Prediction Model of Photosynthetic Rate Based on SOPSO-LSSVM for Regulation of Greenhouse Light Environment

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Abstract—**It is difficult to accurately predict the photosynthetic rate of crops in the greenhouse, which affects the implementation of greenhouse light environment regulation considering photosynthesis demand. Therefore, this paper takes tomato as the test crop, and through the combination experiment on photosynthetic rate with the condition of nested temperature, humidity, photon flux density and CO_2 concentration, the sample data is obtained. Then, the training samples are selected from the sample data to train the SOPSO-LSSVM algorithm, and a soft sensing model for predicting the photosynthetic rate is established, which can realize the accurate prediction of tomato photosynthetic rate. Finally, the simulation results indicate when the model is used to predict the photosynthetic rate, it has the smaller maximum relative error and root mean square error, which are 0.0264 and 0.2926 respectively. The average relative prediction error is only 0.0078 and the coefficient of determination is 0.9953. More shows that the established model can provide a reliable objective function for the regulation of greenhouse light environment considering the photosynthesis demand, and then guide the regulation of light environment.**

Index Terms—**photosynthetic rate, multiple environmental factors, SOPSO-LSSVM, light environment regulation.**

I. Introduction

CROP photosynthesis refers to the biochemical process that converts the carbon dioxide and the water into the organic matter under the condition of photon flux density, and realizes the material accumulation, which determines the yield and quality of crops. Therefore, creating a microclimate environment to meet the photosynthesis demand is the key to improve the photosynthetic rate, accelerate the material accumulation, and improve the yield and quality of crops. However, owing to the influence of inclination structure, covering materials, solar height angle and surface cleanliness, the light intensity in the greenhouse is only half of that in the field[1]-[4], the illumination in the greenhouse is not suitable for the growth of crops. Especially in winter, spring and persistent rainy seasons, the light intensity in the greenhouse is usually lower than the light saturation point of crop photosynthesis, which leads to the decline of crop photosynthetic capacity, the slow growth and development, and the sharp increase of the occurrence probability of diseases and pests. Moreover, the physiological and biochemical indexes such as fusing efficiency, maximum regeneration rate are decreased under low light stress, which leads to the decrease of net photosynthetic rate[5]-[7]. Meanwhile, it affects the synthesis and distribution of photosynthetic products, reduces the dry matter accumulation of plants, and then has a great impact on the yield and quality of photophilic crops such as tomato[8]. Therefore, under certain conditions, regulating the light environment is very important to improve the development of greenhouse industry, and it is also an urgent task to speed up the upgrading of greenhouse industry.

As the establishment of photosynthetic rate model is an essential precondition for the regulation of light environment, and some scholars have carried out research on its establishment[9]-[13]. Most of them can predict the photosynthetic rate under the influence of some environmental factors[14]-[15]. However, according to the process of photosynthetic reaction, temperature, light, CO_2 and water are the main environmental factors affecting photosynthetic rate. When the widely used Support Vector Machine (SVM) technology is adopted to simulate the relationship model between these environmental factors and photosynthetic rate, due to the increase of the number of input variables, there will be some shortcomings, such as the high fitting complexity, the large fitting error and the poor real-time performance. While Least Squares Support Vector Machine (LSSVM)[16]-[17] uses constraints instead of non constraints, and then transforms the nonlinear problem into a linear problem, which has the advantages of simplifying the model, solving quickly and accurately [18]-[20], so it has good prediction performance.

Therefore, in this paper, tomato as the main cultivated crop is selected as the test crop, the prediction model of photosynthetic rate affected by various environmental factors is established by using LSSVM. But the parameters of LSSVM model are usually given by experience, which will affect the prediction performance of the model. In order to quickly and accurately determine the optimal values of these parameters, this paper uses SOPSO algorithm [21] to solve the parameter optimization problem of LSSVM model and determine their optimal values. In view of this, SOPSO algorithm is integrated into the LSSVM model, and the prediction model of tomato photosynthetic rate based on

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SOPSO-LSSVM is constructed. The study in this paper can establish an accurate prediction model of photosynthetic rate directly applied to the regulation of light environment, and provide a reliable objective function support for obtaining the dynamic target value of light environment regulation considering the photosynthesis demand.

II. Collection of Sample Data

By studying the mechanism of environmental factors affecting photosynthesis, this paper selects these environmental factors which have great influence on the photosynthetic rate, such as temperature, humidity, Photosynthetic Photon Flux Density(PPFD) and CO_2 concentration, as the inputs of the photosynthetic rate soft sensing model, accordingly, selects the photosynthetic rate as the output. Therefore, to establish a soft sensing model for predicting photosynthetic rate, there is a need to collect the information of environmental factors and photosynthetic rate, so as to obtain the sample data. The information of environmental factors are achieved through the nodes of wireless sensor network. Firstly, the environmental sensor nodes suspended at 10cm above the measured blade are used to measure the environmental factors in real time, and then the measured values of environmental factors are delivered to the remote data management center by the gateway, and the collection interval of environmental factor parameters is 0.5 hours. The sample data of output is collected through the combination experiment on the photosynthetic rate with the condition of nested these key environmental factors, and the experimental area and specific methods are as follows.

A. Experimental Area

The experimental greenhouse is a solar greenhouse located in the experimental base of Shenyang Agricultural University. The test tomato variety is “Liaoyuan Duoli”, it has the characteristics of vigorous growth, no yellow leaves, no premature senescence and high yield. Firstly, the healthy and plump tomato seeds are chose and soaked, and then sown in 50 hole tray for cultivation. In the cultivation process of tomato seedlings, the special substrate is used with the organic matter content of 50%, PH of 5.5-6.5, and the humic acid content of 20%, and the water and fertilizer are sufficient. When the tomato seedlings grow with 3 leaves and 1 heart, the plant height is about 15 cm, and the stem diameter is about 0.4 cm, they can be planted. And until the width of the fourth leaf is more than 3cm from top to bottom, the tomato seedlings with good illumination, irrigation and growth are selected for photosynthesis experiment, and during this period, no pesticides and hormone drugs are used.

B. Experimental Methods

In order to avoid the “noon break” time of plants, the combination experiment on the photosynthetic rate is conducted between 9:00-11:30 and 14:30-17:30, and the fourth leaf with strong growth and consistent growth is selected to measure the photosynthetic rate by portable photosynthesis instrument, and the measurement diagram is shown in Fig.1.

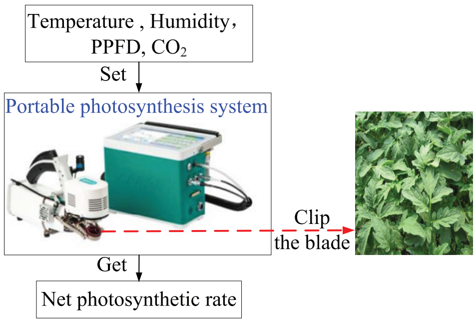

Fig. 1. Measurement Diagram of Photosynthetic Rate

TABLE I
Environment Variables Setting of Experiment

Variable	Gradient settings	Gradient number
X_1(°C)	18,21,24,27,30,33	6
X_2(%RH)	35,45,55,65,75	5
X_3(μmol/m^{2}s)	800,1000,1200,1400,1600,1800	6
X_4(μmol/mol)	600,800,1000,1200,1400	5

It can be seen from Fig.1 that the photosynthetic rate is measured under the condition of nested temperature (X_1), humidity (X_2), PPFD (X_3) and CO_2 concentration (X_4), and the corresponding environmental gradient settings are shown in Table 1.

III. Prediction model of Photosynthetic Rate Based on SOPSO-LSSVM

A. Least Squares Support Vector Machine

Suppose the training sample set $\boldsymbol{S} = (\boldsymbol{X}_i, y_i), i = 1, 2, \cdots n$, $\boldsymbol{X}_i \in \boldsymbol{R}^n$ is the input vector of the i-th sample, the input vector includes temperature, humidity, PPFD and CO_2 concentration, y_i is the corresponding output, and it is the photosynthetic rate. The training sample set $\boldsymbol{S}$ is used to construct the decision function, which is expressed as

$$y(\boldsymbol{X}) = \boldsymbol{\omega}^T \varphi(\boldsymbol{X}) + b \tag{1}$$

where $\varphi(\boldsymbol{X})$ represents the function of the input vector mapping to the high dimensional space, $\boldsymbol{\omega} \in \boldsymbol{R}$ is the weight coefficient, and b is the bias term.

The structural risk function is constructed as

$$J(\boldsymbol{\omega}, \boldsymbol{\zeta}, b) = \frac{1}{2}\boldsymbol{\omega}^T\boldsymbol{\omega} + \frac{1}{2}\gamma\sum_{i=1}^{n}\zeta_i^2 \tag{2}$$

where J is the structural risk, γ is the penalty coefficient, its value determines the degree of penalty to the error, $\boldsymbol{\zeta} = [\zeta_1, \zeta_2, \cdots, \zeta_n]^T$ is the vector of tolerance error.

In order to achieve $\boldsymbol{\omega}$ and b, basing on the principle of minimizing the structural risk, the following optimization problem needs to be calculated when using LSSVM to regress (1).

$$\begin{aligned} minJ(\boldsymbol{\omega}, \boldsymbol{\zeta}, b) &= \frac{1}{2}\boldsymbol{\omega}^T\boldsymbol{\omega} + \frac{1}{2}\gamma\sum_{i=1}^{n}\zeta_i^2 \\ s.t. \quad y_i &= \boldsymbol{\omega}^T\varphi(\boldsymbol{X}_i) + b + \zeta_i \\ i &= 1, 2, \cdots, n \end{aligned} \tag{3}$$

By using the Lagrange function and the duality theory, the above optimization objective function can be transformed into the following form.

$$L(\boldsymbol{\omega}, b, \boldsymbol{\zeta}; \boldsymbol{\alpha}) = J(\boldsymbol{\omega}, b, \boldsymbol{\zeta}) - \sum_{i=1}^{n} \alpha_i \{\boldsymbol{\omega}^T \varphi(x_i) + b + \zeta_i - y_i\} \tag{4}$$

where α_i is the Lagrange multiplier, and $\alpha_i \geq 0$.

Calculate the partial derivatives of L to $\boldsymbol{\omega}$, b, ζ_i, α_i separately, and make them to be 0.

$$\begin{cases} \frac{\partial L}{\partial \boldsymbol{\omega}} = 0 \rightarrow \boldsymbol{\omega} = \sum_{i=1}^{n} \alpha_i \varphi(\boldsymbol{X}_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{n} \alpha_i = 0 \\ \frac{\partial L}{\partial \zeta_i} = 0 \rightarrow \alpha_i = \gamma \zeta_i, i = 1, 2, \cdots, n \\ \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \boldsymbol{\omega}^T \varphi(\boldsymbol{X}_i) + b + \zeta_i - y_i = 0 \end{cases} \tag{5}$$

The formula can be obtained by simplifying (5), and expressed as

$$\begin{bmatrix} 0 & \boldsymbol{I}_u^T \\ \boldsymbol{I}_u & \boldsymbol{\Omega} + \frac{1}{\gamma}\boldsymbol{I} \end{bmatrix} \begin{bmatrix} b \\ \alpha_i \end{bmatrix} = \begin{bmatrix} 0 \\ y_i \end{bmatrix} \tag{6}$$

where $\boldsymbol{I}_u = [1, 1, \cdots, 1]$, $\Omega_i = K(\boldsymbol{X}, \boldsymbol{X}_i)$ is the element in the matrix, expressed as in (7), and $\boldsymbol{I}$ is the identity matrix.

$$K(\boldsymbol{X}, \boldsymbol{X}_i) = \varphi(\boldsymbol{X})\varphi(\boldsymbol{X}_i) \tag{7}$$

Because the Gaussian radial basis function needs fewer preset parameters, and it can be adopted to solve practical problems. Therefore, it is selected as the kernel function, expressed as

$$K(\boldsymbol{X}, \boldsymbol{X}_i) = exp(-\frac{\|\boldsymbol{X} - \boldsymbol{X}_i\|^2}{2\sigma^2}) \tag{8}$$

where σ is the kernel constant.

According to (8), b and α_i can be obtained by solving (6), and then basing on LSSVM, the prediction model of photosynthetic rate can be established as

$$\hat{y}(\boldsymbol{X}) = \sum_{i=1}^{n} \alpha_i K(\boldsymbol{X}, \boldsymbol{X}_i) + b \tag{9}$$

where $\hat{y}(\boldsymbol{X})$ is the prediction value of photosynthetic rate.

Aiming at the parameter selection problem of LSSVM model, that is to determine the optimal values of the penalty coefficient γ and kernel constant σ in LSSVM model, the following SOPSO algorithm can be used to solve this problem.

B. SOPSO Algorithm

In SOPSO algorithm, the particle of particle swarm can update its velocity and position according to (10).

$$\begin{cases} v_{id}(k+1) = wv_{id}(k) + c_1 r_1(k)(pbest_{id}(k) - \\ (1+\xi_1)x_{id}(k) - \xi_1 x_{id}(k-1)) + c_2 r_2(k) \\ (gbest_{id}(k) - (1+\xi_2)x_{id}(k) + \xi_2 x_{id}(k-1)) \\ x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \end{cases} \tag{10}$$

where $v_{id}(i = 1, 2, \cdots, M, d = 1, 2, \cdots, N)$ is the particle velocity in d-dimension, M is the size of particle swarm, and k is the iterative times, x_{id} is the current particle position (solution) in d-dimension, w is the inertia weight. $pbest_{id}$ represents the local optimal position of particle, and $gbest_{id}$ represents the global optimal position of particle swarm. r_1 and r_2 are two random numbers between 0 and 1. c_1 and c_2 are learning factors. ξ_1 and ξ_2 are also two random numbers, when $k < k_{max}/4$, ξ_1 and ξ_2 are set as $\xi_1 < (2\sqrt{c_1 r_1} - 1)/c_1 r_1$ and $\xi_2 < (2\sqrt{c_2 r_2} - 1)/c_2 r_2$ respectively, it ensures the algorithm has oscillatory convergence and strong global search ability. And at the later stage of the algorithm when $k > k_{max}/4$, ξ_1 and ξ_2 are set as $\xi_1 \geq (2\sqrt{c_1 r_1} - 1)/c_1 r_1$ and $\xi_2 \geq (2\sqrt{c_2 r_2} - 1)/c_2 r_2$ respectively, which guarantees the asymptotic convergence of algorithm.

Since SOPSO algorithm is used to optimize the penalty coefficient γ and kernel constant σ of LSSVM model, the vector $[\gamma_i, \sigma_i], i = 1, 2, \cdots, M$ is set as the particle, and the root mean square error of prediction is constructed as the fitness function, expressed as

$$fit = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{11}$$

where y_i is the measured value of the i-th sample, $\hat{y}_i$ represents the prediction value of the i-th sample, n is the number of prediction samples. When fit is the minimum, the corresponding particle position is the optimal values of γ and σ.

C. Prediction Model of Photosynthetic Rate Based on SOPSO-LSSVM

To solve the parameter selection problem of LSSVM model, this paper uses SOPSO algorithm to search the optimal values of γ and σ, and establishes a prediction model of photosynthetic rate by SOPSO-LSSVM algorithm. The corresponding modeling flow based on SOPSO-LSSVM is shown in Fig.2.

In Fig.2, the implementation steps are as follows:

Step 1: Normalization of sample data. All of the sample data are divided into the training sample set $\boldsymbol{S}$ and the prediction sample set $\boldsymbol{T}$, and they are normalized as follows:

$$X_i^{'}(j) = \frac{X_i(j) - X_i}{sqrt_i} \tag{12}$$

where $X_i(j)$ represents the j-th sample value of the i-th variable, and

$$sqrt_i = \sqrt{\frac{1}{m-1} \sum_{j=1}^{m} (X_i(j) - X_i)^2} \tag{13}$$

$$X_i = \frac{1}{m} \sum_{j=1}^{m} X_i(j) \tag{14}$$

where $i = 1, 2, \cdots, n_i$ represents the number of variables, and $j = 1, 2, \cdots, m$ represents the number of samples.

Step 2: Set the parameters of SOPSO algorithm, and then initialize the velocity and position of particles $[\gamma_i, \sigma_i], i = 1, 2, \cdots, M$.

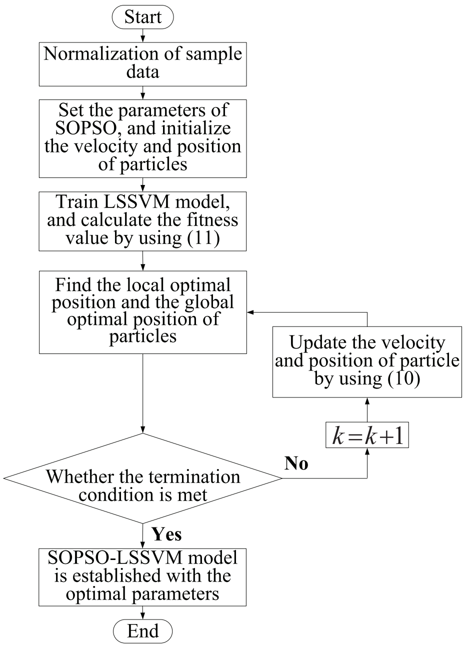

Fig. 2. Flow Chart of Modeling Based on SOPSO-LSSVM Algorithm

Step 3: The training samples are put into the LSSVM model for learning, the prediction values of photosynthetic rate are obtained, and the fitness value under $[\gamma_i, \sigma_i], i = 1, 2, \cdots, M$ is calculated by using (11).

Step 4: According to (11), the local optimal position ($pbest_{id}$) and the global optimal position ($gbest_{id}$) of particles $[\gamma_i, \sigma_i], i = 1, 2, \cdots, M$ can be found.

Step 5: Judge whether the maximum iterative times or the minimum fitness value is reached, if so, the iteration ends. Meanwhile, the corresponding particle position represents the optimal values of parameters. Otherwise, the velocity and position of particles $[\gamma_i,\sigma_i]$ are updated by using (10), and the fitness values of the updated parameters are recalculated, and the local optimal position and the global optimal position are searched again.

Step 6: Through the above calculation, the optimal values of γ and σ are brought in (9), which is the prediction model of photosynthetic rate based on SOPSO-LSSVM by training the sample set $\boldsymbol{S}$.

IV. Simulation Results and Analysis

According to the description in Section II, there are 900 groups of samples, and 720 groups are selected as the training sample set $\boldsymbol{S}$ of the model, accounting for 80% of the total samples. The other 180 groups are used as the prediction set $\boldsymbol{T}$ to verify the model, where temperature (X_1), humidity (X_2), PPFD (X_3) and CO_2 concentration (X_4) constitute the input vector, and the photosynthetic rate (y) is the output. The model based on SOPSO-LSSVM for predicting photosynthetic rate is established by MATLAB programming platform, firstly, the penalty coefficient γ and kernel constant σ of LSSVM model are optimized by SOPSO algorithm, and the optimal values of them are 0.21 and 0.098 respectively. Then the optimal values are substituted into the LSSVM model to construct the prediction model of photosynthetic rate. After constructing the model based on SOPSO-LSSVM, both LSSVM algorithm and PSO-LSSVM algorithm are used

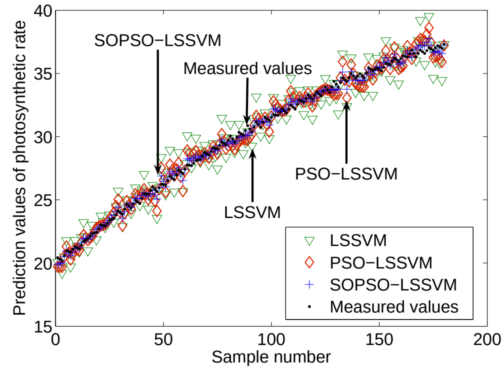

Fig. 3. Prediction Results of Three Models

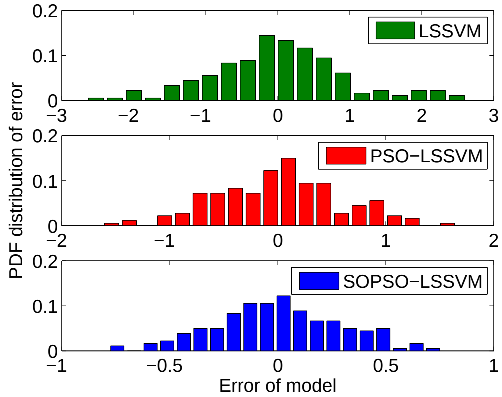

Fig. 4. Error PDF Distribution of Three Models

TABLE II
Comparison of Prediction Errors

Model	MRE	RMSE	MRPE	R^2
LSSVM	0.0827	0.9363	0.0239	0.9637
PSO-LSSVM	0.0493	0.5783	0.0152	0.9848
SOPSO-LSSVM	0.0264	0.2926	0.0078	0.9953

to establish the prediction model of photosynthetic rate with the same training set. And in order to verify the prediction performance of the model, these three models are used to predict the same samples. The prediction results are shown in Fig.3.

To further verify the performance of the model based on SOPSO-LSSVM, the probability density function (PDF) distribution of error predicted by these models are given in Fig.4, and the Maximum Relative Error (MRE), the Root Mean Square Error (RMSE), the Mean Relative Prediction Error (MRPE), and the coefficient of determination (R^2) are introduced to evaluate the prediction accuracy of these models, the results are listed in Table 2.

From Fig.4 and Table 2, it can be seen that the model based on SOPSO-LSSVM performs better than the other two models, and it has high prediction accuracy and good fitting effect.

In addition, taking the output of the constructed model as the objective function, under a certain combination condition of temperature, humidity and CO_2 concentration, the target value of light environment regulation can be obtained through optimization, and the results are shown in Fig.5.

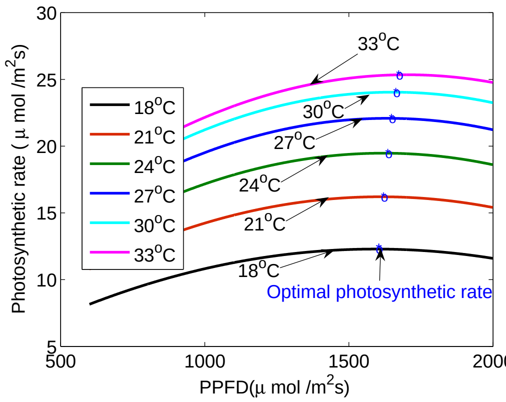

Fig. 5. Optimization Results When Humidity is 65%RH and CO_2 Concentration is 800μmol/mol

As can be seen From Fig. 5, when the temperature factor gradient gradually increases, the photosynthetic rate and the optimal control target of light environment also gradually increase. However, when the temperature factor gradient increases to a certain value, the increasing range of photosynthetic rate is gradually decreased. Meanwhile, the increase range of the optimal control target of light environment is also reduced. According to this result, we can judge whether the current photosynthetic rate is optimal or not, if not, we can regulate the light environment of greenhouse to make the photosynthetic rate optimal, so as to improve the yield and quality of greenhouse crops.

V. Conclusion

This paper proposes a new regression modeling method, in which the parameters of LSSVM model are optimized by SOPSO algorithm. Firstly, the sample data is obtained through the combination experiment on photosynthetic rate with the condition of nested multiple environmental factors. And then the parameters of LSSVM model are optimized by SOPSO algorithm, and the prediction model of photosynthetic rate is established based on SOPSO-LSSVM. The results show that the MRE of the model is 0.0264, RMSE is 0.2926, MRPE is 0.0078 and R^2 is 0.9953, indicating that the model has better fitting effect, smaller prediction error and higher accuracy. Finally, using the model to achieve the control target of light environment can guide the regulation of light environment in solar greenhouse, and ensure that the light environment regulation meets the demand of crop photosynthesis.

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