Performance Prediction Analysis of Hydraulic Pump Based on Improved BP Neural Network

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Keywords: BP neural network, Algorithm optimization, Performance prediction, Hydraulic pump.

Abstract: Aiming at the disadvantages of standard BP neural network about slow convergence rate and getting into local minimum value easily, the momentum factor and conjugate gradient method are introduced to optimize the BP neural network, and the convergence speed and prediction accuracy are improved. The improved BP neural network is applied to the performance prediction of hydraulic pump with different characteristic hydraulic oil, and the forecast result is compared with the standard BP algorithm prediction value and the actual value. The results show that the improved BP algorithm has better prediction results on the performance prediction of hydraulic pump, which not only improves the calculation speed, but also improves the prediction precision greatly, and also has a good application prospectin the intelligent manufacturing industry.

1 INTRODUTION

Hydraulic oil as a kind of liquid working medium, which is used to transfer the energy in hydraulic pump transmission and control system. The hydraulic oil has seven kinds of remarkable characteristics: lubrication, cooling, rust-proof, sealing, cleaning, shock absorption. Whether the hydraulic system can be reliable and effective, depends largely on the performance of hydraulic oil, so choosing the suitable hydraulic oil is the key to improve the performance of the hydraulic pump. In the production process, the choice of hydraulic oil is usually dependent on experience, through repeated experiments to select more suitable hydraulic oil, but the use of this method will lead to a series of problems, including the long research cycle and high cost.

Artificial neural Network (ANN) is a computational model simulating human physiological mechanism, which provides an alternative means for identifying complex and highly nonlinear problems. BP Neural Network is one of the most widely used algorithms in artificial neural networks, and its structure is simple and easy to understand. Li Ping, Shi Lei used BP neural network to predict the performance of magnesium alloys under different deformation parameters and obtained good results. In the reference, the flow stress of high speed steels during thermal deformation is predicted by using BP neural network with 3-9-10-1 structure based on the parameters of strain rate, temperature and strain.

However, the BP neural network is similar to a black box, and the weights of each network affect each output result. Every time's random assignment of weights will result in different prediction results, resulting in the network is not reliable, and cycle training leads to low learning efficiency, long learning cycle. Once the algorithm into the local minimum value, the whole learning convergence process will be oscillated, it is difficult to get accurate predictions. Aiming at the defects of standard BP neural network, this paper first uses standard BP neural network to predict and analyze the performance of hydraulic pump with different properties of hydraulic oil, and obtains the predicted value which is close to the experimental result. Then when the convergence speed of BP algorithm reaches a slow stage, an important unconstrained optimization method-Conjugate gradient method (CG) is used to improve the standard BP algorithm(SBPA). The improved BP algorithm(IBPA) is used to predict the performance of hydraulic pump, and the prediction result with higher precision and smaller error is obtained. This method provides a new way to consider the product performance and improve the product benefit in the design stage.

2 MAIN INFLUENCING FACTORS OF HYDRAULIC PUMP PERFORMANCE

According to the working environment, working conditions and hydraulic system of the oil pump,when selecting hydraulic oil for hydraulic pump, the following factors should be considered emphatically:

① Suitable viscosity:Hydraulic pump is the most sensitive component of hydraulic oil viscosity reaction in hydraulic system. Under the same working pressure, the higher the viscosity of hydraulic oil, the greater the running resistance of hydraulic moving parts, which causes the hydraulic pump temperature rising, the self-priming ability decreasing, the pipeline pressure and power loss increasing. If the oil viscosity is too low, this will increase the volume loss of hydraulic pump and the sliding parts of the oil film thinning, then support capacity decline.

② Good air release characteristics:The hydraulic oil always contains a certain amount of air. When the pressure of the hydraulic oil is below a certain value, the air dissolved in the hydraulic oil will be separated to form a bubble. A large number of bubbles with the oil cycle, not only will reduce the pressure of the system, but also produces a local hydraulic impact, emitting noise and vibration. In addition, the air bubble also increased the contact area between oil and atmosphere, accelerating the oxidation of hydraulic oil. Therefore, the hydraulic oil is required to have good air release characteristics.

③ Adaptation characteristics of sealing materials:Because of the poor adaptability of the hydraulic oil and sealing material, the sealing material will swell, soften or harden to lose the sealing ability, so it is required that the hydraulic oil and sealing material should be adaptable to each other.

Therefore, this paper will take the hydraulic oil viscosity, air release characteristics, the adaptability of sealing materials as variables to predict the hydraulic pump no-load Force, noise, service life and other performance effects.

3 BP NEURAL NETWORK ALGORITHM

3.1 Standard BP Neural Network

The learning and training process of standard BP Neural network is divided into two parts, including the forward propagation of signal and the reverse propagation of error. When the signal is transmitted forward, the parameters are input from the input layer, then processed through the hidden layer, and finally uploaded to the output layer. When the output result is larger than the desired result, the error is transmitted backwards until the error is smaller than the maximum allowable error or the number of training times reaches the starting preset. The reverse propagation of error is actually the process of modifying and adjusting the weight value, and the weight adjustment formula is as follows:

$$\Delta w(n) = -\eta \frac{\partial E}{\partial w(n)} \quad (1)$$

In the formula, n is the iteration number, the η is the learning rateandthe weight adjustment between the nodes, $\partial E / \partial w(n)$ is the gradient of the error, the minus sign represents the descent of the gradient.

3.2 Improved BP Neural Network

3.2.1 Introduction of Momentum Factor

Since the standard BP algorithm adjusts the weights, it only adjusts according to the gradient direction of the n-th iteration error, but the gradient direction of the (n-1)-thiteration error is not considered, thus the training process is concussed and the convergence is slow. In order to increase the training speed of the network, momentum items can be added to the weight adjustment formula. The weight adjustment formula at this time is:

$$\Delta w(n) = -\eta \frac{\partial E}{\partial w(n)} + \alpha \Delta w(n-1) \quad (2)$$

It can be seen that the increased momentum item is added from the previous weight adjustment amount to this weight adjustment amount. α is a momentum factor, generally, $\alpha \in (0,1)$.Momentum terms reflect the accumulation of experience in weight adjustment during the learning process and play a dampening role in the current weight adjustment.

3.2.2 Introduction of Conjugate Gradient Method

Due to the excessive number of learning and training times of the standard BP neural network, the error of the result is large, and the traditional gradient descent method is easy to cause the disadvantage of slow convergence speed and easy to fall into the local minimum of error surface. Therefore, the conjugate gradient algorithm is introduced into the BP neural network with momentum added. The basic idea is to use the gradient of known nodes to construct a set of conjugate directions and search for the extremum of the objective function accordingly. Combining the BP algorithm with the conjugate gradient method, the training process is divided into two stages. In the beginning stage, the BP algorithm is used, when the convergence rate is slow, and the conjugate gradient method is used to give full play to the advantages of the two parties.

The process of the conjugate gradient method introduced is as follows:

$d(n)$ is used to represent the gradient direction, and the minimum value can be obtained by searching:

$$\min E\left(w(n+1)\right) = E\left(w(n) + \eta_n d(n)\right) \quad (3)$$

The objective function is $\min E(w), w \in R$, and η_n is the search step, and the expression is shown in formula (4).

$$\eta_n = \frac{g^T(n) d(n)}{d^T(n) A d(n)} \quad (4)$$

The *A* in the upper form is expressed as the positive definite Hessian matrix of the error function, and $g(n)$ is expressed as the gradient direction of the error function. The gradual search by formula (2) can be obtained:

$$w(n+1) = w(n) + \eta_n d(n) \quad (5)$$

$$\begin{aligned} d(n) &= -g(n) + \beta_n d(n-1) \\ d(0) &= -g(0) \end{aligned} \quad (6)$$

$$g(0) = \nabla E\left(w(0)\right) \quad (7)$$

β_n is expressed as the direction factor of the error function. The expression is:

$$\beta_n = -\frac{g^T(n) g(n)}{g^T(n-1) g(n-1)} \quad (8)$$

When it starts to iterate, $d(0) = -g(0)$. Therefore, the basic idea of the conjugate gradient can be expressed as a linear combination of the iterative direction of the N times and the (N-1) times, and the $d(n)$ and $d(n-1)$ are a pair of conjugate vectors.

During training, in order to avoid over fitting phenomenon, the root mean square error (RME) of the sample is always calculated periodically.

$$\text{RME} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{prediction} - y_{experiment}\right)^2}{n}} \quad (9)$$

When the root mean square error begins to rise, it is proved that the over fitting phenomenon appears, and the neural network obtained by the stop training at this time has a reasonable reliability for future prediction.

3.3 Validation of The Effectiveness of Improved BP Algorithm

In order to study the effect of the improved BP neural network, the nonlinear function formula (10) is used to carry out the experiment, and the results can be compared and analyzed.

$$y = x + 2\sin^2(2x) + \cos^3(x) \quad (10)$$

In the BP neural network, the accuracy of the error is set to 0.0001, and the Sigmoid function is used as the activation function. A BP neural network with a hidden layer is selected for learning and training, and the output layer has a neural unit，That is, *l*=1, the number of nodes in the input layer is set to 5, that is, *n*=5; according to formula (11), the calculation can be obtained: $\beta = 7$, the number of nodes with hidden layer can be calculated to be 9, that is, m=9.

$$m = \sqrt{n + l} + \beta \quad (11)$$

m represents the number of hidden layer nodes, n indicates the number of input layer nodes, and l represents the number of nodes in the output layer, β is constant and $\beta \in [1,10]$.

According to the above selection, the BP neural network structure of the experiment is 5-9-1, and the number of hidden layer nodes is 9. The result of the improved BP neural network is shown in Table 1.

Table 1:Convergence rate of improved BP algorithm.

No.	Time（s）	Number of iterations
1	19.34	4681
2	24.51	4963
3	21.67	4826
4	24.03	4901
5	19.41	4689
6	20.89	4736
7	24.18	4930
8	18.37	4597
9	22.15	4885
10	21.14	4782
Average value	21.569	4802.3

Using the improved BP algorithm to train, the average convergence time is 21.57s and the average number of iterations is around 4800. The error curve is recorded as shown below. Figure 1 shows that as the number of iterations increases, the error decreases. When the number of iterations reaches 4800 or more, the accuracy can reach 0.0001. During the iteration process, the error curve remains smooth and no jitter occurs. The entire learning process is fast and smooth.

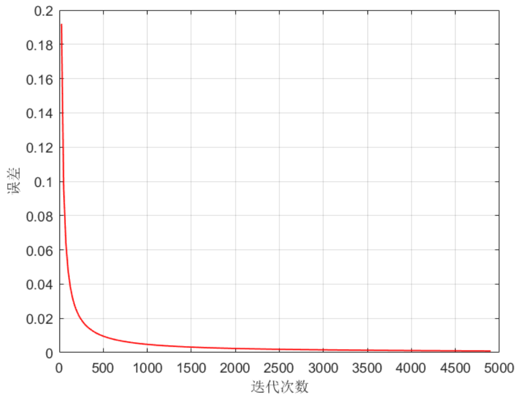

Figure 1: Improved BP neural network algorithm error.

Compare the average time and number of iterations of the improved BP algorithm with the standard BP algorithm. The results are shown in Table 2:

Table 2:Comparison result.

Items	Average time（s）	Iterations	Error accuracy
SBPA	52.86	14558.0	0.0009
IBPA	21.57	4802.3	0.0001

According to Table 2, it can be concluded that the main reason for the slow error convergence rate of the standard BP algorithm is the defect of the algorithm itself; however, the improved BP algorithm can be used to complete the training in a shorter time and the error accuracy is less than 0.0001. This not only reduces the training time to a great extent, but also improves the accuracy of the prediction results.

4 APPLICATION OF IMPROVED BP ALGORITHM IN PERFORMANCE PREDICTION OF HYDRAULIC PUMPS

4.1 Neural Network Model Construction

① Determine the object of the experiment: in this paper, YYB1-AA6/14B-Y2 type hydraulic pump is selected as the research object, and orthogonal test is used to study and analyze the influencing factors. According to the relevant theoretical knowledge and previous experience, the effects of the viscosity of hydraulic oil, the air release of hydraulic oil and the adaptability of hydraulic oil and sealing materials on the no-load force, noise and service life of the hydraulic pump are considered. In the experiment, the selected factors are shown in Table 3.

Table 3:Influencing factors.

No.	viscosity （cst）	air release (min)	adaptability to sealing materials
1	34.7 （class 32）	<5	better
2	46.5 （class 46）	5~10	good
3	63.4 （class 68）	>10	substandard

In orthogonal experiments, in order to reduce the numberof the selected samples and workload, we choose the least orthogonal table. The orthogonal array of hydraulic pump is selected through influencing factors (shown in Table 4 below). The number of test samples is 9, that is, the number of tests is 9 times. Compared with all tests (3^3=27 times), 18 times of repeated trials can be effectively reduced. This greatly reduces the time and workload of the test.

Table 4:Orthogonal test table for hydraulic pump.

No.	A (Viscosity)	B (Air release)	C (Adaptability)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

② Determine the learning rate and momentum factor: In the training of BP neural network, the selection of learning rate has an important influence on the effect of training. Excessively increasing the learning rate will fluctuate the error function. If the learning rate is too small, it will lead to slow convergence. After repeated experiments, the learning rate in this paper is 0.035. The momentum factor can effectively avoid the error surface falling into the minimum value, reducing the trend of oscillation and improving the training speed. Its value is 0.65.

③ Determine the number of hidden layer nodes: The viscosity of the hydraulic oil, the air release characteristics and the adaptability of the hydraulic oil and sealing materials are used as the input level of the input layer, that is, n=3; the output of the output layer are the no-load force, noise and service life of the hydraulic pump, that is, l=3. According to the formula (11), after repeated tests, the number of nodes in the hidden layer is calculated to be m=8, so the prediction model of BP neural network is 3-8-3.

4.2 Comparison and Analysis of The Results of Training and Learning

4.2.1 The Result of Training

Using Numpy and Matplotlib two library functions in Python to achieve the prediction of the two algorithms. The final results obtained by orthogonal tests are shown in Table 5 below.

Table 5:Training results of standard BP algorithm and improved BP algorithm.

No.	A	B	C	actual value			Standard BP algorithm			Improved BP algorithm		
				No-load force (N)	Noise (db)	Service life (a)	No-load force (N)	Noise (db)	Service life (a)	No-load force (N)	Noise (db)	Service life (a)
1	1	1	1	17.56	19.24	7.67	16.48	18.37	7.51	17.71	19.30	7.73
2	1	2	2	17.64	35.21	5.34	18.49	38.42	5.08	17.60	35.22	5.36
3	1	3	3	17.59	51.72	2.23	16.53	50.04	2.43	17.67	52.16	2.24
4	2	1	2	22.48	21.13	6.16	23.51	24.21	5.82	22.54	21.34	6.19
5	2	2	3	22.54	33.56	2.63	22.98	31.13	2.75	22.66	33.78	2.69
6	2	3	1	23.01	46.61	5.26	23.97	42.58	5.52	23.06	46.62	5.27
7	3	3	3	28.96	24.32	3.17	30.13	22.97	2.91	29.12	24.81	3.22
8	3	2	1	29.13	28.87	6.88	30.41	30.12	6.69	29.07	29.27	6.92
9	3	3	2	28.88	49.25	4.79	30.26	51.21	4.57	29.09	49.66	4.83

4.2.2 Analysis Results

The training results shown in Table 5 can be shown in Figures 2, 3, and 4:

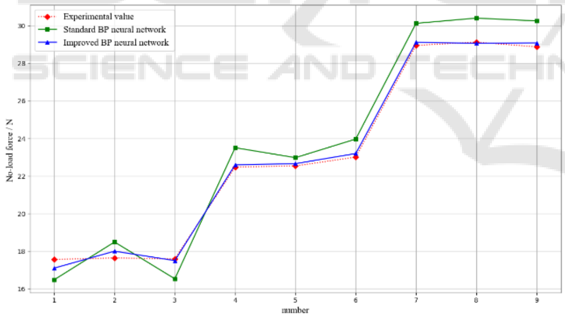

Figure 2 :Actual value and training value of the unloaded force.

According to table 4, it can be seen that when the viscosity of hydraulic oil is the same, the no-load force of the hydraulic pump is on the same horizontal line. When the viscosity of the hydraulic oil increases, the unloaded force of the hydraulic pump increases significantly. Thus, it can be seen that the effect of the unloaded force of the hydraulic pump on the viscosity of the hydraulic oil is greater than that of other factors. In addition, the prediction results obtained by the improved BP algorithm are closer to the actual values.

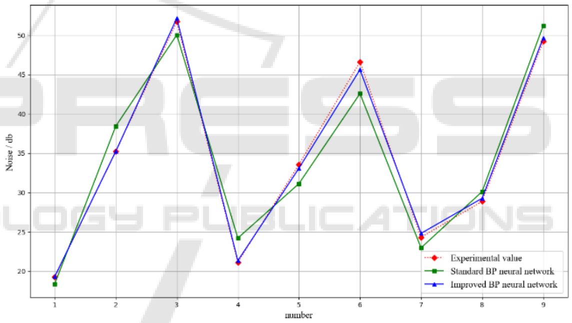

Figure 3:Actual value and training value of noise.

The peaks of curves in Figure. 3 appear in third, sixth, ninth sets of tests. It is shown from table 4 that the poor air release performance of hydraulic fluids is the common ground of these three sets of tests. The trough of the curve appeared in the first, fourth, seventh group of experiments. The good release of the hydraulic oil was the common point of the three groups. It can be concluded that the noise of hydraulic pump is greatly influenced by the air release of hydraulic oil, which is also consistent with the cavitation phenomenon introduced in the introduction. In addition, the prediction results obtained by the improved BP algorithm are closer to the actual values.

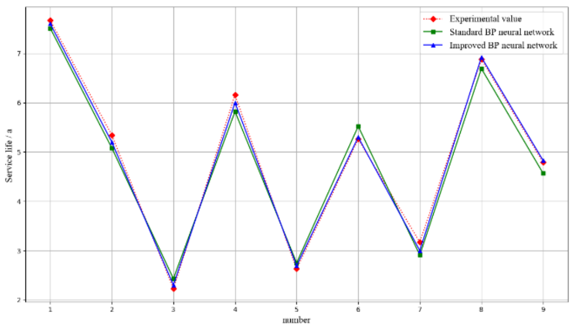

Figure4: Actual value and training value.of service life.

The wave peaks in Figure 4 appear in groups 1, 4, 6 and 8. The hydraulic oil used in the four groups can be well adapted to the sealing material, so the service life of the products is relatively long. On the contrary, the hydraulic oil and seal materials used in other tests can not be well adapted, which causes the wear and tear of products and the service life greatly reduced. This is also in line with our daily experience. In addition, the prediction results obtained by the improved BP algorithm are closer to the actual values.

In summary, the prediction results obtained by the standard BP algorithm are obviously deviated from the actual value; the predicted value of the improved BP neural network is basically consistent with the actual value, and the relative error is smaller (as shown in Table 6), the learning rate and the convergence speed are all improved, which can meet the requirement of prediction precision.

Table6:Relative error of BP algorithm before and after improvement.

Items	Standard BP algorithm			Improved BP algorithm		
Relative error	No-load force （N）	Noise （db）	Servie life（a）	No-load force （N）	Noise （db）	Servie life（a）
Average value	0.53%	0.44%	0.51%	0.08%	0.09%	0.09%

5 CONCLUSIONS

1) In this paper, the BP neural network is improved by introducing momentum factor and conjugate gradient method, the nonlinear mapping model between hydraulic oil characteristics and hydraulic pump performance is established. The model has shorter prediction time and higher prediction precision, which effectively solve the shortcomings of the standard BP algorithm in the slow convergence speed and easy to fall into the local minimum.Through the comparison between the standard BP algorithm and the improved BP algorithm for the prediction of the performance of the hydraulic pump, it is concluded that the improved BP neural network algorithm is effective and feasible.

2) Based on the product performance prediction model constructed, the performance of the products can be predicted during the design period; this method can instruct the developers to design the hydraulic pump and choose the required hydraulic oil quickly and reasonably. At the same time, the proposed BP neural network provides a new way of thinking and new means for the performance prediction of industrial products affected by complex parameters, which greatly shortens the development cycle and reduces the research and development cost. It has high theoretical significance and engineering application value in the fast intelligent manufacturing industry.

ACKNOWLEDGEMENTS

Thank the National Natural Science Foundation of China (Grant No. 51475129,51675148, 51405117) for its strong support for this paper.In the writing of this paper, I got the careful guidance of my tutor, Mr. SuShaohui. At the same time, thanks to the research platform provided by Anji Intelligent Manufacturing Research Institute.

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