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Optimization of extraction technology of alkaloids in lotus leaf based on BP neural network

Zhigui DONG[1], Qingfeng SONG[2], Jinghong YANG[3]*

Abstract

In order to overcome the bad precision of fitted error, lower accuracy optimization results and other flaws, when extraction technology of the lotus leaf alkaloids was optimized by response surface method or regression analysis method, a linear constraint optimization method based on BP neural network is proposed. The testing program of three factors, three level was designed, which selected the hydrochloric acid mass fraction, ultrasound time, liquid-solid ratio as experimental factors. Taking the experiment data as training sample, the BP neural network model of the lotus leaf alkaloid yield and the influencing factors was obtained, and it was optimized by the proposed optimization method. The optimal parameter combination of extraction technology for lotus leaf alkaloid was obtained as follows: extraction temperature 60 °C, ultrasonic power 500W, hydrochloric acid mass fraction 0.3%, ultrasonic time 43 min, liquid-solid ratio 27, the yield of lotus leaf alkaloids under this process condition is 4.26 mg/g. It better than the best extraction technology obtained by response surface method. The obtained results is used for verification experiment, the verification results shown that the method has high fitting accuracy and stable optimization results, which optimize the extraction technology for lotus leaf alkaloid.

Keywords: lotus leaf; alkaloids; BP neural network; extraction Technology; optimization.

Practical Application: The extraction technology of alkaloids of lotus leaf was optimized by BP neural network-based optimization method, and the optimal combination of technology parameters was obtained for extraction of alkaloids of lotus leaf, and the yield was improved.

1 Introduction

As a kind of homologous food and medicine, lotus leaf contains multiple chemical components in common plants such as carbohydrates, lipids, tannins (Huang et al., 2017; Liu et al., 2016), but also contains more than 20 alkaloids include lotus alkaloid, N-dimethyl lotus leaf alkaloid, Asiatic papaverine and so on (Pan et al., 2019; Ren & Yang, 2022). Lotus leaf alkaloid not only has the effect of blood circulation, lowering blood fat and losing weight, lowering blood pressure, present arteriosclerosis (Li et al., 2011; Wang, 2012), and antiviral, but also has the effect of anti-mitotic and strong bacteriostatic (Wang et al., 2011; Yan et al., 2022a). As a by-product of lotus product processing, lotus leaf is often used as waste and cannot be effectively utilized. Studies have shown that the lotus leaf alkaloid is insoluble in water, although it can be absorbed and involved in metabolism under the condition of lipid solubility in the body, but the onset of action is slow and cannot be fully utilized. Another study found that the alkaloid salts have good water solubility, the alkaloid in the lotus leaf are extracted in the form of salt, which is not only conducive to optimizing the resources, improving the utilization rate and the economic benefits, but also facilitates better absorption by the body (Yan et al., 2022b). Therefore, it has important academic value and application prospect to study the optimization of extraction process conditions of lotus leaf alkaloids.

The extraction yield of lotus leaf alkaloids is affected by the interaction of various factors such as acid type, acid mass fraction, liquid-solid ratio, ultrasonic power, extraction temperature, pH value and extraction time (Pan et al., 2019; Li et al., 2011; Wang, 2012). The relationship between the extraction yield and influence factors of lotus leaf alkaloid extraction, which has strong nonlinear and black-box characteristics. Therefore, the optimization problem of lotus leaf alkaloid extraction process belongs to black box problem. Currently, the regression analysis and response surface method are normally method about the yield with influence factor of lotus leaf alkaloid extraction process at home and aboard. These methods design the experimental program using the orthogonal or orthogonal rotation and obtain the corresponding data relation, the parameter was estimate by using least square method and the nonlinear equation was built about yield with influence factors. And then, the experimental result was analyzed by variance components method, single factorial effect method, response surface method and interaction effect method, and the optimal extraction process under experiment condition was obtained. However, these transition methods have obvious imperfection limitations: Firstly, the greater error affect the accuracy of regression model which generated by approximate calculation, and secondly, the regression has definite limitations based on the hypothesis model, and thirdly,

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[1] *College of Electronic and Information Engineering, Liaoning Institute of Science and Technology, Benxi, China*
[2] *School of Materials Science and Engineering, Shenyang Jianzhu University, Shenyang, China*
[3] *College of Management and Science, Shandong Institute of Business and Technology, Yantai, China*
*Corresponding author: 201513424@sdtbu.edu.cn

the variable substitutions is difficulty for multivariable variable, and fourthly, the regression equation has worse processing power for noise built-in sample data. The above-mentioned defects and limitations of traditional methods seriously affect the precision and accuracy of the optimal combination obtained by optimization (Wang et al., 2017; Moloto et al., 2022).

The optimization method based on BP neural network is an optimization method proposed by the iterative optimization principle of mathematical programming method on the basis of BP neural network function fitting (Wang et al., 2017; Zhang et al., 2016; Zhao et al., 2020; Dong et al., 2022). This method provides a new idea and method for the optimization of the extraction process of lotus leaf alkaloids. Wang et al. (2017) used this method to study the corn planting density and fertilizer application, and the optimization results provided theoretical guidance for corn planting in Hongxing Farm. Dong et al. (2017) used this method to study the suction pressure loss of combine harvesters, and the obtained process parameter combination was better than the regression analysis method and the response surface method, which reduced the suction pressure loss of machinery and equipment. Dong et al. (2018a) used this method to study the soybean planting model, and provided a set of optimal planting models for soybean planting in Shanhe Farm, which reduced soybean planting costs and improved soybean yield. Dong et al. (2018b, 2022) improved the optimization method based on BP neural network and optimized the power consumption of the straw returning machine, and obtained the parameter combination of the minimum power consumption. Zhao et al. (2018) used this method to optimize the parameters of the baling mechanism, and obtained the optimal combination of disc diameter, feed amount, steel roll speed, aspect ratio and minimum power consumption value, the optimization result was verified by experiments is correct and feasible. Theoretical and applied research shows that the optimization method based on BP neural network is used to solve the black-box optimization problem, and the obtained optimization results have high precision and good stability.

In order to overcome the defects and limitations of traditional methods in the optimization of lotus leaf alkaloid extraction process, and improve the accuracy and precision of optimization results, this paper takes the optimization of lotus leaf alkaloid extraction process as the research object, and uses the linear constraint optimization method based on BP neural network to optimize the extraction process of lotus leaf alkaloid. Firstly, the Box-Behnken test model is used to design a three-factor and five-level extraction process test program and obtain the test data. And then, the test data is applied to establish the BP neural network model of lotus leaf alkaloid extraction process. Second, the optimization method based on BP neural network for linear constrained is used to optimize the parameters of lotus leaf alkaloid extraction process. Finally, the verification test was carried out to verify the correctness and feasibility of the optimization results.

2 Material and methods

2.1 Test design

The hydrochloric acid mass fraction, the ultrasound time and liquid-solid ratio were selected as the experimental factors, and the yield of lotus leaf alkaloid was selected as influence index. The Box-Behnken test model (Zhan et al., 2022) was used to design the three-factor and five-level extraction process experimental program. The experimental factor level code as shown in Table 1. On the basis of the single factor experiment, the experimental temperature is 60 °C, and the ultrasonic power is 500 W, the experimental program and results as shown in Table 2.

2.2 BP Neural Network-Based Linear Constrained Optimization Method (BPNN-LCOM)

There are two steps of the BPNN-LCOM: designing and training of the BP neural network model and global optimization of parameters.

Designing and training of the BP neural network model

A single hidden layer BP neural network was applied to establish the network structure model of the lotus leaf alkaloid yield and the influencing factors. The number of the input layer neuron is 3, x_1 is the hydrochloric acid mass fraction, x_2 is the ultrasound time, x_3 is the liquid-solid ratio, the number of output layer neuron is 1, y_1 is the yield of lotus leaf alkaloid. The hidden layer neuron was estimated according to empirical formulas, the network performance was tested, and the number of hidden layer neuron was determined to be 7. The structure of the BP neural network is shown in Figure 1.

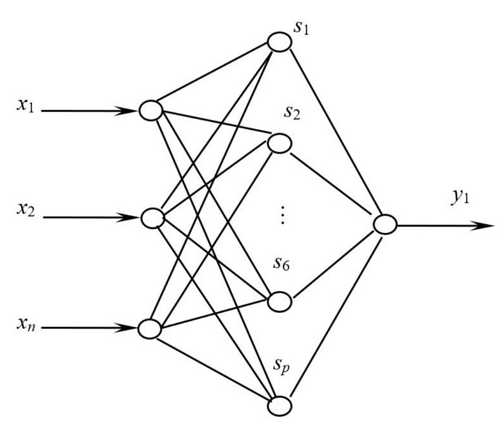

Figure 1. Structure diagram of BP neural network.

Table 1. Code of Factorial level.

Factors	Step	Level		
		-1	0	1
Hydrochloric acid mass fraction /(%)	0.1	0.2	0.3	0.4
Ultrasound time /(min)	10	30	40	50
Liquid-solid ratio	10	20	30	40

Table 2. Experiment scheme and results.

No.	Hydrochloric acid mass fraction / (%)	Ultrasound time / (min)	Liquid-solid ratio	Alkaloid yield / (mg/g)
1	0(0.3)	0(40)	0(30)	4.21
2	0(0.3)	1(50)	-1(20)	3.61
3	-1(0.4)	-1(30)	0(30)	3.17
4	1(0.2)	-1(30)	0(30)	3.29
5	-1(0.4)	1(50)	0(30)	3.20
6	0(0.3)	0(40)	0(30)	4.18
7	-1(0.4)	0(40)	1(40)	3.69
8	-1(0.4)	0(40)	-1(20)	3.25
9	0(0.3)	0(40)	0(30)	4.05
10	0(0.3)	0(40)	0(30)	4.07
11	1(0.2)	1(50)	0(30)	3.44
12	1(0.2)	0(40)	1(40)	3.60
13	0(0.3)	1(50)	1(40)	3.64
14	1(0.2)	0(40)	-1(20)	3.40
15	0(0.3)	-1(30)	-1(20)	3.22
16	0(0.3)	-1(30)	1(40)	3.63
17	0(0.3)	0(40)	0(30)	4.10

Where, x_1 is the hydrochloric acid mass fraction, x_2 is the ultrasound time, x_3 is the liquid-solid ratio; $s_1 \sim s_7$ are the neurons of the hidden layer; y_1 is the yield of lotus leaf alkaloid.

The single-stage sigmoid function is selected as the transfer functions of BP neural network model. We can obtain the objective function between the lotus leaf alkaloid yield and influencing factors as shown in Equation 1.

$$\boldsymbol{Y} = F(\boldsymbol{X}) = f\left[V \cdot f(W \cdot \boldsymbol{X} + \theta_1) + \theta_2\right] \tag{1}$$

Where, $f\,()$ is the transfer function; X is the input vector (test factor), and $X=[x_1,x_2,x_3]^T$; Y is the output vector (influencing index) and $\boldsymbol{Y}=[y_1]$; $F(X)$ is the relationship between the lotus leaf alkaloid yield and influencing factors; $\boldsymbol{W}$ is the weight matrix between the input layer and the hidden layer; θ_1 is the threshold value of the hidden layer; $\boldsymbol{V}$ is the weight matrix between the hidden layer and the output layer, and θ_2 is the threshold value of the output layer.

Training samples based on the test program and test results in Table 2 were constructed, and Python 3.7 was applied to write the computer program of the overall learning rate of the BP neural network, and perform function fitting on the training samples, and determine the network parameters of the parameter optimization model of the lotus leaf alkaloid extraction process. Suppose the normalized interval of the data of training sample is [0.2, 0.6], initial learning rate is 0.8, while the network output error E = 0.0001, the weight matrix W of input layer and hidden layer is

$$\boldsymbol{W} = \begin{bmatrix} -2.3101 & -0.2541 & -8.2886 & -1.9690 & -1.2872 & 3.2886 & 1.7342 \\ 11.1513 & -4.2653 & -0.4406 & -0.1008 & -4.1585 & -1.1846 & 1.4411 \\ -2.7719 & 1.9068 & 1.1071 & -1.8919 & -5.1741 & 1.4132 & 0.0115 \end{bmatrix}^T$$

The threshold value θ_1 of the hidden layer

$$\boldsymbol{\theta}_1 = \begin{bmatrix} -0.9309 & -1.0233 & -0.5596 & -0.8668 & -1.8576 & 0.3993 & 1.7224 \end{bmatrix}^T$$

The weight matrix $\boldsymbol{V}$ of hidden layer and output layer

$$\boldsymbol{V} = \begin{bmatrix} 5.4091 & 4.1567 & -9.3373 & 3.2353 & -8.0897 & -3.8686 & -8.3943 \end{bmatrix}$$

The threshold value θ_2 of the output layer, $\boldsymbol{\theta}_2 = [0.5763]$

Global optimization method for the influencing factors of alkaloid yield in lotus leaf

According to the model design and training results, the mathematical model of lotus leaf alkaloid extraction process parameter optimization problem can be expressed in Equation 2.

$$\begin{cases} \max\ y_1 = F(\boldsymbol{X}) = f\left[V \cdot f(W \cdot \boldsymbol{X} + \theta_1) + \theta_2\right] \\ \boldsymbol{X} \in R \end{cases} \tag{2}$$

Where, $\boldsymbol{R}$ is the feasible region formed by constraint conditions.

The global optimization method for solving the optimal value of the lotus leaf alkaloid yield is as follows (Dong et al., 2021, 2022).

Step 1: Initialize, preset the convergence precision ε_1 and ε_2 of termination criterion, select a initial feasible point $\boldsymbol{X}(t)(t \geq 0)$.

Step 2: Calculate the output value $F(\boldsymbol{X}(t))$ at point $\boldsymbol{X}(t)$ by the trained BP neural network model.

Step 3: According the transfer function of BP neural network model, calculate the first-order and second-order partial derivative of output versus input at $\boldsymbol{X}(t)$, and then obtain the gradient and Hessian matrix of objective function at $\boldsymbol{X}(t)$.

Step 4: Verify whether the gradient vector of objective function at $\boldsymbol{X}(t)$ satisfies Equation 3.

$$\| \nabla F(\boldsymbol{X}(t)) \| \leq \varepsilon_1 \tag{3}$$

Where, $\|\nabla F(\boldsymbol{X}(t))\|$ is the modulus of $\nabla F(\boldsymbol{X}(t))$, $\varepsilon_1(\varepsilon_1 \geq 0)$ is a preset precision, If satisfies, $\boldsymbol{X}(t)$ is the optimal solution obtained by global optimization based on the BP neural network as shown in Equation 4.

$$\boldsymbol{X}^* = \boldsymbol{X}(t) \tag{4}$$

its corresponding output $\boldsymbol{Y}^* = F(\boldsymbol{X}^*)$ is the optimal output value, and the iteration will terminate. If not, turn to next step.

Step 5: Calculate the search direction $\boldsymbol{S}(t)$ at $\boldsymbol{X}(t)$ by the gradient method as shown in Equation 5.

$$\boldsymbol{S}(t) = \frac{\partial F(\boldsymbol{X}(t))}{\partial \boldsymbol{X}(t)} = \left(\frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \cdots, \frac{\partial F}{\partial x_n}\right) \tag{5}$$

Step 6: Calculate the optimal step size $\lambda(t)$ by Equation 6.

$$\lambda(t) = -\frac{\boldsymbol{S}(t)^T \nabla F(\boldsymbol{X}(t))}{\boldsymbol{S}(t)^T \nabla^2 F(\boldsymbol{X}(t))\boldsymbol{S}(t)} \tag{6}$$

Where, $\boldsymbol{S}(t)$ is the search direction at $\boldsymbol{X}(t)$, $\nabla F_1(\boldsymbol{X}(t))$ is the gradient of objective function at $\boldsymbol{X}(t)$, which obtained by the first-order partial derivative of the network output versus input; $\nabla^2 F_1(\boldsymbol{X}(t))$ is the Hessen matrix at $\boldsymbol{X}(t)$, which obtained by second-order partial derivative of the network output versus input.

Step 7: Calculate the iteration amount $\Delta\boldsymbol{X}(t)$ by Equation 7 along the search direction $\boldsymbol{S}(t)$ as the optimal step size $\lambda(t)$

$$\Delta\boldsymbol{X}(t) = \lambda(t)\boldsymbol{S}(t) \tag{7}$$

Step 8: Verify whether the correction amount $\Delta\boldsymbol{X}(t)$ satisfies Equation 8.

$$|\Delta\boldsymbol{X}(t)| \leq \varepsilon_2 \tag{8}$$

If meet, the iteration will terminate, $\boldsymbol{X}(t)$ is the optimal solution, and its corresponding network output is the optimal value. If not, turn to next step.

Step 9: $\boldsymbol{X}(t)$ iterates along the search direction $\boldsymbol{S}(t)$ with the optimal best step $\lambda(t)$ and a new iteration point $\boldsymbol{X}(t+1)$ is obtained by Equation 9.

$$\boldsymbol{X}(t+1) = \boldsymbol{X}(t) + \lambda(t)\boldsymbol{S}(t) \tag{9}$$

Step 10: Calculate the function value $g_h(\boldsymbol{X}(t+1))$ $(h = 1, 2, \cdots, m)$ of all constraint functions at $\boldsymbol{X}(t+1)$, and the maximum $g(t+1)$ can be obtained by Equation 10.

$$g(t+1) = \max\{g_h(\boldsymbol{X}(t+1)) \mid (h = 1, 2, \cdots, m)\} \tag{10}$$

Step 11: Judge the relative position $\boldsymbol{X}(t+1)$ with the feasible region. If $g(t+1)<0$, then $\boldsymbol{X}(t+1)$ locate in the feasible region, let $t = t+1$, turn to step 11. If $g(t+1)>0$, then $\boldsymbol{X}(t+1)$ locate outside the feasible region, turn to step 12. If $g(t+1)=0$, then $\boldsymbol{X}(t+1)$ locate on the feasible region boundary, turn to step 13.

Step 12: Suppose $g_h(\boldsymbol{X}) = 0$ is the constraint condition that have the most constraint function value at $\boldsymbol{X}(t+1)$. The interpolation method (Equation 11) was used to calculate the adjustment step size $\lambda_c(t)$ along search direction $\boldsymbol{S}(t)$ at $\boldsymbol{X}(t)$

$$\lambda_c(t) = \frac{0 - g_h(\boldsymbol{X}(t))}{g_h(\boldsymbol{X}(t+1)) - g_h(\boldsymbol{X}(t))}\lambda(t) \tag{11}$$

Where, $g_h(\boldsymbol{X}(t))$ and $g_h(\boldsymbol{X}(t+1))$ respectively denote the function value of constraints function $g_h(\boldsymbol{X})$ $(h = 1, 2, \cdots, J < m)$ at $\boldsymbol{X}(t)$ and $\boldsymbol{X}(t+1)$. $\lambda(t)$ is the iteration step size that $\boldsymbol{X}(t)$ iterates along search direction $\boldsymbol{S}(t)$ to $\boldsymbol{X}(t+1)$.

Let $\lambda(t) \Leftarrow \lambda_c(t)$, the iteration continues from $\boldsymbol{X}(t)$, and it iterates along the search direction $\boldsymbol{S}(t)$ with $\lambda(t)$. The iteration point is adjusted to the boundary of constraint condition $g_h(\boldsymbol{X}) = 0$. Let $t = t+1$,turn to Step 13.

Step 13: Let $t = t+1$,found the set of contributing constrained functions by Equation 12.

$$J = \{h \mid g_h(\boldsymbol{X}(t)) = 0\}(h = 1, 2, \cdots, m) \tag{12}$$

Calculate the gradient of objective function $\nabla F(\boldsymbol{X}(t))$ and the gradient of contributing constrained function $\nabla g_h(\boldsymbol{X}(t))(h = 1, 2, \cdots, J < m)$ at $\boldsymbol{X}(t)$. Verify whether the gradient of objective function and the contributing constrained function at $\boldsymbol{X}(t)$ satisfies Equation 13.

$$\begin{cases} \nabla F(\boldsymbol{X}(t)) + \sum_{h=1}^{J} \beta_h \nabla g_h(\boldsymbol{X}(t)) = 0 \\ \beta_h \geq 0 (h = 1, 2, \cdots, J < m) \end{cases} \tag{13}$$

Where, $\beta_h(h = 1, 2, \cdots, J < m)$ is the Lagrangian multiplier of the h^{th} constraint condition, $\beta_h \geq 0$. If meet, the iteration will terminate, $\boldsymbol{X}(t)$ is the optimal solution and its corresponding network output is the optimal value. If not, turn to next step.

Step 14: According the set of contributing constrained function J, the gradient matrix $\boldsymbol{M}$ and identity matrix $\boldsymbol{I}$ of contributing constrained function was calculated by Equation 14 and Equation 15, the applicative feasible direction $\boldsymbol{S}(t)$ at $\boldsymbol{X}(t)$ was determined by Equation 16.

$$\boldsymbol{M} = [\nabla g_1(\boldsymbol{X}(t)), \nabla g_2(\boldsymbol{X}(t)), \cdots, \nabla g_J(\boldsymbol{X}(t))] \tag{14}$$

$$\boldsymbol{P} = \boldsymbol{I} - \boldsymbol{M}[\boldsymbol{M}^T\boldsymbol{M}]^{-1}\boldsymbol{M}^T \tag{15}$$

$$\boldsymbol{S}(t) = -\frac{\boldsymbol{P}\nabla F(\boldsymbol{X}(t))}{\|\boldsymbol{P}\nabla F(\boldsymbol{X}(t))\|} \tag{16}$$

Where, $\nabla F(\boldsymbol{X}(t))$ is the gradient of objective function at $\boldsymbol{X}(t)$. $\boldsymbol{P}$ is the projection operator, which is an $n \times n$-order matrix. $\boldsymbol{I}$ is an $n \times n$-order unit matrix, and $\boldsymbol{M}$ is a gradient matrix that contributes constraint functions at $\boldsymbol{X}(t)$.

Step 15: calculate the optimal constrained step size $\lambda_s^*(t)$ along search direction $\boldsymbol{S}(t)$ at $\boldsymbol{X}(t)$ by Equation 17

$$\lambda_s^*(t) = \min_{\lambda_{th} > 0} \{\lambda_h(t) \big| (h = J+1, J+2, \cdots, m)\} \tag{17}$$

Where, $\lambda_h(t)$ is the step size that $\boldsymbol{X}(t)$ iterates along the search direction $\boldsymbol{S}(t)$ to the h^{th} non-contributing constraint boundary.

For all (m-J) non-acting constraints, the step size $\lambda_h(t)$ that $\boldsymbol{X}(t)$ iterates along search direction $\boldsymbol{S}(t)$ to the constraint boundary $g_h(\boldsymbol{X}) = A_h\boldsymbol{X} + B_h = 0$ must satisfy Equation 18.

$$\lambda_h(t) = \frac{-g_h(\boldsymbol{X}(t))}{A_h\boldsymbol{S}(t)} \quad (h = J+1, J+2, \cdots, m) \tag{18}$$

Let $\lambda(t) = \lambda_{th}^{*}$, turn to Step 7.

3 Results and discussion

3.1 Results and analysis based on the BP neural network and regression equation

According the experimental results in Table 2, Design-Expert 8.0 is applicated to fit the experimental data, the significance and variance analysis of regression model are shown in Table 3.

It can be seen from Table 3, the primary term C and the Quadratic term A^2、B^2、C^2 of model is extremely significant, the primary term and Quadratic term of model is significant. The P-test is applied to analyze the main effect relationship of each factor, and obtain the sequence is liquid-solid ratio> ultrasound time> hydrochloric acid mass fraction. The regression equation relating lotus leaf alkaloid yield Y(mg/g)to hydrochloric acid mass fraction x_1 (%), ultrasound time x_2 (min), liquid-solid ratio is

$$Y = 4.12 + 0.053x_1 + 0.073x_2 + 0.14x_3 + 0.030x_1x_2 - 0.060x_1x_3 - 0.095x_2x_3 - 0.044x_1^2 - 0.40x_2^2 - 0.19x_3^2 \tag{19}$$

The fitted value compared with experimental value of different model for lotus leaf alkaloid yield as shown in Figure 2 (Figure 2a is the BP neural network model, and Figure 2b is the quadratic regression model). It can be concluded from Figure 2 that the R^2 of the BP neural network fitting model is 0.9863 ($P < 0.01$), the root-mean-square error (RMSE) is 0.033 mg/g, the R^2 of the quadratic regression model is 0.9806 ($P < 0.05$), and the RMSE is 0.0.046 mg/g. The statistical significantly of BP neural network model better than regression model. The fitted function that using the BP neural network model can better reveal the functional relationship between the lotus leaf alkaloid yield and influence factors.

Table 3. Significance and variance analysis of regression model.

Source	Sum of squares	*DF*	Mean square	*F value*	*P value*
Model	2.110	9	0.230	39.22	<0.0001
x_1	0.022	1	0.022	3.69	0.0960
x_2	0.042	1	0.042	7.05	0.0327
x_3	0.150	1	0.150	24.43	0.0017
$x_1 x_2$	0.004	1	0.004	0.60	0.4628
$x_1 x_3$	0.014	1	0.014	2.41	0.1643
$x_2 x_3$	0.036	1	0.036	6.05	0.0435
x_1^2	0.830	1	0.830	138.76	<0.0001
x_2^2	0.690	1	0.690	114.86	<0.0001
x_3^2	0.160	1	0.160	26.41	0.0013
bias	0.042	7	0.006		
Lock of fit	0.022	3	0.007	1.53	0.3373
Error	0.019	4	0.005		
Total	2.150	16			

Note: p < 0.05 means the difference is significant, p < 0.01 means the difference is extremely significant. DF = Degrees of Freedom.

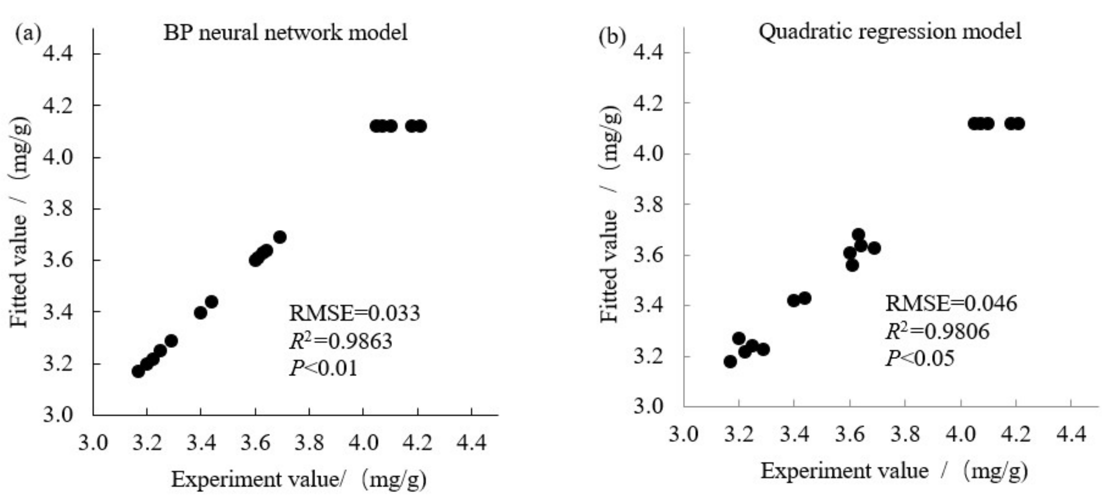

Figure 2. Comparison of the fitted and measured values of lotus leaf alkaloids in different models. (a) BP neural network model; (b) Quadratic regression model.

In order to further study the interaction between related variables, the sensitivity analysis was performed on the influencing factors and target variables by the fitted BP neural network model. While the liquid-solid ratio is constant, the hydrochloric acid mass fraction and ultrasonic time have a significant influence on the yield, and with the increase of hydrochloric acid mass fraction and ultrasonic time, the yield of lotus alkaloids first increases and then decreases. While the ultrasonic time is constant, the effect of hydrochloric acid mass fraction on yield is not significant, and the liquid-solid ratio has a significant effect on yield, and with the increase of liquid-solid ratio, it must first rise significantly and then decrease slightly. While the hydrochloric acid mass fraction is constant, the effect of ultrasonic time on the yield is not significant, and the effect of liquid-solid ratio on the yield is significant, and with the increase of the liquid-solid ratio, it must first rise significantly and then decrease slightly.

3.2 Optimization result of lotus leaf alkaloid extraction process

Taking the trained BP neural network model as objective function, the optimization method base on BP neural network for linear constrained problem was used to optimize the lotus leaf alkaloid extraction process, and solved the network input which makes network output to obtain the maximum value. According to the upper and lower limits of each factor level, the constraint conditions of optimization problem of soybean planting density and fertilization application rate is

$$\max\ y_1 = F(\boldsymbol{X}) = f\left[V \cdot f\left(W \cdot \boldsymbol{X} + \theta_1\right) + \theta_2\right]$$
$$s.t.\begin{cases} 0.2 \le x_1 \le 0.4 \\ 30 \le x_2 \le 50 \\ 20 \le x_3 \le 40 \end{cases} \tag{20}$$

Ten different combination of influence factors is selected by randomly as the initial points, the optimal results are shown in Table 4.

It can be concluded from Table 4, under the experimental conditions, the optimal parameter combination of lotus leaf alkaloid extraction process is hydrochloric acid mass fraction x_1 = 0.30%, ultrasound time x_2 = 42.85 min, liquid-solid rate x_3 = 27.18, the optimal yield of lotus leaf alkaloid under this parameter combination is Y = 4.260 mg/g.

The regression equation of quadratic regression model was optimized and obtained the optimal parameter combination is hydrochloric acid mass fraction x_1 = 0.30%, ultrasound time x_2 = 40.53 min, liquid-solid rate x_3 = 26.65, the optimal yield of lotus leaf alkaloid under this parameter combination is Y = 4.15 mg/g.

Compared the optimal results obtained by two methods, the RMSE, R_2, and P value of fitting function obtained by BP neural network method are all both better than quadratic regression model. The optimal lotus leaf alkaloid yield optimized by the optimization method based on BP neural network for linear constrained problem is better than regression model. The optimization problem of lotus leaf alkaloid extraction process belongs to black-box problem, the optimization solution of black-box problem is indeterminacy. So the good or bad of the optimization results obtained by two method can't be judged. The optimization research of two method all both establishes on the basic of function fitted. Theoretically, the fitting function with relatively small average errors is closer to the real function of the problem, and the obtained optimized results have a higher degree of accuracy (Dong et al., 2022).

3.3 Result of experimental verification

In order to check the reliability of results obtained by the linear constrained optimization method based on BP neural network, the verification experimental was processed on November 2021, all experimental equipment is qualified metrological verification. Taking into account the metering operation in the verification process, the optimization results were fine-tuned, the hydrochloric acid mass fraction was 0.3%, the ultrasonic time was 43 min, and the liquid-solid ratio was 27. The BP neural network model was used for forward fitting of this parameter combination, and the yield of lotus leaf alkaloids was 4.26 mg/g under this parameter combination. The verification experimental was carried out under this parameter condition, repeated 10 times and the experimental results of lotus leaf alkaloid yield are shown in Table 5.

Table 4. Optimization results of BP neural network.

No.	Initial Point			Optimal solution			Optimal value alkaloid yield / (mg/g)
	Hydrochloric acid mass fraction / (%)	Ultrasound time /(min)	Liquid-solid ratio	Hydrochloric acid mass fraction / (%)	Ultrasound time /(min)	Liquid-solid ratio	
1	0.25	40	25	0.30	42.85	27.18	4.27
2	0.34	35	30	0.30	42.85	27.18	4.27
3	0.32	45	28	0.30	42.85	27.18	4.27
4	0.28	48	33	0.30	42.85	27.18	4.27
5	0.37	40	29	0.30	42.85	27.18	4.27
6	0.35	38	34	0.30	42.85	27.18	4.27
7	0.22	48	35	0.30	42.85	27.18	4.27
8	0.36	32	39	0.30	42.85	27.18	4.27
9	0.30	42	28	0.30	42.85	27.18	4.27
10	0.38	44	3	0.30	42.85	27.18	4.27

Table 5. Verification result for extraction technology parameters of alkaloids in lotus leaf.

Method	Index	Alkaloids yield /(mg/g)
Test	Minimum value	4.24
	Maximum value	4.36
	Mean value	4.28
BP neural network	Optimal value	4.26
Relative errors /(/%)		0.46

BP = Back Propagation.

We can seen from Table 5, the lotus leaf alkaloid yield of verification experimental is 4.28 mg/g, the absolute error is 0.02 mg/g and the relative error is 0.46%. Although there is a certain error between the verification results and the theory optimization results, but considering the comprehensive impact of measure error and Metrology error of experimental process, the error of the test results is within the allowable range. Therefore, the results of the verification test were consistent with the optimized results obtained by the optimization method, and the optimized results obtained by the BP neural network were accurate and reliable.

4 Conclusions

In this paper, the experimental program of extraction process was designed by the Box-Behnken model, and the experimental data were obtained. The BP neural network was applied to train and fit the experimental data, and the mathematical model of the lotus leaf alkaloid extraction process was established. The fitted precision of model is higher and the statistical significantly better than regression model. The fitted function can better reveal the functional relationship between the lotus leaf alkaloid yield and influence factors under experimental conditions.

The linear constrained optimization method based on the BP neural network was used to optimize the extraction process of lotus leaf alkaloid, and obtained the optimal parameter combination under the experimental condition is hydrochloric acid mass fraction is 0.3%, the ultrasonic time is 43 min, and the liquid-solid ratio is 27. The yield of lotus leaf alkaloids is 4.26 mg/g, which is better than the regression model. The verification experimental was carried out and the optimization results of optimal alkaloid yield was obtained, the relative error of experimental results and theory optimization results is 0.46%, the verification results is congruous with theory optimization results. The verification result shown that the optimization result obtained by linear constrained optimization method based on BP neural network is accurate and reliable.

The application of the linear constrained optimization method based on BP neural network in parameters of lotus leaf alkaloid extraction process, it has important significant to guide the effective utilization of lotus leaf resources. At the same time, this method provides a new method and idea to the extraction process of agricultural products.

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