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Modeling and optimization of activated carbon carbonization process based on support vector machine

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Abstract: Product prediction and process parameter optimization in the production process of activated carbon are very important for production. It can stabilize product quality and improve the economic efficiency of enterprises. In this paper, three process parameters of a carbonization furnace, namely feeding rate, rotation speed, and carbonization temperature, were adopted to build a quality optimization model for carbonized materials. First, an orthogonal test was designed to obtain the preliminary relationship between the process parameters and the quality indicators of a carbonized material and prepare data for modeling. Then, an improved SVR model was developed to establish the relationship between product quality indicators and process parameters. Finally, through the single-factor experiments and the Monte Carlo method, the process parameters affecting the quality of a carbonized material were determined and optimized. This showed that a high-quality carbonized material could be obtained with a smaller feeding rate, larger rotation speed, and higher carbonization furnace temperature. The quality of activated carbon reached its maximum when the feeding rate was 1.0 t/h, the rotation speed was 90 r/h, and the temperature was 836°C. It can effectively improve the quality of carbonized materials.

Keywords: carbonization process, optimization, modeling, support vector machine

1. Introduction

The carbonization process is a critical phase in the production of activated carbon. The product resulting from the carbonization process is the semi-finished product of activated carbon, which is called "carbonized material". As the input product of the later activation process, the quality of the carbonized material directly determines the quality of the activated carbon (Xie and Bian, 2002) and the service lifetime of the carbonization equipment. The quality indexes of carbonized materials mainly include strength, moisture, particle size, and volatile matter and iodine value (Linares-Solano et al., 2000; Lozano-Castelló et al., 2001; Wu and He, 2004; Xie and Chen, 1996; Xie and Zhang, 2002). When the source of raw material and the production process are fixed, the quality indexes are significantly influenced by the production operation. At present, the typical carbonization process only relies on the experience of workers to control the important process parameters. This process requires a wide range of control and provides low precision, resulting in an unstable quality of carbonized material. This will not only affect the later activation process but will also be directly related to the economic benefits of the company. Therefore, a model that can predict the quality of carbonized materials according to the process parameters is greatly needed for the carbonization process. For example, Liao et al. (Liao et al., 2020, 2019) applied artificial neural networks to the activation process to predict the quantity, quality, and environmental footprints of activated carbon products derived from different biomass feedstock.

However, the artificial neural networks model lacks the generalization capability (Solgi et al., 2017) in small sample problems, and SVM (Dou et al., 2020c; Xue et al., 2020) is considered to be the best method for classification and regression problems of small samples (Zhao et al., 2009). Besides, the support vector regression (SVR) model is adaptable for solving both linear and nonlinear prediction problems. It has been widely used in many fields (Andre et al., 2020; Kalhori and Bagherpour, 2019; Khosla et al., 2020; Ren et al., 2005; Yan and Wang, 2009) and can better solve the problem of quality index prediction of carbonized materials. Jiang et al. (Jiang et al., 2019) used support vector regression and other machine learning approaches to predict the methylene blue number and iodine number of the strawbased activated carbon product. Solgi et al. (2017) investigated the support vector machine combined with genetic algorithm and artificial neural network to predict the percentage of chromium removal from aqueous solution using synthesized activated carbon. Nevertheless, previous studies only performed a predictive analysis of the researched problems, and only a few of them used predictive models to optimize and adjust the process parameters in their researched problems. For example, Dou et al. (Dou et al., 2015) adopted a uniform design to reduce the number of experiments and established a prediction and optimization model for the performance index of dense-medium cyclone by using the genetic algorithm and the regression analysis method.

This work fills gaps in prior work. In this study, an orthogonal test was designed to obtain both the optimal combination of process parameters and the preliminary relationship between the process parameters and the quality index of the carbonized material. Then, an improved SVR model was developed. Finally, the prediction results of the model were used to adjust and optimize the process parameters that affect the quality of the carbonized material. This study provides a foundation for quality index prediction of carbonized materials and optimization of process parameters in the carbonization process.

2. Materials and methods

Owing to the combined effect of many factors, the quality control of carbonized materials is notably complicated. Therefore, this work is dedicated to finding out the relationship between process parameters and quality index of carbonized materials by modeling method, so that high quality carbonized materials can be obtained by selecting reasonable process parameters according to the established model.

First, an orthogonal test was designed to obtain the preliminary relationship between the process parameters and the quality indicators of a carbonized material. Then, based on the data prepared in the orthogonal test, an improved SVR model was developed to establish the relationship between product quality indicators and process parameters. Finally, through the single-factor experiments and the Monte Carlo method, the process parameters affecting the quality of a carbonized material were determined and optimized.

2.1. Orthogonal test

In the orthogonal test, volatile matter (Aworn et al., 2008) and iodine value (Jiang et al., 2019) were selected to indicate the quality of the carbonized material, which is inversely proportional to the volatile matter (Shamsuddin et al., 2016) and directly proportional to the iodine value (Mianowski et al., 2007; Nunes and Guerreiro, 2011). According to the field practice, the feeding rate, rotation speed, and temperature of the carbonization furnace were selected as the three relevant factors for this orthogonal test, which are denoted as A, B, and C. Three levels were selected for each factor. The level table of orthogonal test factors was designed as shown in Table 1 and the table head was designed according to L9 (3³). The data, shown in Table 2, were extracted from Ningxia Boteli Activated Carbon Co., Ltd.

By calculating the k_1 , k_2 , k_3 , and R values of each factor, the order of the relevant factors which affect the quality of carbonized materials was determined. Note that k_1 , k_2 , and k_3 represent the sum of the volatile or iodine values under level i of a certain factor. The largest value among k_1 , k_2 , and k_3 is the optimum of the corresponding level for a certain factor. Note also that R represents the range, which is the difference between the maximum and minimum values of k_1 , k_2 , and k_3 for each factor:

$$R = (k_1, k_2, k_3)_{max} - (k_1, k_2, k_3)_{min} \quad (1)$$

The magnitude of R was used to measure the effectiveness of the corresponding factors in the test. A factor with a large R value means that its three levels have a great influence on the quality of the carbonized material, which is usually an important factor. Conversely, a factor with a small R value is often unimportant.

Table 1. Level table of orthogonal test factors

Level	A	B	C
	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)
1	1	70	650
2	1.2	80	750
3	1.5	90	850

Table 2. Orthogonal test design table and results

No.	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)	Volatile Matter (%)	Iodine Value (mg/g)
1	1	70	650	9.2	278
2	1	80	750	8.8	292
3	1	90	850	7.4	322
4	1.2	70	750	11.8	266
5	1.2	80	850	10.2	287
6	1.2	90	650	9.4	294
7	1.5	70	850	12.7	235
8	1.5	80	650	11.1	252
9	1.5	90	750	9.6	277

2.2. Support vector regression model

The support vector machine (SVM) is a machine learning method based on statistical learning theory (Vapnik, 2013). It was proposed by Corinna and Vapnik in 1995 (Cortes and Vapnik, 1995). SVM (Dou et al., 2019b; Dou and Zhou, 2016) was originally applied to solve pattern recognition problems and has a high generalization ability. With the introduction of Vapnik's ε -insensitive loss function (Vapnik et al., 1994), SVM was extended to solve the problem of nonlinear regression prediction, giving rise to the SVR prediction algorithm (Smola and Schölkopf, 2004). The core idea of SVR is the risk minimization principle, which is based on the construction of nonlinear mappings that use kernel functions to transform nonlinear regression in the original sample space into linear regression in a higher-dimensional space.

Consider the sample $\{(x_i, y_i), i = 1, 2, \dots, m\} \in R^n$, where m is the number of samples, n is the sample dimension, and the regression function is expressed as follows:

$$f(x) = \omega^T \phi(x) + b \quad (2)$$

where $\phi(x)$ is the nonlinear mapping from R^n to a higher dimensional feature space, ω is the weight vector of the hyperplane, and b is the bias.

The basic idea of SVM is to separate the two types of samples to find an optimal hyperplane, while the basic idea of SVR is to obtain an optimal hyperplane with the least error from all training samples. By applying the principle of risk minimization in statistical learning theory, the objective function of the optimization problem is expressed as follows:

$$\min \left[\frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*) \right] \quad (3)$$

$$s.t. \begin{cases} y_i - [\omega^T \phi(x_i) + b] \leq \varepsilon + \xi_i \\ \omega^T \phi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, m \end{cases} \quad (4)$$

where the constant C is the penalty coefficient, m is the sample size, ξ_i and ξ_i^* are the slack variables, and ϵ is the insensitive loss factor.

By introducing the Lagrange multiplier, the dual problem of the above optimization problem can be obtained (Osuna et al., 1997):

$$\max \left\{ -\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m [(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j)] - \epsilon \sum_{i=1}^m (\alpha_i + \alpha_i^*) + \sum_{i=1}^m y_i (\alpha_i - \alpha_i^*) \right\} \quad (5)$$

$$\text{s.t.} \begin{cases} \sum_{i=1}^m (\alpha_i - \alpha_i^*) = 0 \\ 0 \leq \alpha_i, \alpha_i^* \leq C \end{cases} \quad (6)$$

where α_i , α_i^* , α_j , and α_j^* are Lagrange multipliers, and $K(x_i, x_j)$ is the kernel function.

Then, the nonlinear regression function of the SVM can be obtained:

$$f(x) = \sum_{i=1}^m (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \quad (7)$$

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) \quad (8)$$

The introduction of the kernel function replaces the dot product in the higher dimensional space and avoids the solution of the nonlinear mapping function $\phi(x)$, which greatly reduces the amount of computation and complexity. Different kernel functions correspond to different SVM models. There are roughly four types of commonly used kernel functions: sigmoid, radial basis, polynomial, and linear. Considering the advantages of the radial basis function (RBF) (Keerthi and Lin, 2003), this study selected it as the kernel function of SVR:

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (9)$$

Given that it is finally transformed into a convex optimization problem with linear constraints (Cortes and Vapnik, 1995), the solution exhibits global optimality.

2.3. Model construction

2.3.1 Data preprocessing

To meet the requirements of model training, avoid the influence of outliers and extreme values, reduce errors, and speed up the model training, it is necessary to normalize the original data. Normalization is a process of data standardization that maps the data into the interval [0,1] with the following formula:

$$x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (10)$$

where x_i denotes the sample data, x_{min} is the minimum value in the sample data, and x_{max} is the maximum value in the sample data.

2.3.2. Model parameter optimization

The SVR model is adaptable for solving both linear and nonlinear prediction problems and can better solve the problem of quality index prediction of carbonized materials. Based on data pre-processing, the SVR model can also optimize the model parameters to improve the prediction accuracy further. The main parameter that affects the prediction accuracy of the SVR model is the penalty coefficient C , which reflects the generalization ability of the model. If C is too large, overfitting easily occurs, and conversely, if it is too small, underfitting easily occurs.

2.3.3. Model evaluation indexes

To determine whether a model can be applied in practice, some evaluation indexes are needed to reflect its quality. In this study, the mean absolute error (MAE), mean squared error (MSE), and correlation

coefficient R-Square were used as the basis for evaluating the model performance. The corresponding calculation formulas are as follows:

$$MAE = \frac{1}{m} \sum_{i=1}^m |\hat{y}_i - y_i| \quad (11)$$

$$MSE = \frac{1}{m} \sum_{i=1}^m (\hat{y}_i - y_i)^2 \quad (12)$$

$$R^2 = 1 - \frac{\sum_{i=1}^m (\hat{y}_i - y_i)^2}{\sum_{i=1}^m (\bar{y} - y_i)^2} \quad (13)$$

where \hat{y}_i is the predicted value, y_i is the actual observation, \bar{y} is the mean of the actual observation, and m denotes the total number of samples.

The mean absolute error (MAE) was used to evaluate the degree of closeness between the predicted results and the real dataset. The smaller the value of this error, the better the fitting effect and the prediction accuracy. The mean square error (MSE) is the mean value of the squared sum of the errors between the fitting data and the original data corresponding to the sample points. The smaller the value of this error, the better the fitting effect and the prediction accuracy. Finally, the correlation coefficient R-Square is the score that explains the variance of the regression model. The closer it is to 1, the more the variance of the dependent variable is representative of the independent variable, and the more the predicted value is consistent with respect to the measured value.

2.3.4. Model Selection Method

To select a good model, the method of leave-one-out cross-validation is used to select the model. The method is as follows: K-fold cross-validation can be used as follows: first, randomly slice the given data into K disjoint subsets of the same size; then train the model using the data from K - 1 subsets, and test the model using the remaining subsets; repeat this process for the possible K choices; finally select the model with the lowest average test error among the K reviews. When K is equal to the capacity of a given data set, it is called leave-one-out cross-validation.

2.3.5. Model Optimization Process

According to the characteristics and influencing factors of the production process of carbonized materials, this study selected the SVR model to predict and optimize their quality indexes. In the process of building the model, the data are first normalized, and then the parameters of the prediction model are optimized. Subsequently, the optimized parameter values are substituted into the regression model to output the prediction results, which are inversely normalized to calculate the evaluation indexes of different models. Finally, the best model is selected according to the evaluation index of the model and cross-validation. The process of model optimization and prediction analysis is shown in Fig. 1. Besides, with only three input parameters, there is a possibility of a simple linear relationship between them and the quality index. So, the linear regression (LR) model (Dou et al., 2020a, 2020b) was chosen as the baseline for comparison with the SVR model.

2.4. Parameters and quality optimization methods

2.4.1 Single-factor experiment

According to the relevance order of the factors obtained in the orthogonal test, the single-factor experiment was carried out to optimize the process parameters. Assuming the frequently used initial conditions of feeding rate 1.2 t/h, rotation speed 80 r/h, and temperature 750°C under normal production, the process parameters change in a certain range under the premise of meeting the actual production. The optimized SVR model was used to predict the quality index of the carbonized material, and the process parameters are obtained when the best quality indexes are achieved.

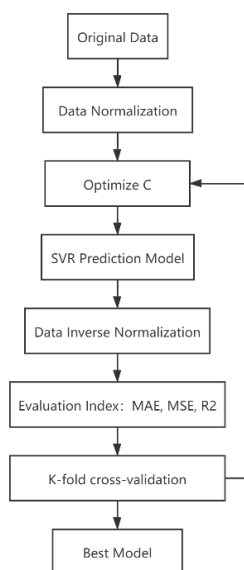


Fig. 1. Process of model construction

2.4.2. Monte Carlo method

Due to the use of the single-factor experiment to optimize the process parameters, local optimal values may appear. Therefore, the Monte Carlo method was used to optimize the process parameters again. The results of the two optimization methods were compared to determine the best process parameters. The Monte Carlo method, also known as the statistical simulation method, is a method of numerical calculation by random sampling from a probabilistic model. In this paper, the Monte Carlo method was used to generate a large number of random number combinations of process parameters and input them into the optimization model. When a process parameter combination obtains the best quality index, it is the best process parameter combination.

3. Results and discussions

3.1. Orthogonal test results and analysis

By directly comparing the 9 groups of volatile matter and iodine value obtained from the test, it is easy to conclude that the carbonized material quality of test No. 3 was the highest, with a volatile matter of 7.4 % and an iodine value of 322 mg/g. The test condition was $A_1B_3C_3$. Taking volatile matter as the quality index, the values of k_1 , k_2 , k_3 , and R for each factor were calculated, as shown in Table 3. Likewise, taking the iodine value as the quality index, the values of k_1 , k_2 , k_3 , and R for each factor are calculated, as shown in Table 4.

Table 3. The values of k_1 , k_2 , k_3 , and R - Volatile matter

No.	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)
k_1	25.4	33.7	29.7
k_2	31.4	30.1	30.2
k_3	33.4	26.4	30.3
R	8.0	7.3	0.6

Table 4. The values of k_1 , k_2 , k_3 , and R - Iodine value

No.	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)
k_1	892	779	824
k_2	847	831	835
k_3	764	893	844
R	128	114	20

According to the comprehensive analysis summarized in Tables 3 and 4, the order of relevant factors that affect the quality of the carbonized material is Feeding Rate (A) > Rotation speed (B) > Temperature (C). Therefore, the optimal combination of process parameters is $A_1B_3C_3$, that is, a feeding rate of 1 t/h, a rotation speed of 90 r/h, and a temperature of 850°C.

The relationship between the factors and the quality index is plotted in Fig. 2 by using the levels of the factors as the horizontal axis and the sum of the volatile matter or iodine value at the same level as the vertical axis. Fig. 2 shows that if we want to obtain a higher quality for a carbonizing material, which means that the carbonized material should have a lower volatile matter and higher iodine value, achieving a smaller feeding rate, larger rotation speed, and higher temperature of the carbonization furnace should be targeted to the greatest possible extent.

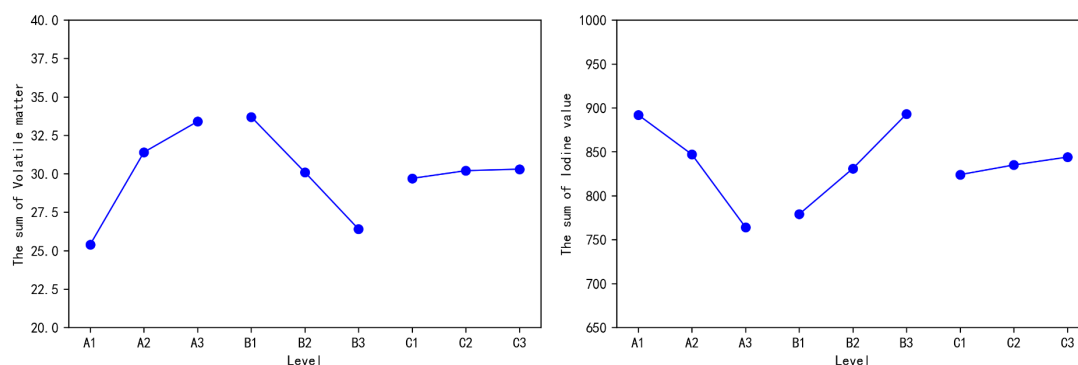


Fig. 2. Relationship between the factors and the quality index

3.2. Optimized model and prediction effect

In this study, Python was used to build the model and the MultiOutputRegressor function in Scikit-Learn was used to address the multi-output regression problem. Considering the prediction accuracy and the generalization ability of the model, the penalty coefficient C was set to 30 to optimize the SVR model. The optimized SVR model and LR model (Dou et al., 2019a; Qiu et al., 2020) were used to predict the quality index of the carbonized material, and the effectiveness of the models was tested through the evaluation indexes MAE, MSE, and R-Square. The results are shown in Table 5 and the prediction effect of the optimized models on the quality-index data of the carbonized material is shown in Figs. 3 and 4.

As can be seen from the three evaluation indexes in Table 5, although the optimized SVR model was slightly inferior to the LR model in the MSE evaluation index, it is better in MAE and R-Square evaluation index. In Fig. 3, the prediction effect of the optimized SVR model on the volatile matter index is generally better than that of the LR model, while in Fig. 4, the optimized SVR model is slightly worse than the LR model in level 3 and Level 7, but predictions at other levels are also far better than the LR model. On the whole, the optimized SVR model has a more significant prediction ability to the quality index of carbonized materials. Therefore, the optimized SVR model was selected to predict and optimize the quality index of carbonized materials.

Table 5. Results of models evaluation indexes.

Model	Index	MAE	MSE	R- Square
SVR	Volatile Matter	0.1000952	0.0100191	0.9957336
	Iodine Value	2.6025436	27.542566	0.9517633
	Average	1.3513194	13.776293	0.9737485
LR	Volatile Matter	0.4103314	0.2619591	0.8884519
	Iodine Value	2.9629630	11.529240	0.9798083
	Average	1.6866472	5.8955996	0.9341301

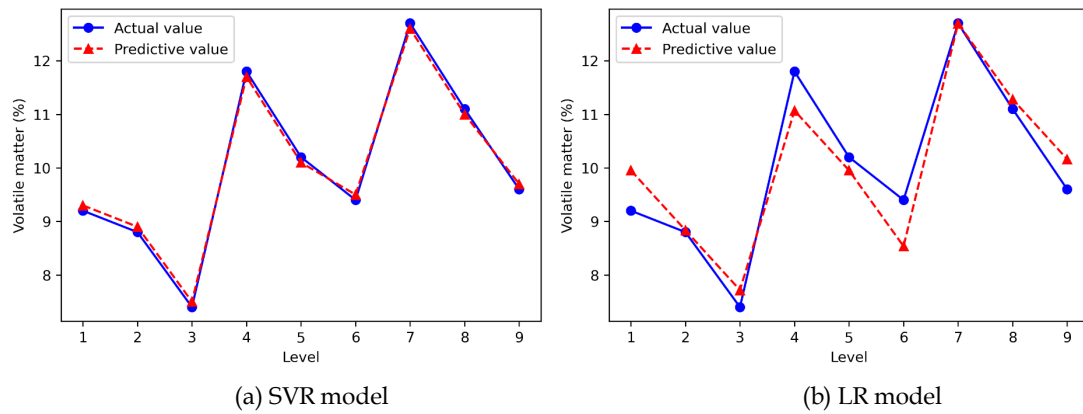


Fig. 3. Prediction effect of the optimized models on the volatile matter

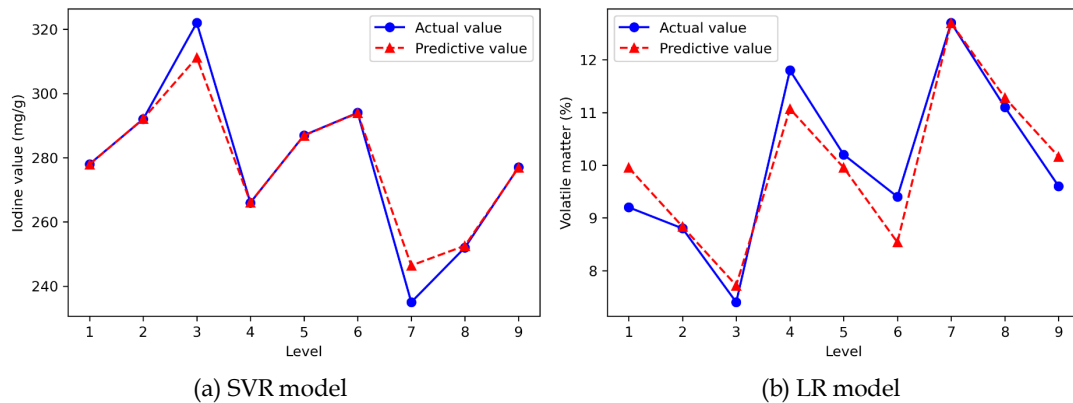


Fig. 4. Prediction effect of the optimized models on the iodine value

3.3. Parameters and quality optimization

3.3.1. Single-factor experiment

The single-factor experiment was carried out to optimize the process parameters by the relevance order of the factors obtained in the orthogonal test. First, the feeding rate was optimized. Under the condition of rotation speed 80 r/h and temperature 750°C, the feeding rate was varied in the range [1,1.5] t/h, and the optimized SVR model was used to predict the quality index of the carbonized material. The results are shown in Fig. 5. When the other parameters are fixed, increasing the feeding rate leads to an increase in volatile matter and a decrease in iodine value. Therefore, if we want to obtain a higher-quality carbonizing material, which means that the carbonized material should have lower volatility and higher iodine value, a smaller feeding rate should be applied. Therefore, the optimal feeding rate is 1.0 t/h.

Then, the rotation speed was optimized. Under a feeding rate of 1.0 t/h and a temperature of 750°C, the rotation speed was varied in the range of [70,90] r/h, and the optimized SVR model was used to predict the quality index of the carbonized material. The results are shown in Fig. 6. When the other parameters are fixed, increasing the rotation speed reduces the volatile matter and increases the iodine value. The lowest volatile matter was obtained at a rotation speed of 89.39 r/h, whereas the highest iodine value was obtained at a rotation speed of 90 r/h; note that both values of rotation speed are almost the same. For the convenience of operation, the value 90 r/h was selected as the optimum for rotation speed.

Finally, the temperature was optimized. Under a feeding rate of 1.0 t/h and a rotation speed of 90 r/h, the temperature was varied in the range of [600,900] °C. Then, the optimized SVR model was used to predict the quality index of the carbonized material. The results are shown in Fig. 7. When the other parameters are fixed, increasing the temperature reduces the volatile matter and increases the iodine value. The lowest volatile matter and the highest iodine value were obtained at 836.36°C. Higher temperature values lead to an increase in the volatile matter and a decrease in the iodine value, which

means that the quality index of the carbonized material becomes worse. Therefore, the optimal temperature was 836.36°C.

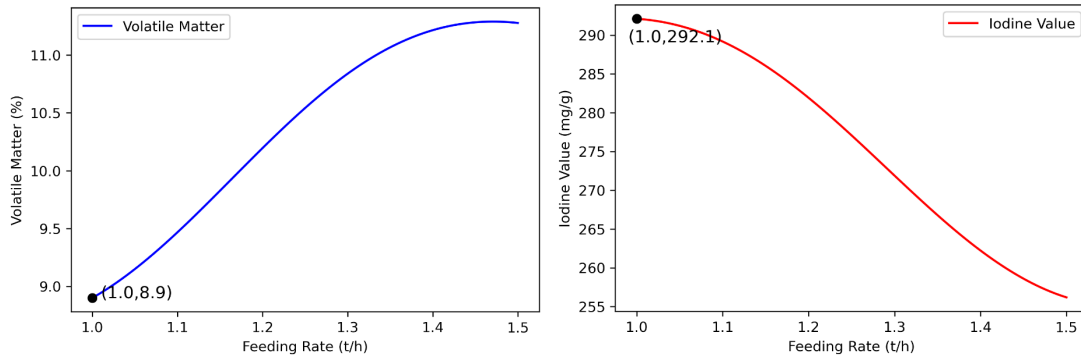


Fig. 5. Trend of the quality index for varying feeding rate

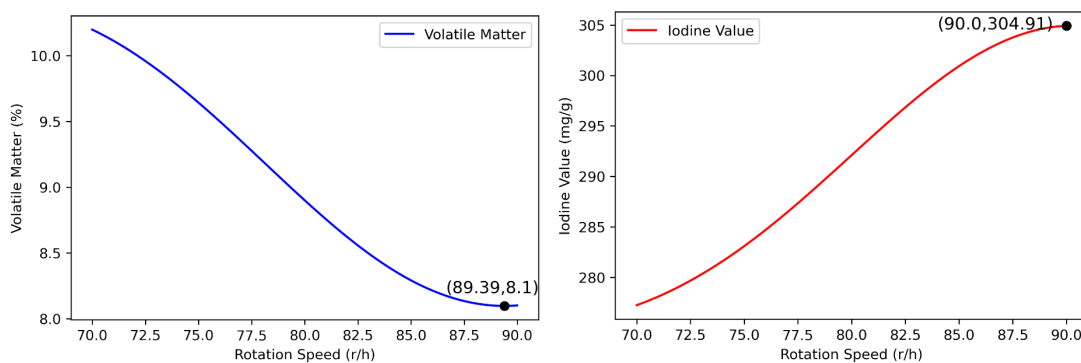


Fig. 6. Trend of the quality index for varying rotation speed

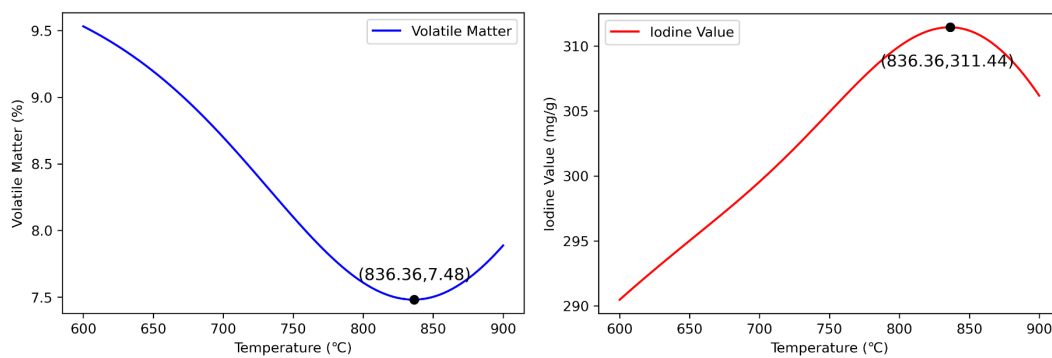


Fig. 7. Trend of the quality index for varying temperature

Based on the conclusions drawn from Figs. 5, 6, and 7, the best process conditions for carbonized material production are as follows: feeding rate 1.0 t/h, rotation speed 90 r/h, and temperature 836.36°C. Note that, according to the above three figures depicting the changing trend of the quality index of the carbonized material, to obtain high-quality carbonized materials, it is necessary to ensure a smaller feeding rate, a larger rotation speed, and a higher temperature of the carbonization furnace. This conclusion is the same as that of the previous orthogonal test, thereby proving the correctness of the model again.

Figs. 8, 9, and 10 show the changing trend of the volatile matter and iodine value caused by the change in the other two parameters when one parameter is fixed to the optimal value. In these figures, the process parameters for obtaining the lowest volatile matter and highest iodine value were marked and summarized in Table 6. Note from Table 6 that the values of the process parameters for obtaining the lowest volatile matter and highest iodine value basically coincide. Note also that the values are

almost the same as the optimal process conditions (feeding rate 1.0 t/h, rotation speed 90 r/h, and temperature 836.36°C), thereby confirming the correctness and effectiveness of the model again. The model can be used to guide actual production.

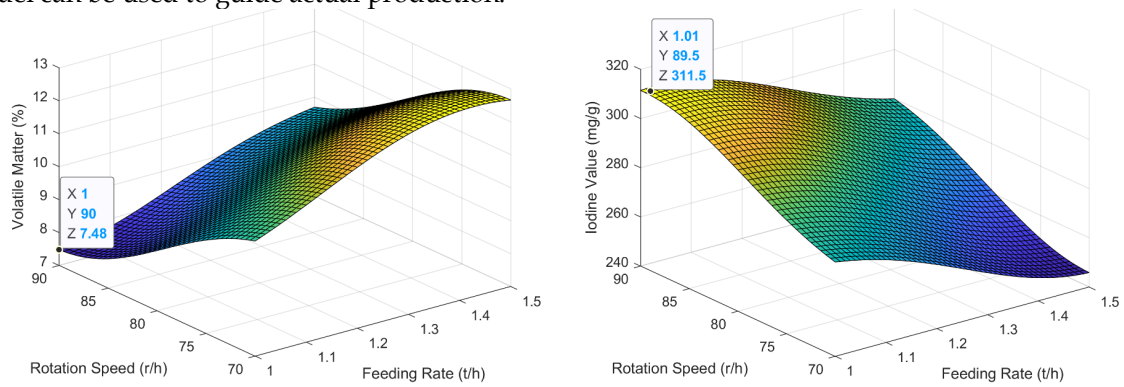


Fig. 8. Changing trend of the quality index at fixed temperature

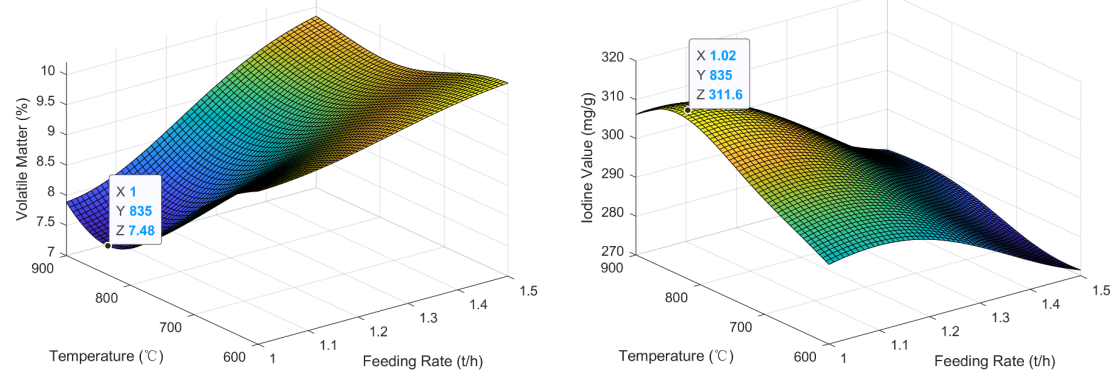


Fig. 9. Changing trend of the quality index at fixed rotation speed

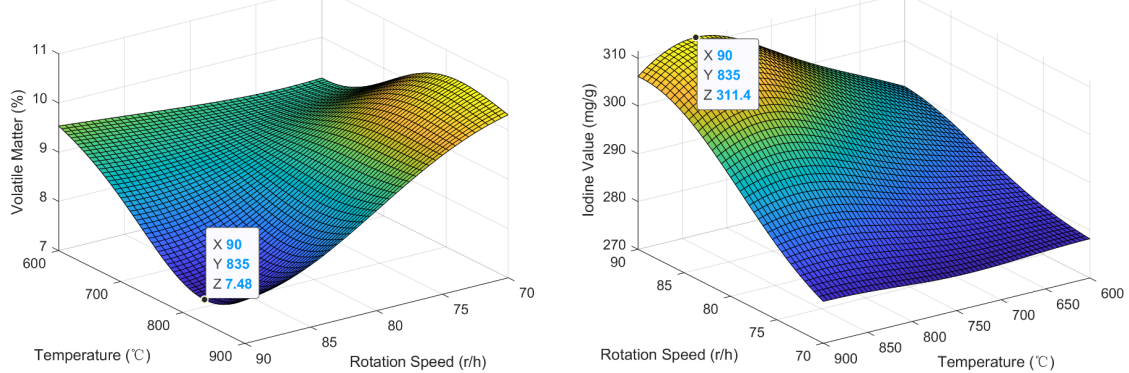


Fig. 10. Changing trend of the quality index at fixed feeding rate

Table 6. Values of optimal process parameters

Fixed-Parameter	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)
Temperature	1.00	90	836.36
	1.01	89.5	836.36
Rotating Speed	1.00	90	835
	1.02	90	835
Feeding Rate	1.00	90	835
	1.00	90	835

3.3.2. Monte Carlo Method

The random.uniform function of Numpy was used to generate 1×10^5 random values of process parameters. Among them, the feeding rate was varied in the range [1,1.5] t/h, the rotation speed was varied in the range of [70,90] r/h, and the temperature was varied in the range of [600,900]°C. The generated process parameter combinations were input into the optimized prediction model, and the process parameter combination that obtained the best quality index was recorded, as shown in Table 7. The Monte Carlo method was used to optimize the process parameters for 10 times, and the average of the results of 10 times was taken as the best process parameter combination.

Table 7. Values of optimal process parameters by the Monte Carlo method

Index	Feeding Rate (t/h)	Rotation Speed (r/h)	Temperature (°C)
1	1.01	89.80	835.82
2	1.01	89.86	835.52
3	1.02	89.86	837.74
4	1.01	89.84	834.08
5	1.01	89.88	836.43
6	1.01	89.79	832.06
7	1.01	89.89	835.46
8	1.01	89.81	836.50
9	1.01	89.89	834.12
10	1.01	89.65	835.38
Mean	1.01	89.83	835.31

The best combination of parameters using the Monte Carlo method was: feeding rate 1.01 t/h, rotation speed 89.83 r/h, and temperature 835.31°C. This result was almost the same as the result of the single-factor experiment, which could verify the correctness of the best parameter combination. Considering the feasibility of practical operation, the optimal process parameters can be combined as feeding rate 1.0 t/h, rotation speed 90 r/h, and temperature 836°C.

In the optimization problem of process parameters, only one process parameter can be optimized at a time by using the single-factor experiment method. To get the optimum combination of process parameters, different single-factor experiments need to be designed, which is a tedious experiment process. In contrast, the Monte Carlo method can optimize all process parameters simultaneously, which greatly simplifies the design process of the experiment. Although the Monte Carlo method has a certain degree of randomness, the errors caused by randomness can be well offset by averaging the optimization results through multiple repetitions of the test. Under comprehensive consideration, the Monte Carlo method is more suitable for optimization problems of multiple process parameters.

4. Conclusions

In this paper, the orthogonal test and SVR model were used to find the relationship between process parameters and the quality index of the carbonized material. Besides, the single-factor experiment and the Monte Carlo method were used to find the optimal process parameters for obtaining a high-quality carbonized material from the optimized SVR model.

According to the results of the orthogonal test, the order of relevant factors that affect the quality of the carbonized material is feeding rate (A) > rotation speed (B) > temperature (C). The optimal combination of process parameters is $A_1B_3C_3$, which denotes the case of feeding rate 1 t/h, rotation speed 90 r/h, and temperature 850°C. Then, an optimized SVR model was established, which had a more significant prediction ability to the quality index of carbonized materials. The optimum process parameters (i.e. feeding rate 1.0 t/h, rotation speed 90 r/h, and temperature 836°C) were obtained by

the single-factor experiment and the Monte Carlo method. It will simplify the indicator monitoring, and provide guidance for operators to improve the production process. The operator can adjust the process parameters according to the optimized SVR model proposed in this paper to obtain the carbonized material with the desired quality index.

The method proposed in this paper provides a new idea for parameter optimization of the carbonization process, that is, the use of predictive models to find the best process parameters. In this paper, there is no restriction on the feedstock and operational conditions in the carbonization process, and researchers can refer to the method proposed in this paper to optimize the process parameters of the carbonization process with different feedstock and operational conditions. Besides, this paper compares the results of the orthogonal test with the optimization results of the prediction model and compares the results of the single-factor experiment method with those of the Monte Carlo method. This method of comparing multiple methods to verify the correctness of the results has some reference value for researchers. In future research, more experimental data and methods are planned to explore the relationship between more process parameters and quality indexes of carbonized materials.

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