Performance optimization of combine harvester inertia separation chamber based on BPNN

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Abstract: In order to overcome the flaws and limitation, and obtain the optimal performance of combine harvester inertia separation chamber, an BP neural network-based optimization method that using hyperbolic tangent function as transfer function was proposed. This method was built on the basic of BP neural network function fitting. In view of minimizing mathematic model of network output, basic ideas of the optimization method was illuminated, the computational formula of search direction of Newton type arithmetic and optimum step were given, and the first and two partial derivatives of the network's output versus its input were deduced. On this basis, the terminate rule and realization process of BP neural network-based optimization method were carried out. The optimization method was used to determine the optimal input process parameters of the combine harvest inertial separation chamber to give minimum optimum pressure loss of combine harvest inertial separation chamber. The optimization results are as follows: inlet gas velocity of inertia separation chamber was 9.8 m/s, clapboard length was 780 mm, height of inertia separation chamber was 1120 mm, length of inertia separation chamber was 2036.6360 mm, and minimum suction system pressure loss minimum value was 129.3533 Pa. The optimization result showed that, it is a stable and feasible arithmetic for similar optimization problems of agriculture engineering field.

Keywords: combine harvester, inertia separation chamber, BP neural network, optimization method, Newton type arithmetic, optimal step

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1 Introduction

The performance of combine harvester inertia separation chamber (4ZTL-1800, invented by academician Jiang Yiyuan) is affected by many factors, such as physical property of grain, mass and flux of grain, length and installation height of clapboard, length and dip of back wall, aperture and shape of baffle and so on. It is the traditional method that regression equation was used to confirm the effect of each factor to performance of inertia separation chamber and obtain the optimal performance combination (Jiang et al., 2000; Wang et al., 2007; Wang, 2006; Wang et al., 2005), but this method have many obvious flaws and limitation. Firstly, the error caused by approximate calculation affects the precision of regression model. Secondly, the regression equation built on the presumptive model has especial limitations. Thirdly, the variable substitution is difficult to be multivariable. Fourth, regression equation lacks the processing capacity to noise of sample itself. Therefore, in order to obtain the optimal performance of combine harvester inertia separation chamber, it is necessary to propose a new method to solve this optimization problem.

BP neural network model, which is one of the most important artificial neural network models, is a multi-layer forward neural network being most widely studied and used at present. Theories have proved that if a three-layer BP neural network has enough hidden layer nodes, it can simulate any complex nonlinear mapping(Hecht-Nielsen, 1992; Villiers and Barnard, 1993; Funahashi, 1989). In recent years, with the

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development of BP neural network algorithm, people began to study the BP neural network-based optimization method on the basis of BP neural network fitting. Although some studies were called BP neural network-based optimization researches, these so-called researches are actually considered as not really optimization since they obtained the optimal value by using orthogonal experimental design (Wang et al., 2014), numerical simulation (Merad et al., 2007; Gulati et al., 2010; Wang et al., 2009; Liu, 2010), or genetic algorithm (Zhou et al., 2012). The BP neural network-based optimization method is a kind of global search optimization method proposed by Liu et al. (2010), and this method can adjust the input values of BP neural network to obtain the optimal output values (globally optimal solution), which was built on the neural network fitting. However, the theoretical study of their article was not systematic, and the method had errors when solving constrained optimization problems since it could not guarantee solution within feasible region (Liu et al., 2010). Although Wang et al. (2010) proposed an unconstrained BP neural network-based optimization method and studied systematic, but the partial derivative of network's output versus its input is incorrect (Wang et al., 2010). Zhang et al. (2016) made utilization of the unipolar Sigmoid transfer function to construct the BP neural network model and studied the optimization method, in which a gradient direction of the network output versus input was selected as search direction, the number of initial search step was given in a form of constant, and the next iterative generation of search step number is inherited from the previous iteration in accordance with the principle of the transformation step adjustment (Zhang et al., 2016). Sometimes, this method cannot be used to obtain the optimal solution in essence, because the optimal iteration will terminate when a better point can't be obtained by using the gradient direction.

In order to overcome the above-mentioned flaws and limitations, and improve the optimization result, this paper proposes an BP neural network-based optimization method, which is applied to obtain an optimal performance of combine harvester inertia separation chamber. The BP neural network model is built by considering the hyperbolic tangent function as transfer function, and the search step was confirmed by using optimal step formula in optimization process. This paper can be divided into four parts. In the first part, the aim and significance of the research and the status quo is discussed. The second part mainly involves the BP neural network-based optimization method, including mathematics model, the basic idea, the partial derivative of network's output versus its input, termination criterion, and realization process of optimization method. In the third part, the minimum pressure loss of combine harvester inertia separation chamber is obtained by using the proposed method. And in the last part, the achievement and conclusion of this research is demonstrated.

2 BP neural network-based optimization method

2.1 Mathematical model

The minimum output problems of BP neural network are used as an example to illustrate the optimization method. If $F(X)$ expresses the relationship between input and output, a generalized mathematical model of unconstraint optimization based on BP neural network can be expressed as follows:

$$\begin{cases} \min Y = \min F(X) \\ X \in R^n \end{cases} \quad (1)$$

In Equation (1), X is a input vector and $X=(x_1, x_2, \ldots, x_q)^T$; R^n is a feasible region, and Y is the output of BP neural network. If the maximum output of BP neural network is desired, the objective function can be transformed to max $F(X)$ =-min[-$F(X)$].

2.2 Basic ideas

First, an initial feasible point $X(t)$ (t=0) is artificially selected or randomly generated, and the gradient with respect to $X(t)$ is computed. If the gradient of $X(t)$ satisfies the termination criterion, then, $X(t)$ is an optimal solution and its corresponding network output Y is the optimal solution. Otherwise, we searched for a new iterative point $X(t+1)$ being along the search direction of $X(t)$, and calculated the gradient with respect to $X(t+1)$. If the gradient of $X(t+1)$ point dissatisfied the termination criterion, the next iteration was continued from $X(t+1)$, until the gradient of $X(t+1)$ point satisfied the termination criterion or was unable to obtain another better point. In this case, $X(t+1)$ value was the optimal input and its corresponding network output Y was the optimal output.

2.3 Method of generating search direction

$F(X)$ is a multivariate function, X^* is a minimal point of $F(X)$, and $X(t)$ is an approximate point of X^*. The Taylor expansion of $F(X)$ at $X(t)$ point was reserved and the quadratic term was obtained as follows

$$F(X) \approx \varphi(X) = F(X(t)) + \nabla F(X(t))(X - X(t)) + \frac{1}{2}(X - X(t))^{\mathrm{T}} \nabla^2 F(X(t))(X - X(t)) \quad (2)$$

where, $\nabla F(X(t))$ is the gradient and $\nabla^2 F(X(t))$ is the Hessian matrix of $F(X)$ with respect to $X(t)$.

By setting $X(t+1)$ as the minimal point and taking it as a next approximate point of X^*, we can obtain the Equation (3) according to the requirement of extremum

$$\nabla \varphi(X(t+1)) = 0 \quad (3)$$

thus,

$$\nabla F(X(t)) + \nabla^2 F(X(t))(X(t+1)) - X(t)) = 0 \quad (4)$$

then,

$$X(t+1) = X(t) - [\nabla^2 F(X(t))]^{-1} F(X(t)) \; (t=0,1,2,\ldots) \quad (5)$$

Equation (5) is the extremum iterative formula of Newton algorithm for multivariate function, and this method is quadratic convergence to quadratic function. Sometimes, the function values will increase when the Equation (5) was used on non-quadratic function. That is to say, $F(X(t+1)) > F(X(t))$. Therefore, mathematical programming approach was lead up to improve the aforementioned Newton algorithm, and the "damped Newton method" was proposed.

If we defined the $d(t)$ as follows

$$d(t) = -[\nabla^2 F(X(t))]^{-1} F(X(t)) \quad (6)$$

It be called Newton direction and can be regarded as search direction, and the iteration formula of damped Newton method was as follows

$$X(t+1) = X(t) + \lambda d(t) = X(t) - \lambda[\nabla^2 F(X(t))]^{-1} F(X(t)) \quad (7)$$

where, λ is the optimal step along Newton direction, or it can be called damped factor.

2.4 Optimal step

The optimum step size λ was defined as a step size which can obtain the minimum value of this search direction in optimization process, when the iteration point $X(t)$ is searching along search direction. That is

$$\min F(X(t+1)) = \min(F(X(t)) + \lambda d(t)) \quad (8)$$

The Taylor expansion of Equation (8) at $X(t)$ point was reserved the quadratic term and obtained

$$(F(X(t)) + \lambda d(t)) \approx F(X(t)) + \lambda (d(t))^{\mathrm{T}} \nabla F(X(t)) + \frac{1}{2}\lambda^2 (d(t))^{\mathrm{T}} \nabla^2 F(X(t)) d(t) \quad (9)$$

to deduce the partial derivative of Equation (9) with respect to λ and let it equals to 0, thus the optimal step λ of $d(t)$ direction was obtained (Chen, 2005)

$$(d(t))^{\mathrm{T}} \nabla F(X(t)) \quad (10)$$

Because the geometrical significance of $(d(t))^{\mathrm{T}} \nabla F(X(t))$ is a permanent negative, the optimal step λ is a positive value, that is to say, $\lambda>0$.

2.5 The first-order and second-order partial derivatives of network's output versus input

The gradient vector of function $F(X)$ is

$$\nabla F(X) = \frac{\partial F(X)}{\partial X} = \left(\frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \ldots, \frac{\partial F}{\partial x_n} \right) \quad (11)$$

Thus, as long as the partial derivative of function $F(X)$ is calculated, the gradient of function $F(X)$ can be obtained. The following is the procedure to derive the partial derivative of the network's output versus its input, with the hyperbolic tangent function used as network transfer function. Let x_i and x_l (i, l=1,2,⋯, n) to be the i^{th} and the j^{th} variables of network,and y_k (k=1,2,…,q) to be the k^{th} output of network. The weight value linking the i^{th} neuron and the j^{th} neuron is expressed as w_{ij} (i=1, 2, …, n; j=1, 2, …, p). The weight linking the j^{th} neuron and the k^{th} neuron is expressed as v_{ij} (j=1, 2, …, p; k=1, 2, …, q). The arbitrary neuron's input value of hidden layer is denoted by I_{1j} (j=1, 2, …, p) and the output value is denoted by s_{1j} (j=1, 2, …, p). The arbitrary neuron's input of output layer is denoted by I_{2k} (k=1, 2, …, q).

The first-order partial derivative of the network's output y_k versus the input x_i is

$$\frac{\partial y_k}{\partial x_i} = \frac{\partial y_k}{\partial I_{2k}} \cdot \sum_{j=1}^{p} \left(\frac{\partial I_{2k}}{\partial x_i} \right) = \frac{\partial y_k}{\partial I_{2k}} \cdot \sum_{j=1}^{p} \left(\frac{\partial I_{2k}}{\partial s_{1j}} \cdot \frac{\partial s_{1j}}{\partial I_{1j}} \cdot \frac{\partial I_{1j}}{\partial x_i} \right) \quad (12)$$

$$v_{jk} = \frac{\partial I_{2k}}{\partial s_{1j}} \quad (13)$$

$$w_{ij} = \frac{\partial I_j}{\partial x_i} \tag{14}$$

The hyperbolic tangent function is expressed as follows

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{15}$$

The first-order partial derivative of hyperbolic tangent function is

$$f'(x) = 1 - f^2(x) \tag{16}$$

We suppose that,

$$a_k = \frac{\partial y_k}{\partial I_{2k}} = 1 - y_k^2 \tag{17}$$

$$b_{jk} = \frac{\partial s_{1j}}{\partial I_{1j}} = 1 - s_{1j}^2 \tag{18}$$

thus,

$$\frac{\partial y_k}{\partial x_i} = a_k \sum_{j=1}^{p} (v_{jk} \cdot b_{jk} \cdot w_{ij}) \tag{19}$$

Hessian matrix $\nabla^2 F(\boldsymbol{X}(t))$ is a square matrix which is formed by second-order partial derivatives of function $F(\boldsymbol{X})$ at $\boldsymbol{X}(t)$ point. Thus, as long as the second-order partial derivative of function $F(\boldsymbol{X})$ is calculated, the Hessian matrix of function $F(\boldsymbol{X})$ can be obtained. According to the above result, the second-order partial derivative of network's output y_k versus input x_i and x_l is derived as follows

$$\frac{\partial^2 y_k}{\partial x_i \partial x_l} = \frac{\partial\left(\frac{\partial y_k}{\partial x_i}\right)}{\partial x_l} = \frac{\partial\left(\frac{\partial y_k}{\partial I_{2k}}\right)}{\partial x_l} \cdot \sum_{j=1}^{p} \frac{\partial I_{2k}}{\partial x_i} + \frac{\partial y_k}{\partial I_{2k}} \cdot \frac{\partial\left(\sum_{j=1}^{p} \frac{\partial I_{2k}}{\partial x_i}\right)}{\partial x_l} \tag{20}$$

$$\frac{\partial\left(\frac{\partial y_k}{\partial I_{2k}}\right)}{\partial x_l} = \left(\frac{\partial y_k}{\partial I_{2k}}\right)' \cdot \sum_{j=1}^{p} \frac{\partial I_{2k}}{\partial x_l} \tag{21}$$

$$\frac{\partial\left(\sum_{j=1}^{p} \frac{\partial I_{2k}}{\partial x_i}\right)}{\partial x_l} = \sum_{j=1}^{p}\left(\frac{\partial I_{2k}}{\partial s_{1j}} \cdot \frac{\partial I_{1j}}{\partial x_i} \cdot \left(\frac{\partial s_{1j}}{\partial I_{1j}}\right)' \cdot \frac{\partial I_{1j}}{\partial x_l}\right) \tag{22}$$

The second-order partial derivatives of hyperbolic tangent function was obtained by Equations (15) and (16)

$$f''(x) = -2f(x)(1 - f^2(x)) \tag{23}$$

We suppose that,

$$c_k = \left(\frac{\partial y_k}{\partial I_{2k}}\right)' = -2y_k(1 - y_k^2) \tag{24}$$

$$d_{jk} = \left(\frac{\partial s_{1j}}{\partial I_{1l}}\right)' = -2s_{1j}(1 - s_{1j}^2) \tag{25}$$

Based on Equations (12) to (25), it can be obtained:

$$\frac{\partial y_k}{\partial x_i \partial x_l} = c_k \sum_{j=1}^{p}(v_{jk} b_{jk} w_{ij}) \sum_{j=1}^{p}(v_{jk} b_{jk} w_{lj}) + a_k \sum_{j=1}^{p}(v_{jk} d_{jk} w_{ij} w_{lj}) \tag{26}$$

2.6 Termination criterion

According to the fundamental of unconstraint optimization, it must be judge whether the iteration point $\boldsymbol{X}(t)$ is convergence or not after every iteration, that is judge whether the iteration point $\boldsymbol{X}(t)$ is the optimal point or not. If the gradient of iteration point $\boldsymbol{X}(t)$ satisfied the Equation (27), $\boldsymbol{X}(t)$ is the optimal input and the corresponding network output is the optimal output.

$$\|\nabla F(\boldsymbol{X}(t))\| \leq \varepsilon, \quad t \in [0,1,2,...] \tag{27}$$

where, ε is a pre-establish convergence precision.

2.7 The optimization method and realization process

The BP neural network-based optimization method and its realization process were as follows:

Step 1: Organize training samples and create BP neural network model, initialize network's weight and biases. Train BP neural network after preset expectation error of network, and save the network's weight and biases when the error meets the expected accuracy.

Step 2: Primary iteration point $\boldsymbol{X}(t)(t=0)$ is artificially selected or randomly generated, and the convergence precision ε is given.

Step 3: The network's output $\boldsymbol{Y}$ of $\boldsymbol{X}(t)$ point is calculated through propagation process, and the gradient $\nabla F(\boldsymbol{X}(t))$ is calculated by using Equation (19).

Step 4: If the modulus of gradient of $\boldsymbol{X}(t)$ point satisfied the Equation (27), the iteration will termination, $\boldsymbol{X}(t)$ is the optimal input and its corresponding network output $\boldsymbol{Y}$ is the optimal output. Otherwise, go to Step 5.

Step 5: The second-order partial derivative of network output versus input at $\boldsymbol{X}(t)$ point was calculated by using Equation (26), thus the Hessian matrix of function $F(\boldsymbol{X})$ can be obtained. Calculate search direction by using Equation (6) and the optimal step λ by using Equation (10). The new iteration point $\boldsymbol{X}(t+1)$ was generated by using Equation (11), let $t=t+1$, go back Step 4.

3 Process parameters optimization of combine harvester inertial separation chamber

3.1 Experimental results of combine harvester inertial separation chamber

We used the BP optimization network to investigate how the main factors of combine harvester inertial separation chamber affect performance index. For this purpose, we chose 4 input parameters as inlet gas velocity (IGV), clapboard length (CL), height of the inertia separation chamber (HISC) and length of the inertia separation chamber (LISC), and used the pressure losses of the combine harvester inertial separation chamber suction system (PLSC) as output evaluation index. The actual experimental data used for training the network are shown in Table 1 (Wang, 2006).

Table 1 Training data for BP learning

No.	IGV x_1, m/s	CL x_2, mm	HISC x_3, m	LISC x_4, mm	PLSC y, Pa	No.	IGV x_1, m/s	CL x_2, mm	HISC x_3, m	LISC x_4, mm	PLSC y, Pa
1	15.2	1080	1060	2300	546.2	19	13.4	1180	1000	2100	370.3
2	15.2	1080	1060	1900	509.9	20	13.4	780	1000	2100	425.6
3	15.2	1080	940	2300	418.5	21	13.4	980	1120	2100	409.3
4	15.2	1080	940	1900	445.2	22	13.4	980	880	2100	409.5
5	15.2	880	1060	2300	459.6	23	13.4	980	1000	2500	349
6	15.2	880	1060	1900	462.9	24	13.4	980	1000	1700	408.7
7	15.2	880	940	2300	506.1	25	13.4	980	1000	2100	414.1
8	15.2	880	940	1900	570.7	26	13.4	980	1000	2100	417.1
9	11.6	1080	1060	2300	313.8	27	13.4	980	1000	2100	414.3
10	11.6	1080	1060	1900	318.4	28	13.4	980	1000	2100	415.3
11	11.6	1080	940	2300	222.8	29	13.4	980	1000	2100	418.1
12	11.6	1080	940	1900	274.1	30	13.4	980	1000	2100	415.4
13	11.6	880	1060	2300	248.8	31	13.4	980	1000	2100	416.5
14	11.6	880	1060	1900	286.6	32	13.4	980	1000	2100	418.6
15	11.6	880	940	2300	317.5	33	13.4	980	1000	2100	415.0
16	11.6	880	940	1900	417.4	34	13.4	980	1000	2100	414.8
17	16.9	980	1000	2100	587.4	35	13.4	980	1000	2100	415.0
18	9.8	980	1000	2100	206.3	36	13.4	980	1000	2100	414.8

The modeling performance of the BP network was compared with the modeling performance by quadratic polynomial regression. For this purpose, the experimental data in Table 1 was also processed with the Reda package of quadratic regression (Wang, 2006). The results are as follows:

$$y = 416.11 + 95.17x_1 - 13.38x_2 - 1.24x_3 - 15.81x_4 - 4.46x_1^2 + 3.84x_1x_2 + 5.97x_1x_3 + 7.95x_1x_4 - 4.55x_2^2 + 42.95x_2x_3 + 10.22x_2x_4 - 2.01x_3^2 + 14.81x_3x_4 - 9.84x_4^2 \quad (28)$$

3.2 Data modeling based on BP neural network

Then, the data in Table 1 was used to train the BP neural network. The structure of the 3-layer BP neural network was chosen as 4-7-1. In order to facilitate programming and avoid saturation, we normalized the input and output data to the interval $[a, b]$ by using

$$x_i' = a + (b-a)\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (i = 1, 2, ..., P) \quad (29)$$

where, x_i is the input sample; x_i' is the input data after normalization, $x_i' \in [a, b]$; $x_{\max}$ and $x_{\min}$ are the maximum and minimum value of the input sample data x_i. The interval $[a, b]$ was chosen as [0.1, 0.8].

The inverse of Equation (29) is given by

$$x_i = x_{\min} + \frac{(x_i' - a)(x_{\max} - x_{\min})}{b - a} \quad (30)$$

The modeling performance of the BP neural network in comparison to the modeling performance of quadratic regression is shown in Figure 1.

The weight and threshold values of the BP neural network learned are as follows:

The weight values between input layer and hidden layer are:

$$W = \begin{bmatrix} 0.4316 & -2.6534 & 0.3417 & -2.6470 & -18.9214 & 0.0978 & -2.1184 \\ 0.3668 & 3.5621 & 0.5042 & -7.9271 & 13.6902 & 0.5170 & -4.1564 \\ -0.3792 & -5.3184 & -0.9534 & -10.0226 & -15.6125 & 0.1403 & -0.7887 \\ 0.2437 & 1.5327 & 0.8539 & -2.0686 & 7.8760 & -0.7006 & 5.7739 \end{bmatrix}$$

The weight values between hidden layer and output layer are:

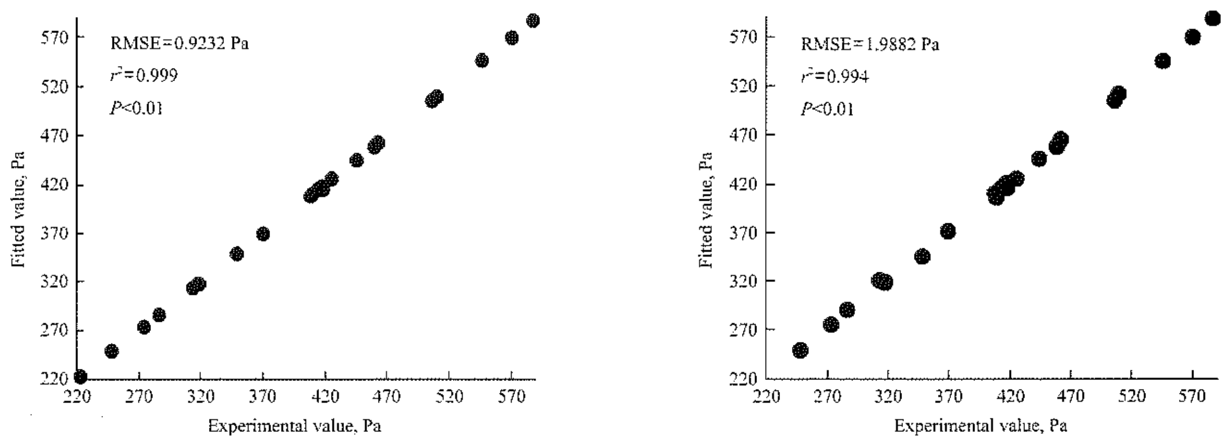
$$V = [3.3197 \ \ -2.2444 \ \ 3.6579 \ \ 0.9150 \ \ 0.5033 \ \ -2.5326 \ \ -0.9313]^{\mathrm{T}}$$

The biases of the hidden layer are:

$$\theta_1 = [0.1679 \ \ 0.1100 \ \ 0.8493 \ \ -6.2989 \ \ -0.0245 \ \ 0.4886 \ \ -0.0336]^{\mathrm{T}}$$

The biases of the output layer is:

$$\theta_2 = [-0.9311]$$



a. Experimental value and fitted value by BP neural network b. Experimental value and fitted value by quadratic regression model

Figure 1 Comparison of experimental and fitted value using different models

The fitted value of BP neural network model compared with experimental value was shown in Figure 1a, and the fitted value of quadratic regression model compared with experimental value was shown in Figure 1b. The R^2 is 0.999 (P<0.01) and the root-mean-square error (RMSE) is 0.9232 Pa in BP neural network fitting model, while the R^2 is 0.994 (P<0.01) and the RMSE is 1.9882 Pa in quadratic regression fitting model. Compared Figure 1a with Figure 1b, the fitting degree and precision of BP neural network model are better than those of regression model, and the relations of experimental factors with experimental object can be truly expressed while using the BP neural network model to fit the function.

With the given data, the minimum suction system pressure loss value appeared to be 206.3 Pa with data order number of 18. The corresponding parameters of the inertia separation chamber are as follows: inlet gas velocity of inertia separation chamber is 9.8 m/s, clapboard length is 980 mm, height of inertia separation chamber is 1000 mm, length of inertia separation chamber is 2100 mm.

3.3 Optimization of the process parameters of combine harvest inertia separation chamber

Then, we used the trained BP network to determine the input parameters that optimized the output according to the method discussed in Section 2. The method was initialized by randomly choosing an initial feasible point $\boldsymbol{X}(0)$. This was followed by the iterations carried out until iteration terminal condition is satisfied.

The optimization results are as follows: inlet gas velocity of inertia separation chamber is 9.8 m/s, clapboard length is 780 mm, height of inertia separation chamber is 1120 mm, length of inertia separation chamber is 2036.64 mm, minimum suction system pressure loss minimum value is 129.35 Pa.

The regression equation of quadratic regression model (Equation 28) was optimized and the optimization results were obtained as follows (Wang, 2006; Wang et al., 2007): inlet gas velocity of inertia separation chamber is

9.8 m/s, clapboard length is 1180 mm, height of inertia separation chamber is 1120 mm, length of inertia separation chamber is 1700 mm, and minimum suction system pressure loss minimum value is 156.34 Pa.

4 Discussion and conclusions

4.1 Discussion

Compared the optimization result obtained by two method, all of the RMSE, R^2, and P value of fitting function obtained by BP neural network method are better than that obtained by quadratic regression model, and the optimal performance optimized by proposed method is better than that optimized by regression model. The performance optimization problem of combine harvester inertia separation chamber belongs to black box problem, good or bad of the optimization result obtained by this two method can't be judged because of the optimal solution of black box problem is indeterminacy. The optimized research on performance optimization of combine harvester inertia separation chamber was done by using the BP neural network-based optimization method or regression analysis method was established on the basic of function fitting. In theory, the fitting function with relatively small average error is closer to the real function of problem, and the accuracy of the obtained optimization results is higher.

4.2 Conclusions

An optimization method based on the BP neural network was proposed in this paper. The optimization method was mainly applied to solve the black box problem. The BP neural network was first trained by using the input-output data. The trained network represents the complex functional relationship between the input and the output. Then the inputs are determined and optimize the output by using the method discussed in this paper.

The optimization method was used to determine the optimal input process parameters of the combine harvest inertial separation chamber. We obtained the minimum optimum pressure loss of combine harvest inertial separation chamber of 129.3533, and the corresponding performance was as follows: inlet gas velocity of inertia separation chamber of 9.8 m/s, clapboard length of 780 mm, height of inertia separation chamber of 1120 mm, length of inertia separation chamber of 2036.6360 mm. The experiment was carried out in comparison with the modeling using second order polynomial regression. The optimization results were also more reliable since the modeling using BP network was superior to modeling using polynomial regression.

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