# A predictive model of photosynthesis for cucumber

Pan Gao[a,b,c] and Jin Hu[a,b,c,*]

[a]College of Mechanical and Electronic Engineering, Northwest A&F University, China; [b]Key Laboratory of Agricultural Internet of Things, Ministry of Agriculture and Rural Affairs, China; [c]Shaanxi Key Laboratory of Agricultural Information Perception and Intelligent Service, China

## ABSTRACT

Photosynthetic rate (Pn) of plants is determined by environment, such as temperature, carbon dioxide ($CO_2$), and light. Light environment includes light intensity (LI) and light quality (LQ). It is important to build a predictive model of protected crops' Pn where LI, LQ and other environmental factors are comprehensively considered. In this paper, cucumber was taken as experimental material, and a nested experiment was designed to measure the Pn under different temperature, $CO_2$ concentration ([$CO_2$]), LI and LQ. On the bases of these measured data, a predictive model of Pn was built by using support vector regression (SVR) algorithm. The performance of training set with coefficient of determination (DC) of 0.9990, and the root-mean-square error (RMSE) of 0.0478 $\mu mol\cdot m^{-2}\cdot s^{-1}$ demonstrated that the model is highly accurate after training. The validation results of predictive model showed that the fitting slope was 1.0015, and the intercept was 0.0223 between measured and predicted Pn values, which indicated that the model was accurate to calculate the Pn of plants under different environment.

**Keywords:** Photosynthetic rate, support vector regression, predictive model, light environment

## 1. INTRODUCTION

Photosynthetic reaction, a core reaction for matter accumulation of plants, is closely related to crop yield and quality[1]. Photosynthetic rate (Pn) would be affected by light, carbon dioxide ($CO_2$) and temperature in greenhouse. Light is not only the light intensity (LI)[2-4], but also the light quality (LQ, the ratio of red light to total light intensity)[5]. In the research of plant photosynthetic rate prediction model, Ye et al.[6] proposed different types of light response models on the basis of traditional photosynthetic physiological models, which laid a good foundation for photosynthetic model research. However, many physiological parameters are hard to determine in these models. These models cannot be applied to protected horticultural environmental regulation, directly. In recent years, predictive model of Pn have been proposed, but the coupling relationship between multiple environmental factors and plant Pn was not considered in the early models[7]. For this reason, scholars have established a Pn prediction model with multi environmental factors as inputs by using multiple non-linear regression method, which improved the accuracy and versatility of the Pn prediction model[8, 9]. But it still had insufficient accuracy in the fitting of multi-dimensional photosynthetic data. Using intelligent algorithm could effectively improve the accuracy of the model, and it has become a new research hotspot[10, 11]. However, most of the existing predictive models of Pn based on intelligent algorithms had not considered the difference of photosynthetic capacity caused by different LQ in the light environment.

Related studies showed that the growth and development of crops was related to the LI and LQ. Some results showed that blue light and red light had different effects on Photosynthetic regulation[12]. Red light could inhibit photosynthetic electron transfer, while blue light could effectively alleviate the above inhibition. The biological effects of different wavelengths of light on the growth of crops are different. Red light could correspond to the light wavelength needed for chlorophyll to transition from the ground state to the first excited state; Blue light could correspond to the light wavelength needed for chlorophyll to transition to a higher excited state. The LQ would affect the growth and development of crops significantly. Integrating the LQ to control the greenhouse light environment can optimize the control effect and improve the photosynthetic capacity and yield of crops to a certain extent, which is one of the keys to realize the efficient production of crops.

In this study, cucumber was selected as the experimental object, and the multi factor nested experiment was designed to obtain the data. The predictive model of Pn was constructed by using SVR algorithm, which would complete the unified

*hujin007@nwsuaf.edu.cn

International Conference on Computer Application and Information Security (ICCAIS 2021), edited by Yingfa Lu, Changbo Cheng, Proc. of SPIE Vol. 12260, 1226013 · © The Authors.
Published under a Creative Commons Attribution CC-BY 3.0 License · doi: 10.1117/12.2637492

prediction of cucumber leaves' Pn in different environments. This would provide the foundation for the regulation of environmental factors in protected agriculture.

## 2. MATERIALS AND METHODS

### 2.1. Experimental materials

The data for model building were collected during the experiment of Pn measurement. This experiment was conducted at College of Mechanical and Electronic Engineering, Northwest A&F University, from December 1, 2019 to January 10, 2020. The cucumber for experiment was "Bonai 14-3". The cucumber seeds were soaked in a petri dish for a week to make them swell and germinate, and then they were planted in 50-hole trays. After these cucumber seedlings grew three weeks, they were planted into flowerpots with size of 15×15×10cm. These seedlings were grown in a growth chamber (MD1400, Sinde, Netherlands). The environment of climate chamber was set as follows: the light period of day and night was 14 and 10 hours; the temperature of day and night was 25 and 16°C; the relative humidity of day and night was 60% and 50%; the [$CO_2$] was 400 μmol·m$^{-2}$·s$^{-1}$. When cucumber seedlings grew five leaves, the fluorescence detection and Pn collection were carried out on the third leaf. Before the experiment, the $F_v/F_m$ of cucumbers were detected by MINI-PAM-II Portable Fluorometer (WALZ company, Germany) to choose leaves with similar chlorophyll fluorescence. And then, the Pn of these leaves under different environment were determined by a portable photosynthesis system (LI-6800, USA). The data collection processes were in Figure 1.

### 2.2. Experimental methods

The chlorophyll fluorescence parameter $F_v/F_m$ of leaves were measured to determine the leaf state, and 90 cucumber seedlings with the same or similar $F_v/F_m$ of the third leaf were selected to measure Pn. The test leaves should be fully dark adapted for 20 minutes by dark blade clamp at the position of Pn data to be collected. Then, the dark blade clamp was opened, and the minimum fluorescence parameter $F_o$ of the test sample was measured under the measurement light (wavelength of 470 nm, LI of 0.05 μmol·m$^{-2}$·s$^{-1}$). After that, the sample was irradiated with saturated pulsed light (wavelength of 470 nm, LI of 6000 μmol·m$^{-2}$·s$^{-1}$) for 300 ms to obtain the maximum fluorescence parameter $F_m$. $F_v/F_m$ could be calculated by:

$$F_v / F_m = \frac{F_m - F_o}{F_m} \tag{1}$$

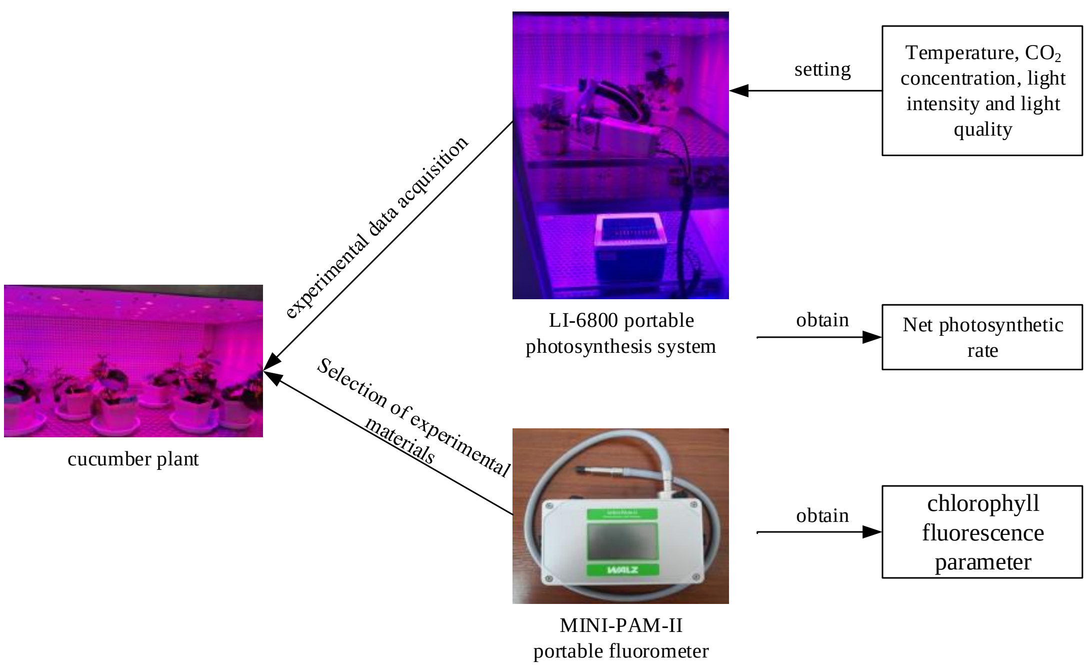


Figure 1. Methods and data collection processes.

Air temperature, [$CO_2$], LI and LQ were selected to design a nested experiment to measure the Pn of the living third leaves of cucumber seedlings. The experiment was carried out from 9:00 to 17:30 every day, and the data was measured by using LI-6800 to control many environmental factors, such as temperature, [$CO_2$], and light of leaves. During the nested experiment, the flow rate was set to 500 μmol·s$^{-1}$ in flow control module, the fan speed was set to 1000 r/min in fan control module, and the moisture control module was used to set the relative humidity of 50%. The gradients of the temperature parameter are set to 18, 21, 24, 27, 30, 33 °C. The gradients of the [$CO_2$] parameter are set to 300, 700, 1000 μmol·mol$^{-1}$. The gradients of the LQ parameter are set to 0.1, 0.3, 0.4, 0.5, 0.6, 0.7, 0.9. The gradients of the LI parameter are set to 0, 30, 75, 150, 200, 300, 500, 600, 700, 800, 1000, 1200, 1400, 1600, 1800 μmol·m$^{-2}$·s$^{-1}$. In the experiment, Pn was collected by the light response program of LI-6800. Before the measurement, the temperature, [$CO_2$], and LQ should be set by respective modules, and the LI of chamber was set to 1800 μmol·m$^{-2}$·s$^{-1}$ to make leaves be adapted to light. After the Pn was stable, the light response program was started to record photosynthetic data. 1890 groups (15×3×6×7) of experimental data were obtained.

### 2.3. Predictive model of photosynthetic rate

In the study of predictive model of Pn, SVR algorithm were widely used. In this paper, the data obtained from the experiment were combined with SVR algorithm to create a predictive model of Pn for cucumber. Temperature, [$CO_2$], LI, and LQ were taken as input, and Pn was taken as output. The process of model building was shown in Figure 2.

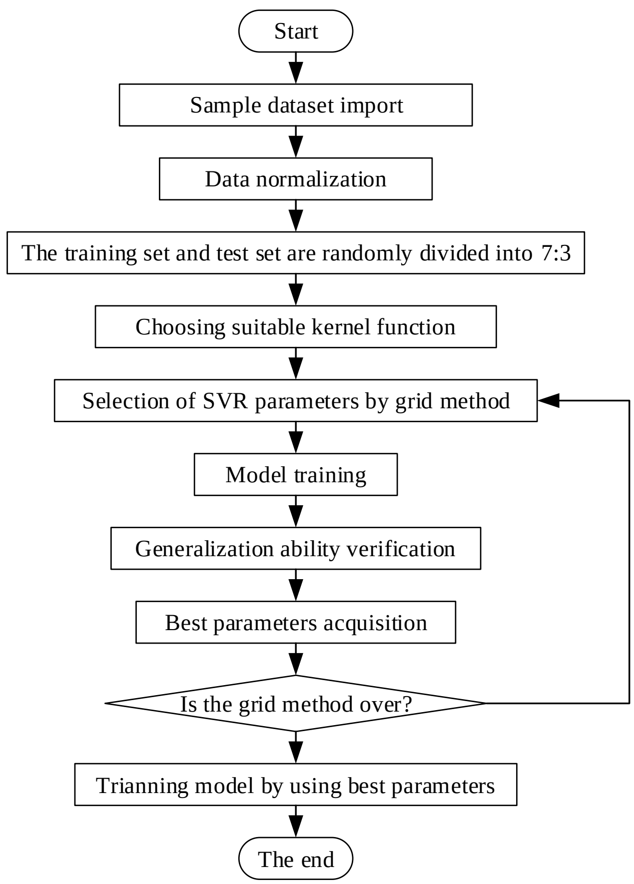


Figure 2. The process of model building.

First of all, it was necessary to normalize the data of different dimensions to make them in the same order of magnitude. 70% of the normalized data was randomly selected as training set, and 30% of the normalized data was randomly selected as prediction set. The inputs of the $i^{th}$ sample were $x_i^1$, $x_i^2$, $x_i^3$, $x_i^4$, and the output was $Pn_i$. $x_i^1$, $x_i^2$, $x_i^3$, and $x_i^4$ were [$CO_2$], temperature, LQ and LI. And $Pn_i$ was the Pn of the $i^{th}$ sample.

In parameters selection, radial basis function (RBF) has the feature that its complexity would not change with the change of parameters. As a kernel function, RBF could convert the data to a higher dimensional space. Then, some nonlinear problem that could not be solved in low dimensional space can be linear problem in high dimensional space. The support vector could be easy to obtained using RBF kernel. Finally, the final regression hyperplane was determined by the support vector. For SVR algorithm, it would be coupled to affect the model performance that the kernel parameter $g$ and penalty coefficient $c$ changed. According to the results of multiple training of the grid validation method, it could be obtained that the generalization ability of the model was the best with the parameter $c$ of 40 and $g$ of 5. The final predictive model of Pn was as follows:

$$f(X) = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i)K(X, X_i) + b \tag{2}$$

where $K(X, X^p) = exp\left(-\frac{\|X-X^p\|^2}{2\delta^2}\right) = \exp\left(-g \cdot \|X - X^p\|^2\right)$, which is RBF kernel function; $X$ is the original data; $X^p$ is the support vector; $\hat{\alpha}_i$, $\alpha_i$ are Lagrange Multiplier in solving process; $b$ is the bias of model.

## 3. RESULTS

### 3.1. Photosynthetic rate results

The partial results of Pn test of temperature, $[CO_2]$, LI and LQ coupling are shown in Figure 3. Pn is directly affected by light, and also affected by temperature and $[CO_2]$.

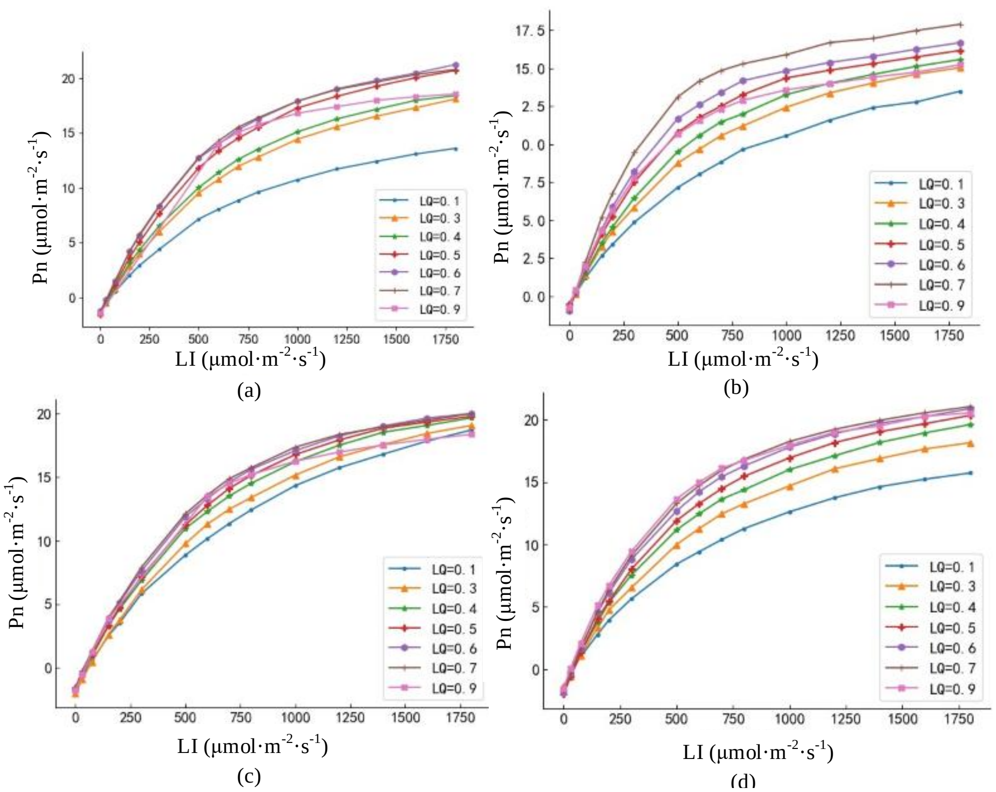


Figure 3. The partial results of experiment.

### 3.2. Prediction results

To verify the performance of SVR model, the other machine learning algorithm of random forest (RF) and a nonlinear regression (NLR) algorithm of quartic cubic polynomial regression are selected to fit the same training set data. The results are shown in Table 1. Among them, SVR model had the highest coefficient of determination (DC), which was 0.9990. Meanwhile, the maximum absolute error (MAE) of 0.6214 $\mu mol \cdot m^{-2} \cdot s^{-1}$ and root mean square error (RMSE) of 0.0478 $\mu mol \cdot m^{-2} \cdot s^{-1}$ were all the lowest in these three models. Accordingly, SVR algorithm had advantages in building photosynthetic model.

Table 1. Comparison of the performance of three models.

| Models | DC | MAE | RMSE |
|---|---|---|---|
| SVR | 0.9990 | 0.6214 $\mu mol \cdot m^{-2} \cdot s^{-1}$ | 0.0478 $\mu mol \cdot m^{-2} \cdot s^{-1}$ |
| RF | 0.9984 | 1.6819 $\mu mol \cdot m^{-2} \cdot s^{-1}$ | 0.0828 $\mu mol \cdot m^{-2} \cdot s^{-1}$ |
| NLR | 0.9359 | 4.8346 $\mu mol \cdot m^{-2} \cdot s^{-1}$ | 3.2154 $\mu mol \cdot m^{-2} \cdot s^{-1}$ |

To further verify the generalization ability of the predictive model of Pn for unknown data, the model validation was used to calculate the DC and RMSE from the prediction set data. As shown from Table 1, the largest DC of 0.9974 and the smallest RMSE of 0.1294 $\mu mol \cdot m^{-2} \cdot s^{-1}$ shows the best performance of SVR model. The fitting results between the predicted value and the real value of the model are shown in Figure 4. The slope of SVR model is 1.0015, which is the nearest of 1, and the intercept is 0.0223, which is the closest to 0. This indicated that the model had accurate results and strong generalization ability.

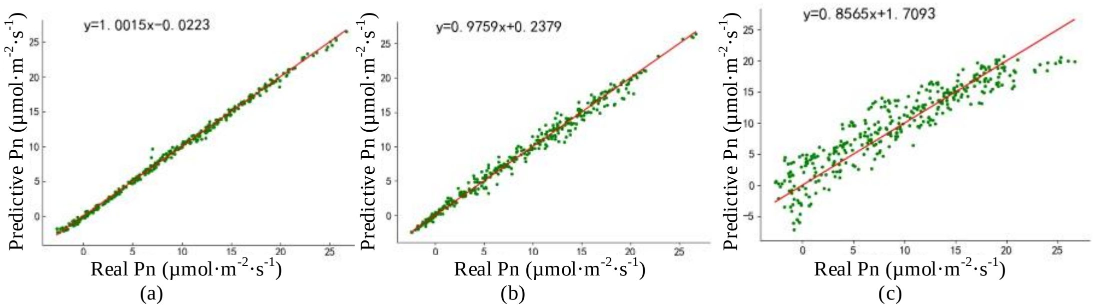


Figure 4. Fitting results of the models: (a), (b) and (c) are fitting graphs of real Pn and predictive Pn of SVR, RF and NLR algorithm respectively.

## 4. DISCUSSION

The [$CO_2$] in the environment will affect the stomatal conductance of crop leaves, which could lead to the change of photosynthesis. Li et al.[13] studied the effect of [$CO_2$] on stomatal conductance of soybean leaves. The results showed that the stomatal conductance of crop leaves decreased with the increase of [$CO_2$]. To explore the effect of [$CO_2$] on crop stomatal conductance, the stomatal conductance of cucumber under different [$CO_2$] was compared, and the results are shown in Figure 5.

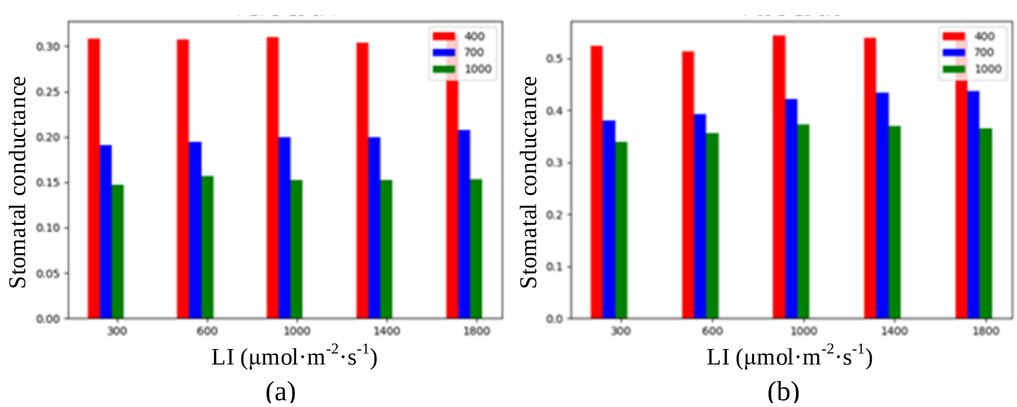


Figure 5. Variation of stomatal conductance of cucumber. (a): the temperature was 21°C and the LQ is 0.4; (b): the temperature was 30°C and the LQ is 0.5.

It could be seen from Figure 5 that the stomatal conductance of cucumber leaves decreased with the increase of [$CO_2$]. It further showed that cucumber would open its own stomata at low [$CO_2$] to absorb $CO_2$ better and carry out photosynthesis; When [$CO_2$] increased, cucumber leaves would close part of stomata to regulate their own photosynthesis. It is proved that the supplement of blue light can promote the stomatal opening of crop leaves. Under red light, the stomatal conductance and photosystem II activity of leaves decreased significantly, and the supplement of blue light could maintain the photosystem II activity and drive photosynthesis. In addition, blue light can rapidly and reversibly adjust the stomatal aperture, thus changing the stomatal conductance of crops. CBC (including CBC1 and CBC2 kinases) can integrate $CO_2$ and blue light signals and promote stomatal opening under the action of low concentration of $CO_2$ and blue light. Therefore, when the [$CO_2$] in the environment increases, crops will adjust photosynthesis by closing stomata, and the required blue light will decrease, that is, the LQ will increase; when the [$CO_2$] in the environment is low, crops will open their stomata, and the required blue light will increase, that is, the LQ will decrease.

Temperature, LI and other environmental conditions can also affect the stomatal conductance of crop leaves. When the environmental temperature is higher, the transpiration of crop leaves becomes stronger. By closing the stomata and other adjustment, the water loss can be prevented. At this time, the blue light required for photosynthesis of cucumber leaves decreases and the LQ increases. The demand for red and blue light in crops may also be closely related to the activities of various enzymes and plant hormones, which is caused by the coupling effects of various factors. Therefore, the coupling dynamic control of LQ and LI is the key to efficient light supplement in facility environment.

## REFERENCES


[1] Duan, M., Yang, W. and Mao, X., "Effects of water deficit on photosynthetic characteristics of spring wheat under plastic-mulching and comparison of light response curve models," Transactions of the Chinese Society for Agricultural Machinery, 49(1), 219-227 (2018). https://doi.org/10.6041/j.issn.1000-1298.2018.01.027

[2] Zhao, G., Zhu, S., Li, D., Shan, G. and Wang, J., "Photosynthetic characteristics of $CO_2$ enrichment in melon seedlings," Transactions of the CSAE, 21(Supp), 103-105 (2015).

[3] Kawasaki, S., Tominaga, J., Yabuta, S., Watanabe, K., Jaiphong, T., Ueno, M. and Kawamitsu, Y., "Responses of growth, photosynthesis, and associated components to hypoxia at different light intensities in red leaf lettuce," Scientia Horticulturae, 193(10), 330-336 (2015).

[4] Daniel, R. and Dason, M., "A new understanding of how temperature affects the catalytic activity of enzymes," Trends in Biochemical Sciences, 35(10), 584-591 (2010).

[5] Zhang, W., Wang, L. and Tong, W., "Effects of planting density on canopy photosynthesis, canopy structure and yield formationof high-yield cotton in Xinjiang," Chinese Journal of Plant Ecology, 28(2), 164-171 (2004).

[6] Ye, Z., Yu, Q. and Kang, H., "Evaluation of photosynthetic electron flow using simultaneous measurements of gas exchange and chlorophyll fluorescence under photorespiratory conditions," Photosynthetica, 50(3), 472-476 (2012).

[7] Wu, K., Zhang, J. and Hao, C., "Simulation of canopy photosynthesis model of greenhouse tomato," Journal of Shanxi Agricultural University (Natural Science Edition), 33(3), 225-229 (2013).

[8] Li, T., Yan, A., Luo, X., Qiu, J., Li, D. and Yao, Z., "Temperature modified model for single-leaf net photosynthetic rate of greenhouse tomato," Transactions of the CSAE, 26(9), 274-279 (2010).

[9] Hu, J., He, D., Ren, J., Liu, X., Liang, Y., Dai, J. and Zhang, H., "Optimal regulation model of tomato seedlings' photosynthesis based on genetic algorithm," Transactions of the CSAE, 30(17), 220-227 (2014).

[10] Hu, J., Xin, P., Zhang, S., Zhang, H. and He, D., "Model for tomato photosynthetic rate based on neural network with genetic algorithm," International Journal of Agricultural and Biological Engineering, 12(1), 179-185 (2019).

[11] Wang, W., Zhang, M., Liu, C., Li, M. and Li, G., "Real-time monitoring of environmental information and modeling of the photosynthetic rate of tomato plants under greenhouse conditions," Applied Engineering in Agriculture, 29(5), 783-792 (2013).

[12] Miao, Y., Wang, X., Gao, L., Chen, Q. and Qu, M., "Blue light is more essential than red light for maintaining the activities of photosystem II and I and photosynthetic electron transport capacity in cucumber leaves," Journal of Integrative Agriculture, 15(1), 87-100 (2016).

[13] Li, F., Liu, L., Zhang, H., Wang, J., Guo, L., Hao, L., Zhang, Q., Cao, X., Liang, W. and Zhen, Y., "Effects of $CO_2$ concentrations on stomatal traits and gas exchange in leaves of soybean," Acta Agronomica Sinica, 44(8), 1211-1220 (2018).