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PARAMETER OPTIMIZATION OF WHOLE-STRAW RETURNING DEVICE BASED ON THE BP NEURAL NETWORK

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KEYWORDS

agricultural mechanization, BP neural network, whole-straw, returning device, parameter optimization.

ABSTRACT

To solve the poor fitting degree of errors in multiobjective parameter optimization and low accuracy, a multiobjective optimization method based on a BP neural network was proposed. By taking the 1ZT-210 type whole-straw returning device as the research object, a BP neural network model on power consumption, straw returning rate and the influencing factors was obtained. By optimizing the model by the proposed method, the optimal parameter combination of the test factors was as follows: the advancing speed of the device was 0.65 km/h, the blade roll rotating speed was 210 rpm, the blade installation angle was 55°, the minimum power consumption was 9.82 kW and the maximum straw returning rate was 93.23%. Under such test conditions, the minimum power consumption was 10.75 kW, and the straw returning rate was 92.46%, which were all better than those obtained by the regression analysis method. Finally, a verification test was conducted on the results of BP neural network optimization. The power consumption of the test was 10.04 kW, the absolute error was 0.22 kW and the relative error was 2.24%. For a straw returning rate of 93.11%, the absolute error was -0.12% and the relative error was 0.13%. The test results indicated that the optimization method was feasible.

INTRODUCTION

Straw returning technology is one of the main methods of returning straw to the field after harvesting in China (Gao et al., 2008; Wang, 2015). Straw returning can not only supplement organic matter in soil and reduce the application of fertilizers but also improve the physical and chemical properties of soil and increase the number of soil microorganisms. Therefore, straw returning plays an important role in moisture preservation, regulation of soil temperature and improvements to agricultural and ecological environments (Zhang, 2013). The research and development of whole-straw burying and returning devices has become a hotspot in straw returning technology since whole-straw returning can not only meet the requirement of implementing conservation tillage technology and improving agricultural mechanization but also ensure the implementation of sustainable development of agriculture as a basic state policy.

Power consumption and straw returning rate are the two key indices in evaluating the functions of the whole-straw returning device. Power consumption affects the matched power and operation cost of the device, while the straw returning rate determines whether the device can meet the agronomic requirements in straw burying and returning (Wang et al., 2009). Power consumption and straw returning rate are affected by the interaction of multiple factors, such as advancing speed of the devide, blade roll rotating speed, blade installation angle, and number of cutting disks. Since the interaction between the factors is unknown, it has strong characteristics of a black box problem (Jia et al., 2005; Wang, 2007; Zhao, 2007; Zhang, 2008, Li, 2009; Wang, 2015). Therefore, the parameter optimization of the whole-straw returning device is a problem of mechanical optimization design with the characteristics of a black box.

The optimization method based on the BP neural network was proposed according to the principle of iterative

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optimization in the mathematical programming approach based on the function fitting of the BP neural network (Liu et al., 2010; Dong, 2018; Dong et al., 2019; Zhang et al., 2016; Dong et al., 2021). The method could provide a new approach for optimization of the black box problem. Wang et al. (2017) performed a study on the optimization between corn planting density and the application rate of fertilizers based on this method, and the optimization results could provide theoretical guidance for corn planting in Red Star Farm in Heilongjiang Province, China. Dong et al. (2017) performed an optimization study on the suction pressure loss of a combine harvester based on this method, and the obtained parameter combination was better than that obtained by the regression analysis method and response surface method and reduced the suction pressure of the harvester. Dong et al. (2018a) performed an optimization study on the soybean planting pattern based on this method, and the optimization results provided a set of optimal planting patterns for soybean planting in Shanhe Farm, Heilongjiang Province, China, and reduced soybean planting cost and enhanced soybean yield. Dong et al. (2018b) optimized the power consumption of a whole-straw returning device by using and improving the optimization method based on a BP neural network and obtained an optimal parameter combination of the advancing speed, blade roll rotating speed, blade installation angle and the minimum power consumption value under such a parameter combination. Zhao et al. (2018) used this method to optimize the parameters of a baling mechanism and obtained an optimal combination of disk diameter, feeding volume, rotating speed of the steel roller, length-width ratio, and the minimum power consumption value. A verification test proved that the optimization results were accurate and applicable. The theoretical and application studies above show that solving the black box optimization problem by using the optimization method based on a BP neural network could achieve optimization results with high precision and good stability. However, existing theories and applications mainly solve the problem of single object optimization, and there are no theoretical and application studies on multiobjective black box problems.

By taking the parameter optimization of the 1ZT-210 type whole-straw returning device for rice as the object of study, the theory of multiobjective optimization and application based on a BP neural network was first discussed. First, on the basis of the optimization method based on a BP neural network, a multiobjective optimization method based on a BP neural network is proposed. The core idea of this method is to introduce the tolerant hierarchical sequence method and distinguish the primary and secondary objective functions of the optimization problem. The objective functions are scored according to their importance, and the optimal solution of each objective function is found in turn. The latter objective function is optimized in the set domain of the optimal solution of the former objective function. The wide capacity for the optimal value of each objective function is a key parameter that can avoid the possible interruption phenomenon in the solution process of the hierarchical sequence method. Second, by taking the advancing speed, blade roll rotating speed, and blade installation angle as influencing factors and power consumption and straw returning rate as optimization indices, a BP neural network model for multiobjective parameter optimization for the whole-straw returning device was established. Then, the optimization method based on the BP neural network was used to optimize the influencing factors, and the optimal power consumption and straw returning rate were obtained. Finally, a verification test was conducted on the model.

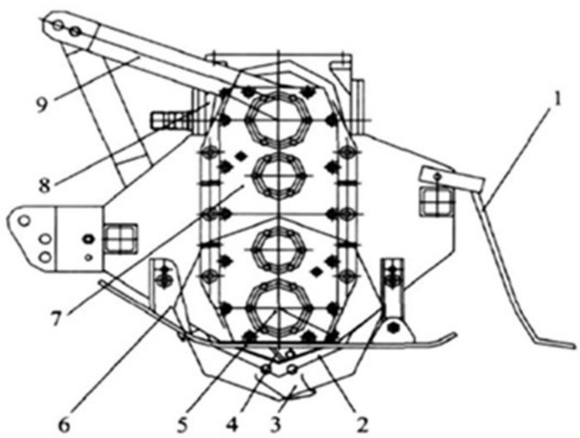
MATERIAL AND METHODS

Test design

Fundamental principles of the 1ZT-210-type whole-straw returning device

The 1ZT-210-type whole-straw returning device for rice is a new kind of straw returning device that can complete clod crushing, rotary tillage, grass cutting, pressing and covering at one time and realize burying and returning of straw with high stubbles, standing and cutting down whole straw after threshing (Jia et al., 2005; Wang et al., 2007; Zhao, 2007; Wang et al., 2015). Compared with other straw treatments, the whole-straw returning device has a deep tillage depth and good returning performance, and the whole straw buried in the field would not emerge above water and affect rice transplanting or growth (Zhang, 2008).

The 1ZT-210 type whole-straw returning device for rice is mainly composed of a hanger, a main reducing gear, a wheel reducing gear, a limit sliding support, a principal axis, a grass cutter, a stubble-mulch cutter, blade roll and grass baffling rack (Zhang, 2008), and the structure is shown in Fig. 1. Unilateral transmission was chosen for the device. The driving force is delivered to the central speed reducer through the cardan joint, while the central speed reducer drives the blade roller to rotate through the drive shaft and the side speed reducer to realize straw returning (Wang, 2015). The main working parameters of the device are as follows: the burial depth of straw is 12-15 cm; the straw coverage rate is higher than 90%, the working width is 2 m, and the matched power is a high-horsepower tractor (New Holland, above 110 horsepower).



1. Grass baffling rack 2. Blade roller 3. Stubble-mulch cutter 4. Grass cutter 5. Principal axis 6. Limit sliding support 7. Wheel reducing gear 8. Main reducing gear 9. Hanger

FIGURE 1. 1ZT-210-type whole-straw returning device for rice.

Test design

To reflect the overall influence law of the advancing speed, rotating speed of the blade roll, and blade installation angle on the power consumption and straw returning rate, advancing speed x_1(km/h), rotating speed of the blade roll x_2(rpm), and blade installation angle x_3(°) were taken as test factors. Power consumption y_1(kW) and straw returning rate y_2(%) were taken as influencing indices in the test. The power consumption should be as small as possible, and the straw returning rate should be as large as possible. According to the test soil conditions, the range of bite length for the returning device is 7~10 cm. Combining the relationship between the bite length, advancing speed and rotating speed of the blade roll, the range of advancing speed is calculated to be 0.4~0.9 km/h, and the range of the rotating speed is calculated to be 195~271 rpm. According to the theoretical analysis of the sliding angle and installation angle of the straw-returning device, the blade installation angle is determined to be in the range of 40°~60°. Using the quadratic rotation orthogonal combination design test, the test factor coding table is shown in Table 1, and the test program and test results are shown in Table 2. The power consumption and returning rate cannot be directly evaluated. The power consumption was indirectly evaluated by the functional relationship between the torque and power consumption, and the torque of the power take-off shaft was measured by the strain gauge method. The straw returning rate was evaluated by the ratio of straw weight before and after returning to the field. Before the test, the test area was gridded, and the average weight of straw in multiple grid areas was sampled and measured. After the test, the weight of exposed rice straw in multiple grid areas was sampled and measured. Then, the returning weight can be obtained by the difference between the two weights, and the returning rate can be indirectly evaluated.

TABLE 1. Factor level coding table.

Factors	Level of factors				
	-1.682	-1	0	1	1.682
Advancing speed, km/h	0.44	0.50	0.65	0.80	0.86
Rotating speed of the blade roll/(rpm)	200	213	233	253	266
Blade installation angle/(°)	41.59	45	50	55	58.41

TABLE 2. Test program and test results.

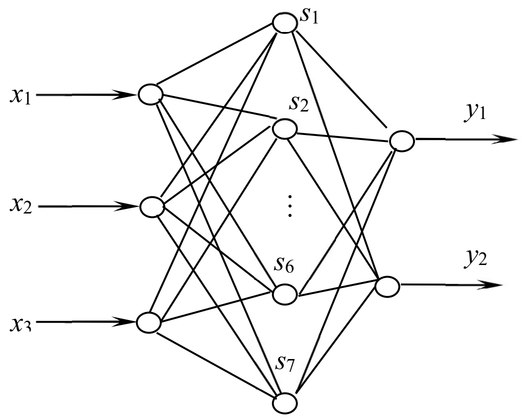
No.	x_1/(km·h^{-1})	x_2/(rpm)	x_3/(°)	y_1/(kW)	y_2/(kW)
1	-1(0.50)	-1(213)	-1(45)	9.275	86.3
2	0(0.65)	0(233)	0(50)	10.266	91.8
3	1(0.80)	1(253)	1(55)	15.051	97.6
4	1(0.80)	-1(213)	-1(45)	9.997	93.7
5	-1.682(0.86)	0(233)	0(50)	9.79	88.2
6	-1.682(0.44)	0(233)	0(50)	13.648	89.1
7	1(0.80)	1(253)	-1(45)	12.963	89.2
8	1(0.80)	-1(213)	1(55)	10.426	94.1
9	-1(0.50)	1(253)	1(55)	12.17	90.2
10	0(0.65)	0(233)	0(50)	9.791	92.4
11	-1(0.50)	-1(213)	1(55)	9.309	86.2
12	-1(0.50)	1(253)	-1(45)	11.297	93.9
13	0(0.65)	0(233)	0(50)	9.914	92.6
14	0(0.65)	0(233)	0(50)	10.015	91.4
15	0(0.65)	0(233)	0(50)	9.888	95.3
16	0(0.65)	0(233)	0(50)	10.186	92.7
17	0(0.65)	0(233)	0(50)	9.724	93.7
18	0(0.65)	0(233)	0(50)	10.065	95.1
19	0(0.65)	0(233)	0(50)	9.945	95.2
20	0(0.65)	0(233)	-1.682(41.59)	9.386	85.7
21	0(0.65)	1.682(266.64)	0(50)	13.281	94.2
22	0(0.65)	-1.682(199.36)	0(50)	9.381	87.5
23	0(0.65)	0(233)	1.682(58.41)	10.922	93.1

Parameter optimization method for the whole-straw returning device based on the bp neural network

There are three steps of the parameter optimization method for the whole-straw returning device based on the BP neural network: structural design of the BP neural network model, training and fitting, and global optimization of parameters.

Structural design of the BP neural network

A three-layer BP neural network (input layer, hidden layer, output layer) was used to construct a structural model of power consumption, straw returning rate and influencing factors. The number of neurons in the input layer is 3, x_1 is the advancing speed of the machine, x_2 is the rotating speed of the cutter roller, x_3 is the blade installation angle, the number of output layer neurons is 2, y_1 is the power consumption, and y_2 is the straw returning rate. The number of neurons in the hidden layer was estimated according to empirical formulas, the network performance was tested, and the number of neurons in the hidden layer was determined to be 7. The structure of the BP neural network is shown in Fig. 2.



Where, x_1 is the advancing speed of the device, x_2 is the rotating speed of the blade roll, x_3 is the blade installation angle; s_1~ s_7 are the nodes in the hidden layer; y_1 is the power consumption; and y_2 is the straw returning rate.

FIGURE 2. Structure of the BP neural network.

The transfer functions from the input layer to the hidden layer and the hidden layer to the output layer are single-stage sigmoid functions. The objective function between power consumption, straw returning rate, advancing speed of the device, rotating speed of the blade roll and the blade installation angle can be expressed by the following:

$$\boldsymbol{Y}=F(\boldsymbol{X})=f\,[\boldsymbol{V}\cdot f\,(\boldsymbol{W}\cdot\boldsymbol{X}+\boldsymbol{\theta}_1)+\boldsymbol{\theta}_2] \tag{1}$$

Where:

$f\,()$ is the transfer function of the BP neural network;

X is the input vector (test factor), and $X=[x_1,\ x_2,\ x_3]^T$;

Y is the output vector (influencing index) and $\boldsymbol{Y}=[y_1,\ y_2]$;

$F(X)$ is the relationship between the input and output;

$\boldsymbol{W}$ is the weight matrix between the input layer and the hidden layer;

$\boldsymbol{\theta}_1$ is the threshold value of the hidden layer;

$\boldsymbol{V}$ is the weight matrix between the hidden layer and the output layer, and

$\boldsymbol{\theta}_2$ is the threshold value of the output layer.

Training and fitting of the BP neural network model

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, perform function fitting on the training samples, and determine the network parameters of the parameter optimization model of the whole-straw returning device. The normalized interval of the data of the training sample is [0.2, 0.8], and the network initial learning rate is 0.8. When the network output error E=0.0001, the weight matrix W of the input layer and hidden layer is the following:

$$\boldsymbol{W}=\begin{bmatrix} -5.7154 & -2.8632 & 1.0913 & -4.4513 & 9.7747 & 4.4477 & 8.0849 \\ -3.8277 & 7.5998 & 0.7928 & -0.5102 & -9.9999 & 7.1987 & 7.5822 \\ 6.6938 & 0.6347 & -3.9722 & -1.1926 & -4.8761 & -6.5369 & -6.5334 \end{bmatrix}^T$$

The threshold value $\boldsymbol{\theta}_1$ of the hidden layer

$$\theta_1=\begin{bmatrix} -1.6535 & 0.6330 & -0.8225 & -3.9855 & -2.0831 & 2.3740 & 3.7461 \end{bmatrix}^T$$

Weight matrix $\boldsymbol{V}$ of the hidden layer and output layer

$$V=\begin{bmatrix} 7.4988 & -2.5557 & 1.2257 & -7.6134 & -0.6597 & 12.9283 & -5.7944 \\ 6.3981 & -4.6265 & 10.4349 & -6.3742 & -4.5869 & -5.8135 & 7.9515 \end{bmatrix}$$

The threshold value $\boldsymbol{\theta}_2$ of the output layer, $\theta_2=\begin{vmatrix} 0.7657 & 0.1977 \end{vmatrix}^{'}$

Global optimization method for the whole-straw returning device based on a BP neural network

Rank the multiple objectives in the parameter optimization of the whole-straw returning device based on their order of importance, and set $F_1(\boldsymbol{X})$ as the main objective and $F_2(\boldsymbol{X})$ as the secondary objective.

(1) For the main objective $F_1(\boldsymbol{X})$, the optimization problem can be expressed by the following:

$$\begin{cases} \min y_1 = F_1\left(\boldsymbol{X}\right) = f\left[V \cdot f\left(W \cdot \boldsymbol{X} + \theta_1\right) + \theta_2\right] \\ \boldsymbol{X} \in D \end{cases} \tag{2}$$

Where:

D is the feasible region formed by constraint conditions. The global optimization method for solving the optimal value F_1^* of the main objective $F_1(\boldsymbol{X})$ is as follows:

Step 1: Generate an initial point $\boldsymbol{X}(0)$ artificially or randomly, and $\boldsymbol{X}(0) \in D$. Set $\boldsymbol{X}(t)$ as the feasible point obtained in the t^{th} iteration.

Step 2: Calculate the gradient of $\boldsymbol{X}(t)$:

$$\frac{\partial F_1\left(\boldsymbol{X}\right)}{\partial \boldsymbol{X}}\Big|_{X=X(t)} \qquad t \in [0,1,2,\cdots] \tag{3}$$

Step 3: Judge if the gradient mode $\left\| \frac{\partial F_1\left(\boldsymbol{X}\right)}{\partial \boldsymbol{X}}\Big|_{X=X(t)} \right\|$ of point $\boldsymbol{X}(t)$ satisfies

$$\left\| \frac{\partial F_1\left(\boldsymbol{X}\right)}{\partial \boldsymbol{X}}\Big|_{X=X(t)} \right\| = 0 \qquad t \in [0,1,2,\cdots] \tag{4}$$

If so, the optimal solution $\boldsymbol{X}^*=\boldsymbol{X}(t)$, and its corresponding network output $F_1(\boldsymbol{X}^*)$ is the optimal value; if not, go to Step 4.

Step 4: Calculate search direction $\boldsymbol{S}(t)$ of point $\boldsymbol{X}(t)$ according to Newton type method:

$$\boldsymbol{S}\left(t\right) = -\left[\nabla^2 F_1\left(\boldsymbol{X}\left(t\right)\right)\right]^{-1} F_1\left(\boldsymbol{X}\left(t\right)\right) \tag{5}$$

and the optimal iteration step length λ can be written as

$$\lambda = -\frac{\left(\boldsymbol{S}\left(t\right)\right)^{\mathrm{T}} \nabla F_1\left(\boldsymbol{X}\left(t\right)\right)}{\left(\boldsymbol{S}\left(t\right)\right)^{T} \nabla^2 F_1\left(\boldsymbol{X}\left(t\right)\right)\boldsymbol{S}\left(t\right)} \tag{6}$$

Where:

$\nabla F_1(\boldsymbol{X}(t))$ is the gradient of point $\boldsymbol{X}(t)$, which can be obtained by the first-order partial derivative of the network output to input, and $\nabla^2 F_1(\boldsymbol{X}(t))$ is the Hesse matrix of point $\boldsymbol{X}(t)$, which can be obtained by the second-order partial derivative of the network output to input.

Step 5: Starting from point $\boldsymbol{X}(t)$, an iterative search is carried out based on

$$\boldsymbol{X}(t+1)=\boldsymbol{X}(t)+\lambda\cdot\boldsymbol{S}(t) \tag{7}$$

and a new iteration point $\boldsymbol{X}(t+1)$ is obtained.

Step 6: Calculate the values of each constraint function at point $\boldsymbol{X}(t+1)$ and verify the position relationship of the iteration point $\boldsymbol{X}(t+1)$ with respect to the feasible region. If there is $g_h(\boldsymbol{X}(t+1)) < 0 \ (h = 1,2,\cdots,m)$, point $\boldsymbol{X}(t+1)$ is located within the feasible region formed by the constraint conditions. Let $t=t+1$, then go to Step 2; if there is $g_h(\boldsymbol{X}(t+1)) = 0 \ (h = 1,2,\cdots,m)$, then $g_h(\boldsymbol{X}(t+1)) = 0$ is the functioning constraint function, and point $\boldsymbol{X}(t+1)$ is located at the boundary of the feasible region formed by the constraint function $g_h(\boldsymbol{X}(t+1)) = 0$. Then go to Step 8; if there is $g_h(\boldsymbol{X}(t+1)) > 0$, then point $\boldsymbol{X}(t+1)$ is located outside the feasible region formed by the constraint conditions. Then go to Step 7.

Step 7: The trial-and-error method was used to adjust the step factor $\lambda(t)$ along the direction $\boldsymbol{S}(t)$. Let $\lambda(t) \Leftarrow 0.5\lambda(t)$ and go to Step 5.

Step 8: Let t=t+1, calculate the gradient vector $\nabla F_1\left(\boldsymbol{X}(t)\right)$ of the objective function at point $\boldsymbol{X}(t)$, and calculate the gradient $\nabla g_h(\boldsymbol{X}(t))$ of the functioning constraint function at point X(t). Then, test if point $\boldsymbol{X}(t)$ satisfies

$$\begin{cases} \nabla F_1(\boldsymbol{X}(t)) + \sum_{h=1}^{m} \beta_h \nabla g_h(\boldsymbol{X}(t)) = 0 \\ \beta_h \geq 0 \ (h = 1, 2, \cdots, \ J < m) \end{cases} \tag{8}$$

Where:

$\beta_h \geq 0 \ (h = 1, 2, \cdots, J < m)$ is the Lagrangian multiplier of the h^{th} constraint condition.

If the condition is satisfied, the iteration terminates, point $\boldsymbol{X}(t)$ is the optimal solution, and its corresponding network output $F_1(\boldsymbol{X}^*)$ is the optimal value; otherwise, go to Step 9.

Step 9: Calculate the search direction $\boldsymbol{S}(t)$ of point $\boldsymbol{X}(t)$ and iteration step length λ according to eqs (5) and (6). Determine if λ satisfies λ≤0. If so, the optimal solution is $\boldsymbol{X}^*=\boldsymbol{X}(t)$, and its corresponding network output $F_1(\boldsymbol{X}^*)$ is the optimal value; otherwise, return to Step 2.

(2) For the secondary objective $F_2(\boldsymbol{X})$, the optimization problem can be expressed by

$$\begin{cases} \max y_2 = F_2\left(\boldsymbol{X}\right) = f\left[V \cdot f\left(W \cdot \boldsymbol{X} + \theta_1\right) + \theta_2\right] \\ \boldsymbol{X} \in D_1 \subset \left\{\boldsymbol{X} \middle| F_1\left(\boldsymbol{X}\right) \leq F_1\left(\boldsymbol{X}^*\right) + \varepsilon\right\} \end{cases} \tag{9}$$

Where:

ε is the tolerance value. To prevent the deviation introduced by the interruption that emerged in problem solving, ε>0.

According to the global optimization method of the main objective $F_1(\boldsymbol{X})$, the optimal solution $\boldsymbol{X}^*$ and the optimal value F_2^* of the secondary objective $F_2(\boldsymbol{X})$ are solved. At this time, the optimal solution $\boldsymbol{X}^*$ and the optimal value F_2^* are the optimal solutions of the parameter optimization problem of the whole straw returning device.

RESULTS AND DISCUSSION

Results and analysis based on the BP neural network

Analysis of the fitting model of power consumption and test factors

Design-Expert 8.0 is used to process the test data in Table 2, and the results of variance analysis of the influence of the test factor on power consumption are shown in Table 3.

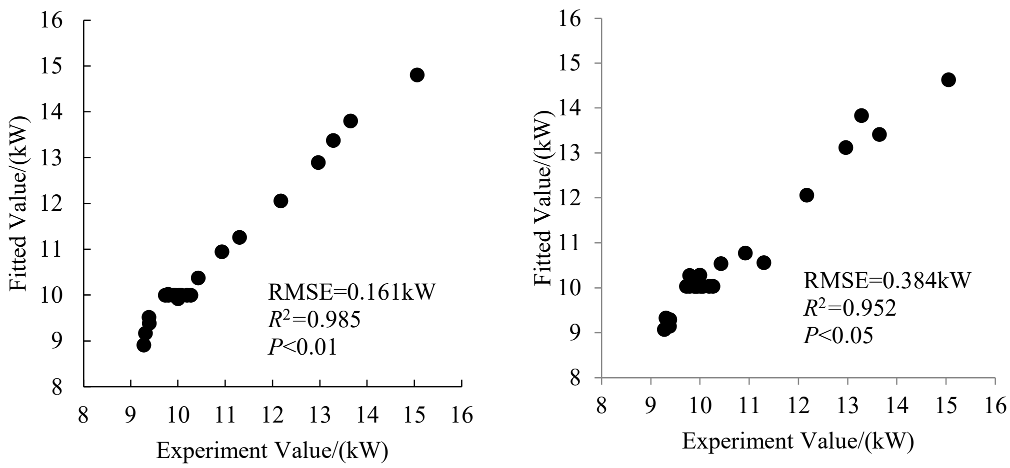
TABLE 3. Results of variance analysis.

Source	Sum of squares	*DF*	Mean square	*F value*	*P value*
Model	54.37	9	6.04	57.44	<0.0001
x_1	12.14	1	12.14	115.40	<0.0001
x_2	26.53	1	26.53	252.22	<0.0001
x_3	2.64	1	2.64	25.13	0.0002
$x_1 x_2$	0.92	1	0.92	8.72	0.0112
$x_1 x_3$	0.32	1	0.32	3.08	0.1027
$x_2 x_3$	0.78	1	0.78	7.42	0.0174
x_1^2	6.77	1	6.77	64.33	<0.0001
x_2^2	4.22	1	4.22	40.12	<0.0001
x_3^2	0.16	1	0.16	1.49	0.2444
Error	0.25	8	0.031		
Total	55.74	22			

It can be seen from Table 3 that the Factors x_1, x_2, x_3, x_1^2, x_2^2 are extremely significant, x_1x_2, x_2x_3 are significant at the level α=0.05, and x_1x_3, x_3^2 are not significant at the level α=0.1, so they were eliminated. The regression equation relating power consumption y_1 (kW) to advancing speed of the device x_1 (km/h), rotating speed of blade roll x_2 (rpm), and blade installation angle x_3 (°) is given as

$$y_1 = 165.90 - 92.43x_1 - 0.83x_2 - 0.64x_3 + 0.11x_1x_2 + 0.003x_2x_3 + 28.97x_1^2 + 0.001x_2^2 \quad (10)$$

The comparison between the fitted value and test value of the power consumption of the BP neural network model is shown in Fig. 3a, and the comparison between the fitted value and test value of the quadratic regression model is shown in Fig. 3b. It can be concluded by comparing Figs. 3a and 3b that R^2 of the BP neural network fitting model is 0.985 (P<0.01), root-mean-square error (RMSE) is 0.161 kW, R^2 of the quadratic regression model is 0.952 (P<0.05), and RMSE is 0.384 kW, showing that both the fitting degree and precision of power consumption of the BP neural network model are higher than those of the regression model. The fitting function of power consumption by using the BP neural network model can better reveal the functional relationship between test factors and influencing indices. The minimum value of power consumption after fitting by the BP neural network was 9.314 kW, and the corresponding test parameters were as follows: the advancing speed of the device was 0.50 km/h, the rotating speed of the blade roll was 213 rpm and the blade installation angle was 55°.



a. Model of the BP neural network b. Model of the quadratic regression

FIGURE 3. Comparison of fitted values and test values of power consumption of different models

Analysis of the fitting model of the straw returning rate and test factors

Design-Expert 8.0 is used to process the test data in Table 2. The results of variance analysis of the influence of the test factor on power consumption are shown in Table 4.

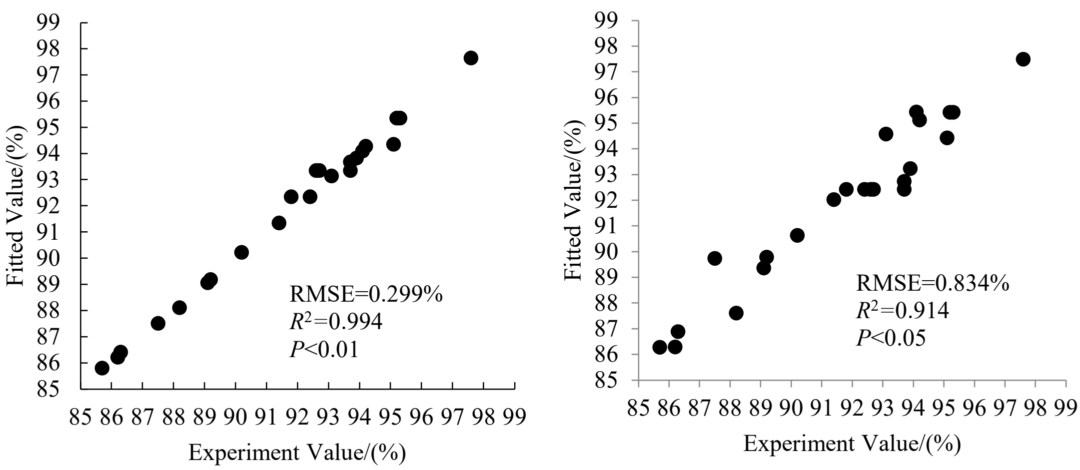
TABLE 4. Results of variance analysis.

Source	Sum of squares	*DF*	Mean square	*F value*	*P value*
Model	170.62	9	18.96	3.48	0.0207
x_1	27.88	1	27.88	5.12	0.0413
x_2	35.02	1	35.02	6.44	0.0248
x_3	22.28	1	22.28	4.10	0.0640
$x_1 x_2$	19.84	1	19.84	3.65	0.0785
$x_1 x_3$	19.85	1	19.85	3.65	0.0785
$x_2 x_3$	2.42	1	2.42	0.44	0.5165
x_1^2	24.85	1	24.85	4.57	0.0522
x_2^2	3.55	1	3.55	0.65	0.4337
x_3^2	15.43	1	15.43	2.84	0.1160
Error	18.50	8	2.31		
Total	241.35	22			

It can be seen from Table 4 that the Factors x_1, x_2, x_3, x_1x_2, x_1x_3, x_1^2 are significant, and x_2x_3, x_2^2, x_3^2 are not significant at the level α=0.1, so they were eliminated. The regression equation relating straw returning rate y_2 (%) to advancing speed of the device x_1 (km/h), rotating speed of the blade roll x_2 (rpm), and blade installation angle x_3 (°) is

$$y_2 = -58.697 + 164.685x_1 + 0.736x_2 - 2.370x_3 - 0.525x_1x_2 + 2.100x_1x_3 - 55.133x_1^2 \quad (11)$$

The comparison between the fitted values and test values of the straw returning rate by the BP neural network model is shown in Fig. 4a, and the comparison between the fitted values and test values of the straw returning rate by the quadratic regression model is shown in Fig. 4b. It can be concluded by comparing Figs. 4a and 4b that the R^2 of the BP neural network fitting model is 0.994 (P<0.01), the root-mean-square error (RMSE) is 0.299%, the R^2 of the quadratic regression model is 0.914 (P<0.05), and the RMSE is 0.834%, showing that both the fitting degree and precision of the straw returning rate of the BP neural network model are higher than those of the regression model. The fitting function of the straw returning rate by using the BP neural network model can better reveal the functional relationship between test factors and influencing indices. The maximum value of the straw returning rate by BP neural network fitting is 95.31%. With the following test data, the advancing speed of the device was 0.80 km/h, the rotating speed of the blade roll was 213 rpm, and the blade installation angle was 55°.



a. Model of the BP neural network b. Model of the quadratic regression model

FIGURE 4. Comparison of fitted values and test values of straw returning rate of different models

Global optimization results

The purpose of parameter optimization of the whole-straw returning device was to find the best parameter combination of advancing speed, rotating speed of the blade roll, and blade installation angle under the required working conditions, reduce power consumption and increase the straw returning rate. The working performance of the straw returning device should meet the following requirement: the straw coverage rate should be above 90%, and the lower the power consumption is, the better. Therefore, power consumption in operation was taken as the main objective, and the straw returning rate was taken as the secondary objective of this study. Taking the fitted BP neural network model as the objective function and the upper and lower limits of the test factors as the constraint conditions, the optimized mathematical model of power consumption was determined.

$$\min y_1 = F_1(\boldsymbol{X}) = f\left[V \cdot f\left(W \cdot \boldsymbol{X} + \theta_1\right) + \theta_2\right]$$
$$s.t.\begin{cases} 0.44 \le x_1 \le 0.86 \\ 200 \le x_2 \le 266 \\ 41.59 \le x_3 \le 58.41 \end{cases} \quad (12)$$

According to the optimization method given in Section 3.3, the optimized mathematical model of power consumption was solved, and the optimal parameter combination of test factors was obtained. The advancing speed was 0.70 km/h, the rotating speed of the blade roll was 220 rpm, and the installation angle was 55°. Under this parameter combination, the output power consumption in operation of the BP neural network model was 9.37 kW.

Set the given tolerance ε=0.5, and the mathematical model of the optimization of the straw returning rate as the secondary objective was obtained by [eq. (9)]:

$$\max y_2 = F_2(\boldsymbol{X}) = f\left[V \cdot f\left(W \cdot \boldsymbol{X} + \theta_1\right) + \theta_2\right]$$
$$s.t.\begin{cases} F_1(\boldsymbol{X}) \le 9.37 + 0.5 = 9.87 \\ 0.44 \le x_1 \le 0.86 \\ 200 \le x_2 \le 266 \\ 41.59 \le x_3 \le 58.41 \end{cases} \quad (13)$$

According to the optimization method given in "Section 3.3", the mathematical model of power consumption was solved, and the optimal parameter combination of test factors was obtained. The advancing speed was 0.70 km/h, the rotating speed of the blade roll was 220 rpm, and the installation angle was 55°. Under this parameter combination, the output power consumption in operation of the BP neural network model was 9.82 kW, and the straw returning rate was 93.23%.

Power consumption in operation was taken as the main objective, and the straw returning rate was taken as the constraint function, according to the agronomic requirements of the straw returning operation. Design-Expert 7 was applied to optimize the quadratic regression Equations (10) and (11). Through software analysis, the optimal results were obtained: the advancing speed was 0.62 km/h, the rotating speed of the blade roll was 219 rpm, and the blade installation angle was 55°. Under this parameter combination, the power consumption in operation of the whole-straw returning device was 10.75 kW, and the straw returning rate was 92.46%.

After comparing the optimization results by the two optimization methods, the RMSE, R^2 and P value of the fitting function obtained by the BP neural network model were all better than those obtained by the quadratic regression model. The power consumption in operation obtained by the optimization method of the BP neural network was lower than that obtained by the regression model, and the straw returning rate was higher than that obtained by the regression model. The parameter optimization of the whole-straw returning device is a black box problem, whose optimal solution is uncertain; thus, it is impossible to determine whether the results obtained by the two methods are better. Both parameter optimization methods based on the BP neural network and regression model on the whole-straw returning device are established on the condition that the functions between the influencing indices and test factors are close to each other. 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.

Verification test

To verify the correctness of the optimized results obtained by the optimization method in this paper, the verification test was carried out in October 2019 (approximately one week after the rice harvest) at Xiangfang Farm in Harbin, Heilongjiang Province, China, and the tractor type was Dongfanghong 120. The soil hardness of the test site was 1060 kPa, and the water content was 36%.

Field plots with high stubble straw and whole straw (standing or cut down) were chosen in the verification test. When the advancing speed of the device was 0.65 km/h, the rotating speed of the blade roll was 210 rpm, and the blade installation angle was 55°. The two field plots were measured 10 times each, and the test results are shown in Table 5. The operation process on the field with high stubbles and its straw returning effect are shown in Fig. 5. The operation process on the standing whole straw and its straw returning rate are shown in Fig. 6, and the operation on the whole straw after cutting down and its straw returning rate are shown in Fig. 7.

TABLE 5. Optimization result verification based on the BP neural network.

Method	Indices	Power consumption/(kW)	Straw returning rate/(%)
Test	Minimum value	9.93	92.85
	Maximum value	10.28	93.71
	Mean value	10.04	93.11
BP neural network	Optimal value	9.82	93.23
Relative errors/(%)		2.24	0.13

FIGURE 5. Operation process on high stubbles and its straw returning effect.


FIGURE 6. Operation process on whole straw (standing) and its straw returning effect.


FIGURE 7. Operation process on whole straw (cut down) and its straw returning effect.

It can be concluded from Table 3 that in the verification test, the power consumption in operation was 10.04 kW, having an absolute error of 0.22 kW with the results of BP neural network optimization and a relative error of 2.24%; the straw returning rate was 93.11%, with an absolute error of -0.12% with the results of BP neural network optimization and a relative error of 0.13%. Although there is a certain error between the test results and the optimized results, considering the comprehensive impact of factors such as straw moisture content, straw thickness, and tillage depth, 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.

After the test, the various technical indices of the device were measured: the tillage depth of the 1ZT-210 straw returning device was 18-20 cm, and the number of buried straw within the tillage depth range (15-18 cm) accounted for approximately 87% of the total straw. This result shows that the method achieved a good straw returning effect, and all the technical data met the agronomic requirements.

CONCLUSIONS

In this study, the test program was designed by the quadratic regression orthogonal rotation combination, and the test data were obtained. The BP neural network was used to train and fit the test data, and the mathematical model of the advancing speed of the device, the speed of the blade roll, the installation angle of the blade on power consumption in operation and straw returning rate were established. After comparison of the fitting accuracy of the two methods, under the same test conditions, it can well reflect the influence law of power consumption and straw returning rate under the test conditions in this study.

Through parameter optimization of the whole-straw returning rate by a multiobjective optimization method based on a BP neural network, it was determined that under the test conditions, the optimal parameter combination of the 1ZT-210 whole-straw returning device for rice in operation was as follows: the advancing speed was 0.65 km/h, the rotating speed of the blade roll was 210 rpm, and the blade installation angle was 55°. Under such parameter combinations, the minimum value of the power consumption of the device in operation was 9.82 kW, and the maximum value of the straw returning rate was 93.23%, which was better than that obtained by the regression model. Verification tests were carried out at Xiangfang Farm, Harbin, Heilongjiang Province. It was measured that the power consumption under such an optimization program was 10.04 kW. The test results had a 2.24% relative error compared with that under optimization, and the straw returning rate under the optimization program and the relative error between the test results and optimized results was 2.24%. The verification test showed that the errors between the test results and optimized results were within the allowable range, and the test results and optimized results were consistent. The results obtained by the multiobjective method based on the BP neural network had greater precision and greater reliability.

The application of the multiobjective optimization method based on a BP neural network in parameters of power consumption of the device is of significant importance to the design of agricultural machinery; meanwhile, it offers a new method to the optimization problems in agricultural production.

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