jyh1009845844@163.com; **Sha Sha**, Master, Research interests: Agricultural informatization, Email: shashaok2010@163.com; **Jiang Yiqiong**, Master, Research interests: Agricultural informatization, Email: 550931538@qq.com; **Li Minzan**, PhD, Professor, Research interests: Precision Agriculture, Email: limz@cau.edu.cn

***Corresponding author: Zhang Man,** Associate Professor, Key Laboratory of Modern Precision Agriculture System Integration Research, Ministry of Education, China Agriculture University, Beijing 100083, China. Tel: +86-10-62737914, Email: cauzm@cau.edu.cn

monitoring and control of greenhouse environments. In order to control and monitor environmental factors, sensors and actuators are essential. Greenhouse crops can benefit a lot from the use of WSN, as WSNs are easier to implement in greenhouses than for outdoor application[2]. Some research has been done on the use of WSNs in greenhouses. Serodio et al.[3] developed a distributed wireless data acquisition and control system for managing groups of greenhouse. Mizunuma et al.[4] designed a wireless LAN for monitoring crop growth in greenhouses. Guo et al., Zou et al., and Zhou et al.[5-7] designed a remote monitoring system for greenhouses based on Zigbee technology. The above research showed that WSNs could play an important role in the management of crop growth. However, less research concerned how to effectively use the collected information and to improve production.

Carbon dioxide (CO_2) is an important raw material for crop growth. During photosynthesis, plants use CO_2 and sunlight to produce carbohydrates for crop growth, so a rich air environment is conducive to crop growth. However, CO_2 should be controlled within a reasonable range. Excess CO_2 not only increases input costs, but also negatively affects the environment. Because of the important role of CO_2 in crop photosynthesis, the regulation of greenhouse CO_2 concentration for optimal growth can improve the efficiency of greenhouse crops and reduce the effects of global warming[8]. To achieve optimal regulation of CO_2, it is necessary to measure the single-leaf photosynthetic rate. Gary et al.[9] developed a tomato photosynthesis model, and the data was mostly obtained from statistical models based on experimental data or the results of previous studies. Jones et al.[10] designed the famous TOMGRO greenhouse tomato growth model, and the majority of their research focused on the relationships among tomato growth, solar radiation, CO_2 concentration, temperature, and other environmental factors. Their aim was to scientifically manage the growth of tomatoes and forecast production. Artificial neural networks (ANNs) offer a superior alternative to traditional physical models. They represent a powerful nonlinear estimator that can be used when the functional form between inputs and outputs is unknown. Moreno et al. and Ehret et al.[11-12] established a photosynthetic rate forecasting model using artificial neural networks that used all available environmental information as input parameters. However, the model needed further optimization. Chen et al.[13] indicated that at noon on sunny days, insufficient CO_2 was provided to the greenhouse crops, so adjusting the CO_2 concentration could increase production and improve the quality of crops. Xiang et al.[14] established two quantitative models comparing greenhouse crop photosynthetic rate and CO_2 concentration, one of which used a BP neural network and one of which used a radial basis function (RBF) neural network. Wang et al.[15] studied variations in CO_2 concentration during different growth processes in greenhouse cultivation. In the most of the above research, manual methods were used to collect environmental information, sampling periods were long, and the data could not well reflect changes in greenhouse environment parameters. Also, few environmental parameters were used in the models, so the output of the models could not accurately predict the photosynthesis rates of a single leaf and could not be used to determine the optimal CO_2 fertilizer supply.

The objective of our research was to quantify the effects of CO_2 on the net photosynthetic rate of a tomato plant by controlling the concentration of CO_2. Tomato was selected as the object of this research because of its wide cultivation. In this study, a WSN and an LI-6400XT portable photosynthesis system were used to automatically measure the environmental parameters in greenhouses and the net photosynthetic rate, respectively. Single-leaf photosynthetic rate prediction models were established based on the BPNN during the late seeding stages. Principal components analysis (PCA) was performed to filter the input variables and make the model more robust. The established model can be used as a basis for regulating levels of CO_2 fertilization under certain environmental conditions.

2 Materials and methods

2.1 Architecture of the system

In order to collect and analyze environmental parameters automatically in a greenhouse, a WSN system was designed and developed. The whole system included sensor nodes, a sink node, and a remote management platform. The sensor nodes, which were connected to sensors, could collect and transmit data to the sink node using the ZigBee protocol. The sink node could start a ZigBee net and establish a connection to the Internet using general packet radio service (GPRS). When the sink node received data from the sensor nodes, it processed and transmitted the data to the remote management platform every two minutes. Through the remote management platform, users could observe and analyze the real-time data in the greenhouse. In this system, five kinds of sensors were connected to the sensor nodes. The sensors measured air temperature and humidity, CO_2 concentration, light intensity, soil temperature and moisture. During the experiment, the air temperature and humidity sensor and the CO_2 concentration sensor were placed in the shade of a shelf, and the light intensity sensor was placed on the top of the shelf. All sensors were installed near the plants.

In order to build a photosynthetic-rate-prediction model and control CO_2 fertilizer accurately, a portable photosynthesis system (LI-6400XT, LI-COR Inc., Lincoln, NE, USA) was used to measure the photosynthetic rate. Photosynthetic responses to environmental variables, such as light, CO_2, humidity and temperature, can also be measured simultaneously. In addition, to extend the range of the data, a 6400-01 CO_2-injector system and a 6400-02B red/blue LED light source were used to control CO_2 concentration and light intensity respectively. Data was transferred to the local PC via an RS232 serial port (Manual LI-6400XT OPEN6.1) and then sent to the remote management platform by the GPRS module. Under artificial conditions, the time interval was set to 3-5 min according to the stability of the photosynthetic rate. Recorded data includes photosynthetic rate, CO_2 concentration, light intensity, air temperature and humidity, and soil temperature and moisture. The methods of PCA and BP network were used to build the prediction model for the photosynthetic rate. The system architecture is shown in Figure 1.

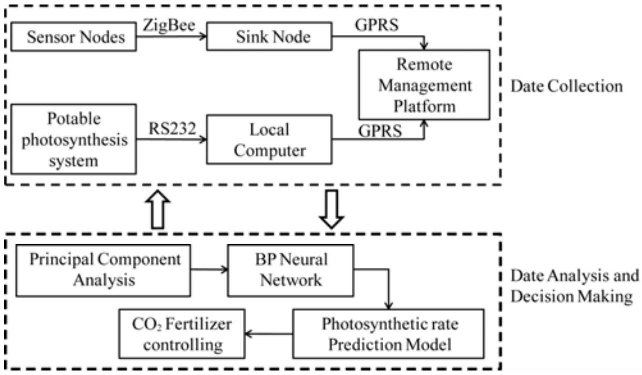


Figure 1 System architecture

2.2 Development of the WSN system

2.2.1 Development of the sensor node

As common communication nodes, sensor nodes could connect to several kinds of sensors. In order to improve utility, four channels of analog and one channel of digital signal were designed for sensor nodes. The output of the majority of analog sensors was a voltage of 0-5 V and current of 4-20 mA; therefore, two types of analog signal interfaces were designed for the sensor node, one that could receive voltage signals in a range of 0-5 V, and the other that could receive current signals in a range from 4-20 mA. A universal asynchronous receiver/transmitter (UART) digital signal interface was used.

The sensor node consisted of a control module, ZigBee wireless module, common interface, and power module. The control module and wireless module were integrated in a micro-processor (Model: JN5139, JENNIC Company, British), which is a low-power, low-cost, and highly reliability wireless microcontroller that is widely used in WSN and ZigBee applications. A high-capacity recharge lithium battery was used to supply the power. The software was programmed using Jennic code blocks. The sensor node program included an analog-to-digital converter (ADC) module, UART module, and ZigBee module.

2.2.2 Development of the sink node

The sink node consisted of a controller module, a GPRS wireless module, and a power module. The JN5139 processor, as a ZigBee coordinator, was also used in the sink node. In addition, a GPRS module was embedded for remote data transmitting. The GPRS module and JN5139 processor were connected in UART mode. The GPRS module was a transparent transmission module from UART to wireless, which provided high-quality communication. External wire power was used for the sink node, because of the relatively high power consumption of the GPRS module.

The sink node program included a UART module and a ZigBee module. The system initialized after being turned on, and then the GPRS module connected to the remote platform using the FTP protocol and continuously maintained that connection. At the same time, the sink node established a ZigBee net, and then the sensor nodes began to search and join it. After that, users could set configuration parameters on the remote platform and then wirelessly transmit to the sink node. The configuration commands included collection start, collection stop, and collection period. The data collected by the sensor nodes from ADCs and UART was processed. The processed data was transmitted to the sink node via ZigBee. The sink node would further process the data and transmit it to the remote management platform.

2.2.3 Development of the remote management platform

The remote management platform was developed based on browser/server (B/S) mode, which allowed users to access this application and query monitoring data or other management operations through a Web browser. For data storage and management, TCP Socket technology was used to receive the uploaded data from stand-alone monitoring software via GPRS.

The platform included five modules: data collection, data storage, basic information maintenance, data analysis, and data output. The data collection module used TCP-socket technology to listen to and receive uploaded data from stand-alone monitoring software, determine whether the data qualified, and store only the valid data. The data storage module could store the received sensor data, the history data for the greenhouse, photosynthetic rate data, basic information, and user information about the greenhouse. In the basic information maintenance module, an administrator could update and maintain the basic information in time, such as allocating the rights of users and updating the information of the greenhouse. The data analysis module could analyze the uploaded data and build a photosynthetic rate prediction model. It could also calculate the best CO_2 value based on the real situation. The data output module could display the uploaded data in a curve or chart format.

2.3 Experimental design

The experimental site was an experimental greenhouse of the College of Water Conservancy and Civil Engineering of China Agricultural University. The area of the greenhouse was approximately 50 m^2. The experiments were carried out on 7–8 July, 2011, from 8:00 to 18:00. Tomatoes in the late seedling stage were selected as the research object. The greenhouse environmental parameters (air temperature and humidity, CO_2 concentration, soil temperature, soil moisture, and light intensity) were automatically collected by the sensor nodes every two minutes. The photosynthetic rate of the single leaf was measured three times by the LI-6400XT every 3-5 min.

In order to measure the photosynthesis rate of tomatoes at different CO_2 concentrations and under different light intensities, the experiment was carried out in an artificial environment. As plants need some time to acclimate and reach the maximum photosynthetic rate, photosynthetic induction was required before measurement. In natural conditions, the saturation intensity of C3 plants is about 1 000 μmol/($m^2\cdot$s)[16], so the measured leaf was first set under a light intensity of 1 000 μmol/($m^2\cdot$s) and atmospheric CO_2 to wait for the photosynthetic rate stability, which took nearly 30 min. Measurement was started after photosynthetic induction of the leaf. A pure liquid CO_2 cylinder was used to control the concentration of CO_2 artificially, and the values of CO_2 concentration were 400, 300, 200, 100, 50, 400, 600, 800, 1 000, 1 300, 1 600, and 2 000 μmol/mol to ensure that the leaf accommodated the change of CO_2 concentration. A red/blue LED light source was used to control light, and the values of light intensity were set to 1 800, 1 500, 1 200, 1 000, 800, 600, 400, 200, 100, 50, 20 and 0 μmol/($m^2\cdot$s). During the experiment, the light intensity was changed according to the above order in every fixed CO_2 concentration, and the light response curves were measured. In order to reduce internal system error and obtain accurate measurements, a matching operation was needed for LI-6400XT when CO_2 concentration was changed. The values of air temperature and humidity used to build the models were measured by the LI-6400XT to match the light intensity and CO_2 concentration. In addition, the leaves of the best-growing plants above the fourth phyllotaxy, which were in the functional-leaf stage, were selected for study in order to measure their photosynthetic rate more accurately and stably[17].

2.4 Prediction Models of Photosynthetic Rate

BPNN models were established using the data collected from the above-described experiments in the late seeding stages. The data was prepared for neural network models using data preprocessing and PCA to make the models more accurate.

2.4.1 Data preprocessing

Because the sensor node and LI-6400XT collected data independently, the data was related firstly. The second step was error correction and negative data deletion. It was necessary to select accurate, typical experimental data for the samples used to train the Neural Networks (NN). Thirdly, because raw data was not all in the same orders of magnitude, the data need to be normalized before training the network, in order to avoid flooding the small pool of data. The hypothesis of the observation matrix of the p-dimensional vector $X=(X_1, X_2, \ldots, X_p)$ is shown in Equation (1), where x_{ij} is the i^{th} observation value of variable X_j and X'_{ij} is the normalized value of x_{ij} according to Equation (2),

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} \tag{1}$$

$$x'_{ij}=2\times\frac{x_{ij}-\min\limits_{1\le k\le n} x_{kj}}{\max\limits_{1\le k\le n} x_{kj}-\min\limits_{1\le k\le n} x_{kj}}-1 \tag{2}$$

where, $\min\limits_{1\le k\le n} x_{kj}$ represents the minimum of variable X_j and $\max\limits_{1\le k\le n} x_{kj}$ represents the maximum of variable X_j. After preprocessing, the minimum and maximum values were normalized to [-1, 1].

2.4.2 Principal component analysis

Taking into account the existence of redundant information in the acquired variables, integrated variables were used to reduce the correlation between variables. PCA can convert the original variables into new integrated variables with a small loss of information. The integrated variables are unrelated to each other, and can reflect the information of the original variables. Each new integrated variable is a linear combination of the original variables.

The integrated variables are called the main principal of the original variables, and the coefficient between K^{th} main principal and the original variables is called the factor-loading capacity, a very important parameter in PCA[18]. Equation (3) indicates the relationship between the integrated variables and the normalized original variables.

$$\begin{cases} Z_1=b_{11}x'_1+b_{12}x'_2+\cdots+b_{1p}x'_p \\ Z_2=b_{21}x'_1+b_{22}x'_2+\cdots+b_{2p}x'_p \\ Z_n=b_{n1}x'_1+b_{n2}x'_2+\cdots+b_{np}x'_p \end{cases} \tag{3}$$

where, b_{ij} is the factor-loading capacity. The size and direction of the factor-loading capacity reflects the relationship between the main components Z_j and the original variables.

Hypothesis C_{ij} is the correlation coefficient of the main components Z_i and the original variables x'_j.

Based on Equation (4), the correlation coefficient C_{ij} can be calculated as

$$C_{ij}=\sqrt{\lambda_i}b_{ij} \tag{4}$$

where, λ_i is the eigenvalue corresponding to the i^{th} principle component.

2.4.3 Establishment and performance evaluation of the photosynthesis prediction model

NN is similar to a black box, and the prediction model can be built for an unknown internal mechanism. It is suitable for a complex prediction model, such as photosynthesis prediction. BPNN is the most commonly used form of NN for backward propagation of errors[19]. The drawback of NNs is the difficulty of interpreting results, which means that better evaluation methods are required[20]. The evaluation indices can be used to quantify the quality of the training model and evaluate training result. In this paper, the evaluation indices include the correlation coefficient (R), average relative error (ARE), mean absolute error (MAE), and root-mean-square error (RMSE).

In order to fully utilize the data and increase the stability of the model, a cross-validation method was used to effectively estimate the generalization error of the experimental method. K-fold cross-validation was used for this paper.

BPNN topology

In this study, the output of the BPNN was the photosynthetic rate of a single leaf. A single hidden layer was used to reduce the complexity of the network. The number of nodes in the hidden layer was usually based on empirical formulas. The appropriate number of nodes was determined as

$$n_h = \sqrt{n_i + n_o} + l \tag{5}$$

where, n_h, n_i, and n_o represent the number of hidden layer nodes, input layer nodes, and output layer nodes, respectively, and l is a constant with a value between 1 and 10. The selection of hidden layer nodes was as follows: firstly, determine the approximate range of the number of nodes with reference to the empirical formula. Secondly, choose the final hidden layer nodes based on training and testing results.

Transfer function

Log-sigmoid, tan-sigmoid, and linear transfer functions can be used as transfer functions. The log-sigmoid and linear transfer functions were used in this study.

Training of BPNN

K-fold cross-validation was accepted in this paper. The validation process was as follows: the training samples were randomly divided into *K* sets, usually divided into *K*-equal sets. Among the sets, *K*-1 sets were used to build the model, and the rest of the sets were used to test the model. This method can obtain valid information as much as possible from limited data, and effectively avoid local minimum and over-fitting problems[21]. The process was repeated *K* times, and the average value of the *K* assessment processes was used as the generalization error. The best BPNN model was chosen based on a suitable network architecture that combined a high *R* and a low *RMSE*[22].

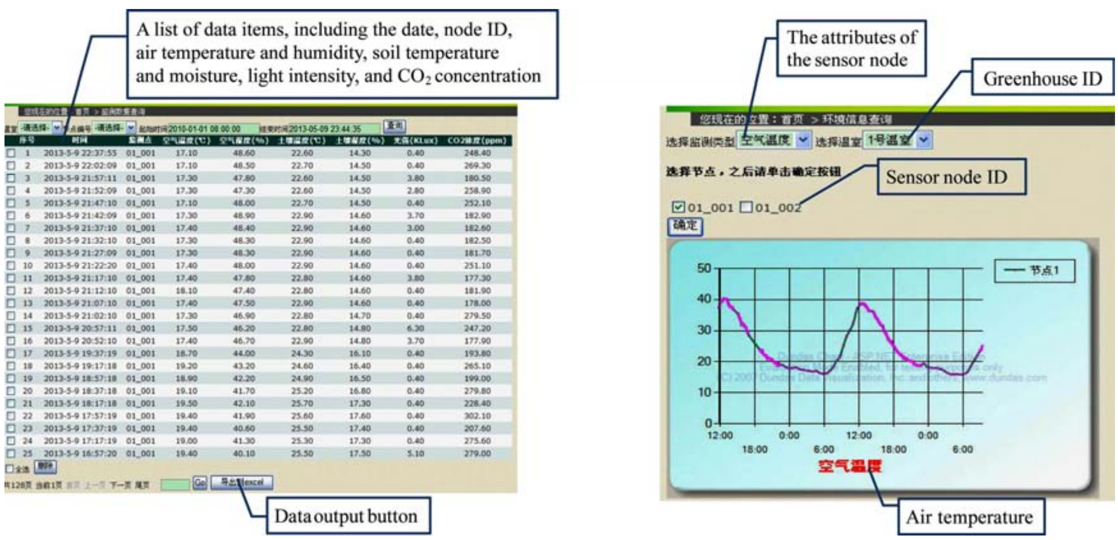
Performance evaluation of models based on the BPNN

The evaluation indices of performance include Correlation coefficient (*R*), Average relative error (ARE), Mean absolute error (MAE), and Root-mean-square error (RMSE).

3 Experiment and analysis

3.1 Performance of the WSN system

After a lot of testing, both sensor nodes and the sink node could collect and transfer data automatically. The remote management system could collect, store, and analyze data, as well as make suggestions based on the analyzed result. For data display and query, the real-time monitoring data of every node could be shown by curve-shaped figures and tables. In table mode, the data wanted to query would be displayed after selecting greenhouse, sensor node ID and setting the time period in sequence. The data could be also outputted and saved in *.xls format, as shown in Figure 2a. Meanwhile, each node has a check box, one or a few sensor nodes could be selected at the same time. In curve-shaped figure mode, after selecting the attributes of sensor node and the data period, the changing curve would be drawn automatically, as shown in Figure 2b.



a. List of real-time monitoring data items

b. Curve shape of real-time monitoring data

Figure 2 System interface

3.2 Results of the experiments

3.2.1 Principal component analysis

In order to reduce the number of input variables and get better training result, the PRINCOMP function in SAS 8.0 (SAS Institute, Cary NC, USA) was used for PCA. The results are shown in Table 1.

Table 1 Eigenvalue and contribution rate of each principal component

Principal component analysis	Eigenvalue	Contribution	Accumulated contribution
1	2.37821896	0.3964	0.3964
2	1.93408019	0.3223	0.7187
3	1.04202940	0.1737	0.8924
4	0.44684185	0.0745	0.9669
5	0.12363916	0.0206	0.9875
6	0.07519044	0.0125	1.0000

According to Table 1, 89.24% of the information in the original variable was contained in the first three principal components. The first four principal components were accepted in order to obtain higher accuracy in this paper.

The correlation coefficient between the original variables and the principal components can be calculated using the SAS correlation (CORR) function, as shown in Table 2. In Table 2, the first line is the correlation coefficient and the second line is the probability under the assumption that the correlation coefficient is equal to zero, i.e., the significance level. The first principle component was significantly correlated with the original variables, except light intensity at the level of 0.05. The second principle component was decided by the original variables except soil moisture. The third and fourth principle components were decided by the original variables except air temperature and humidity.

Table 2 The correlation coefficients between principal component and variables

	Air Temperature	Air Humidity	Light Intensity	CO_2 Concentration	Soil Moisture	Soil Temperature
PC1	0.93124	0.18067	0.12879	-0.66580	0.82390	0.58283
	<.0001	0.0333	0.1308	<.0001	<.0001	<.0001
PC2	0.25005	-0.93702	-0.45973	0.57502	-0.01585	0.67180
	0.0030	<.0001	<.0001	<.0001	0.8531	<.0001
PC3	0.11931	0.07576	0.85388	0.35853	-0.23096	0.33325
	0.1618	0.3754	<.0001	<.0001	0.0062	<.0001
PC4	-0.11561	-0.16201	0.16954	0.23365	-0.25491	0.50884
	0.1753	0.0567	0.0460	0.0056	<.0001	0.0025

Note: PC: principle component.

Equation (6) was obtained from Table 2. Four principal components were used to build the photosynthetic prediction model based on BPNN input variables:

$$\begin{cases} Z_1 = 0.931x_1' + 0.181x_2' + 0.129x_3' - 0.669x_4' + \\ \quad 0.824x_5' + 0.583x_6' \\ Z_2 = 0.250x_1' - 0.937x_2' - 0.460x_3' + 0.575x_4' - \\ \quad 0.016x_5' + 0.672x_6' \\ Z_3 = 0.119x_1' + 0.076x_2' + 0.854x_3' + 0.359x_4' - \\ \quad 0.231x_5' + 0.333x_6' \\ Z_4 = -0.116x_1' - 0.162x_2' + 0.170x_3' + 0.234x_4' - \\ \quad 0.255x_5' + 0.509x_6' \end{cases} \tag{6}$$

3.2.2 Establishment and performance evaluation of the photosynthesis prediction model

Data was randomly divided into two groups: a training group that was used to train the NN and a testing group that was used to verify the effectiveness of the models. In this experiment, 139 sets of samples were used, of which 119 sets were selected as training samples, and 20 sets (14%) were selected as validation samples. Based on Equation (5), the number of hidden layer neurons was determined. The successive ascension method was used, and ultimately the number of hidden layer neurons was set to 10.

After 10-fold cross-validation, the resulting average indices of the cross-validation performance *R,* ARE, MAE and RMSE were obtained as 0.9523, 0.5941, 1.0319 and 1.9428, respectively. Figure 3 is the testing effect of the BPNN. The evaluation indices of the BPNN model performance *R,* ARE, MAE, and RMSE were 0.9899, 0.9682, 1.2309 and 1.4686, respectively. The above results showed that the performance of BPNN prediction results were better than the cross-validation, which meant that the BPNN model had better generalization performance.

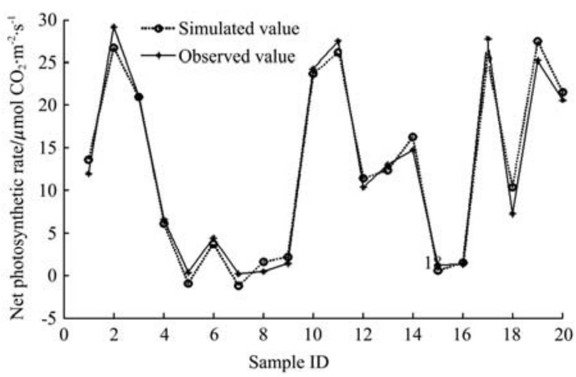


Figure 3 Testing effect of the BPNN

Based on the above photosynthesis rate prediction model, the maximum photosynthesis rate can be found by changing CO_2 concentration under certain environmental conditions. CO_2 concentration corresponding to the maximum photosynthesis rate is the optimal level of CO_2 concentration. Figure 4 shows the relationship between CO_2 concentration and photosynthetic rate according to the prediction model. The CO_2 concentration changed from 300 to 1 800 μmol/mol, and the interval was set to 50 μmol/mol. Other environmental factors were set as follows: air temperature was set to39.8°C, humidity to 42.8%, light intensity to 1 000 μmol/(m^2·s), and soil moisture to 30%. In addition, Figure 5 demonstrates that the maximum rate of photosynthesis was obtained when the CO_2 concentration reached 1 400 μmol/mol. Under this condition, application of the appropriate amount of CO_2 could make the plant grow better.

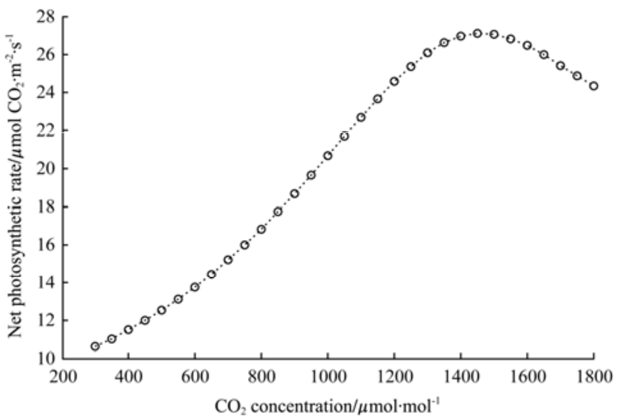


Figure 4 Simulated relationship between CO_2 and photosynthetic rate

4 Conclusions

A monitoring system for greenhouse environment information based on WSN was designed in this study, and a model was established based on BPNN for predicting the rate of photosynthesis of tomato plants in the late seeding stage. The system included sensor nodes, a sink node and a remote management platform, and two kinds of wireless communication techniques were adopted in the system: ZigBee for the communication of sensor nodes and the sink node, and GPRS module for the communication of the sink node and the remote management platform. Users could set parameters for sensor nodes using the remote platform for monitoring environmental parameters which included air temperature, air humidity, light intensity, CO_2 concentration, soil moisture, and soil temperature.

Using the prediction model, the relationship between CO_2 concentration and the rate of photosynthesis was analyzed to ensure that the proper amount of CO_2 was provided to the tomato crop in the late seeding stage. The results showed that CO_2 significantly affected the rate of photosynthesis during this stage. When different CO_2 concentrations were selected as the input of the models to predict the rate of photosynthesis, the simulated and observed data followed the same trend, as long as all other environmental factors remained unchanged. These models are useful for CO_2 fertilization controlling under greenhouse conditions.

Acknowledgements

The authors acknowledge that this work was supported by the National Natural Science Fund (Grant No. 31271619) and the Doctoral Program of Higher Education of China (Grant No. 20110008130006).

[References]

[1] Park D H, Kang B J, Cho K R, Shin C S, Cho S E, Park J W, et al. A study on greenhouse automatic control system based on wireless sensor network. Wireless Pers Commun, 2011; 56: 117–130.

[2] Ruiz-Garcia L, Lunadei L, Barreiro P, Robla J I. A review of wireless sensor technologies and applications in agriculture and food industry: State of the art and current trends. Sensors, 2009; 9: 4728–4750.

[3] Serodio C, Cunha J B, Morais R, Couto C A, Monteiro J L. A networked platform for agricultural management systems. Computers and Electronics in Agriculture, 2001; 31: 75–90.

[4] Mizunuma M, Katoh T, Hata S. Applying IT to farm fields—A wireless LAN. NTT Techinical Review, 2003; 1(2): 56–60.

[5] Guo W C, Cheng H J, Li R M, Liu J, Zhang H H. Greenhouse Monitoring System Based on W ireless Sensor Networks. Transactions of the CSAM, 2010; 41(7): 181–185. (in Chinese with Chinese abstract)

[6] Zou G H. Development of the monitoring system for greenhouse environment based on WSN. Doctoral thesis. Nanjing University of Aeronautics and Astronautics, China,

2012.

[7] Zhou J J, Wang X, Zou W, Zhang R R, Ma W. Remote greenhouse monitor and control system based on Zigbee. China's Rural Water and Hydropower, 2013; (1): 67–69. (in Chinese with Chinese abstract)

[8] Lee D H, Lee K S, Choi C H, Kim H J, Chung S O, Cho Y J. Prediction of CO_2 emission from soil for optimal greenhouse control. In: 2011 ASABE Annual International Meeting, Paper Number: 1111628.

[9] Gary C, Jones J W, Tchamitchian M. Crop modelling in horticulture: State of the art. Scientia Horticulturae, 1998; 74: 3–20.

[10] Jones J W, Dayan E L, Allen H, Keulen V, Challa H. A dynamic tomato growth and yield model (TOMGRO). Transactions of the ASAE, 1991; 34(2): 663–672.

[11] Moreno R S, Aguilar A R, Cruz I L, Reyes M G. Artificial neural network as a prediction tool in agricultural variables. In: 2006 ASABE Annual International Meeting, Paper Number: 063071.

[12] Ehret D L, Hill B D, Raworth D A. Artificial neural network modeling to predict cuticle cracking in greenhouse peppers and tomatoes. Computers and Electronics in Agriculture, 2008; 61(2): 108–116.

[13] Chen S C, Zou Z R, He C X, Zhang Z B, Yang X. Rules of CO_2 concentration change under organic soil cultivation and effects of CO_2 application on tomato plants in solar greenhouse. Acta Botanica Boreali-Occidentalia Sinica, 2004; 24(9): 1624–1629.

[14] Xiang M J, Zhang M. Control of CO_2 based on two kinds of neural network in greenhouse. Agricultural Technology & Equipment, 2010; 184(2): 11–12.

[15] Wang Y, Xie J M, Yu J H, Lü J, Wang X Y. Variations of CO_2 concentration in solar greenhouse on sand land with tomato substrates cultivation. Journal of Gansu Agricultural University, 2012; 47(6): 57–62. (in Chinese with Chinese abstract)

[16] Xu D Q, Chen G Y, Yu G L, Chen Y. Exploring the observation methods of photosynthetic responses to light and carbon dioxide. Journal of Plant Physiology and Molecular Biology, 2006; 32(6): 691–696.

[17] Manual LI-6400XT OPEN6.1. Lincoln, NE, USA: LI-COR Inc.

[18] Chen G Y, Yu G L, Chen Y. Exploring the observation methods of photosynthetic responses to light and carbon dioxide. Journal of Plant Physiology and Molecular Biology, 2006; 32(6): 691–696.

[19] Han L, Li R, Zhu H L. Comprehensive evaluation model of soil nutrient based on BP neural network. Transactions of the CSAM, 2011; 42(7): 109–115. (in Chinese with Chinese abstract)

[20] Xiang M J. Optimization of regulation greenhouse environmental factors based on information fusion Technology. Doctoral thesis. Jiangsu University, China, 2009. (in Chinese with Chinese abstract)

[21] Han M, Ding J. Improvement of BP algorithm based on cross-validation method and its implementation. Computer Engineering and Design, 2008; 29(14): 3738–3739. (in Chinese with Chinese abstract)

[22] Ehret D L, Hill B D, Helmer T, Edwards D R. Neural network modeling of greenhouse tomato yield, growth and water use from automated crop monitoring data. Computers and Electronics in Agriculture, 2011; 79(1): 82–89.