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Hydraulic Pump Fault Diagnosis Control Research Based on PARD-BP Algorithm

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Abstract: Combining working principle and failure mechanism of RZU2000HM hydraulic press, with its present fault cases being collected, the working principle of the oil pressure and faults phenomenon of the hydraulic power unit –swash-plate axial piston pump were studied with some emphasis, whose faults will directly affect the dynamic performance of the oil pressure and flow. In order to make hydraulic power unit work reliably, PARD-BP (Pruning Algorithm based Random Degree) neural network fault algorithm was introduced, with swash-plate axial piston pump's vibration fault sample data regarded as input, and fault mode matrix regarded as target output, so that PARD-BP algorithm could be trained. In the end, the vibration results were verified by the vibration modal test, and it was shown that the biggest upward peaks of vacuum pump in X-direction, Y-direction and Z-direction have fallen by 30.49 %, 21.13 % and 18.73 % respectively, so that the reliability of the fact that PARD-BP algorithm could be used for the online fault detection and diagnosis of the hydraulic pump was verified. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: RZU2000HM hydraulic press, Swash-plate axial piston pump, Vacuum self-priming, FAULT diagnosis, Modal test.

1. Introduction

Hydraulic press bears extremely important work in modern mechanical manufacturing. Hydraulic press failure could cause the halt of production lines and the reduction of production efficiency, and or even could cause the loss of life and property. How to make an accurate judgment on hydraulic work status and ensure orderly production has become the research focus of machinery industry. But the complicated hydraulic structure, the characteristics of collected information which include diversity, complexity, randomness and correlation-hierarchy, the correlation between the characteristic values, and the randomness and uncertainty of the signal, all cause great influence of faults diagnosis of hydraulic press [1].

Hydraulic pump often works in poor environment. It is difficult to use conventional extraction method to extract the pump discharge monitoring signals through a single sensor. So it is necessary to make full use of multi-sensor information sources, in order to obtain reliable estimates of device status. For the hydraulic pump fault diagnosis, there are the comprehensive analysis of the pump shell vibration signals of X-direction, Y-direction and Z-direction, and the results fusion of vibration diagnosis [2]. The PARD-BP (Pruning

Algorithm based Random Degree) neural network is used to diagnose the vibration signal of every direction, and to fuse the results of vibration diagnosis. According to relevant statistics [3, 4], China metallurgical department equipment maintenance cost is as high as 25 billion RMB every year. If the state detection and fault diagnosis technology have popularization and application, which could reduce accident rate, save maintenance cost and possess huge potential economic value. This article focuses on fault diagnosis of hydraulic pump hydraulic power components, treatment of algorithm for calculation and fault phenomenon, then the vibration test instrument is used to test and verify the reliability of algorithm.

2. Hydraulic Power Components

2.1. Working Principle

As the research object, large CNC type single and double dynamic RZU2000HM rapid sheet drawing hydraulic press (Fig.1) is used widely in processing technology of sheet metal, such as stamping, bending, pressing. Because the kind of finished products manufactured goods have the characteristics of shape and dimensional accuracy, high efficiency, stable processing of low cost and are suitable for mass production, which is widely used in automobiles, tractors, ships, kitchen utensils, aircraft and other industries of sheet covering parts processing production [5].

Fig. 1. RZU2000HM sheet drawing hydraulic press.

As the power components of the hydraulic system, it provides the hydraulic pressure with necessary oil. Compared with other forms of positive displacement pump, the swash-plate axial piston pump can obtain higher working pressure, compact size of unit power and high volume efficiency. Airtight work space, which is formed by the piston, cylinder block and oil distribution disc, increases gradually form a partial vacuum and achieves the oil absorption, and it is the hydraulic oil closed in oil pipe to transmission hydraulic power. Because of the huge appearance of the hydraulic press, and many components, it is difficult to remove and maintenance the hydraulic press when the fault occurs. It is necessary to research intelligent fault diagnosis system of power element, which can find fault more rapidly and accurately, operate simply and avoid remove.

2.2. Common Faults of Plunger Pump

The vibration signal of plunger pump is collected when it is working normally and breaking down, and the following 6 kinds of common faults are selected: abnormal wear, anomaly oil temperature, oil distribution plate cylinder body wear, inclined plate wear, too large noise, and the oil leakage. Using parameters as the characteristic parameters, such as peak, root mean square value and pulse index [6, 7].

The calculation methods of parameters respectively are:

Peak: $P_{\max} = \max（P）$

Peak-to-peak value: $P_{pp} = P_{\max} - P_{\min}$

Root-mean- square value: $P_{rms} = \left| \frac{1}{N} \sum_{i=1}^{N} \sqrt{|P_i|} \right|^2$

Waveform indicators: $W_f = P_{rms} / \left|\bar{P}\right|$, among this formula, $\bar{P}$ is the mean;

Peak metric: $K_f = P_{\max} / P_{rms}$

Pulse index: $C_f = P_{\max} \Big/ \left|\bar{P}\right|$

Experimental device is DH5922N dynamic signal testing analyzer of Donghua co., LTD. Due to space limitations, vibration acceleration measured values of normal and various fault state are not given here. Gathering vibration signals of the hydraulic pump when it is working normally and have malfunctions, such as cylinder wear, oil temperature anomalies, oil distribution plate wear, inclined plate wear, too much noise and the oil leakage. For vibration data network extract training of the horizontal direction (X-direction), vertical direction (Y-direction) and axial direction (Z-direction). Extracting 6 sets data of every fault for feature extraction, collecting 150 points every group of data, and training the characteristic signal processing, the data will be input to the neural network.

Building up the above seven kinds of fault symptom table of the horizontal direction (X-direction), vertical direction (Y-direction) and axial direction (Z-direction), which is hydraulic pump work properly (F0) and cylinder wear (F1), anomaly oil temperature (F2), the oil distribution disc wear (F3), inclined plate wear (F4), too large noise (F5) and oil leakage (F6). Fault symptom table of the X-direction is listed only, as shown in Table 1, the failure mode of the above state table as shown in Table 2.

Table 1. Swash-plate axial piston pump fault symptom table (horizontal/X-direction).

Parameter / Failure mode	Peak $P_{\max}$	Peak-to-peak value P_{ff}	Root-mean-square value P_{rms}	Waveform indicators W_{f}	Peak metric K_{f}	Pulse index C_{f}
Normal	0.5268	0.6379	0.4376	0.6325	0.6175	0.6248
Cylinder wear	0.4218	0.3978	0.3366	0.4097	0.3725	0.4421
Anomaly oil temperature	0.3365	0.3962	0.6158	0.3003	0.6200	0.3119
Oil distribution disc wear	0.4456	0.3811	0.6031	0.4568	0.6059	0.4113
Swash plate wear	0.5233	0.6011	0.4425	0.4473	0.4701	0.3668
Too much noise	0.4420	0.5133	0.2716	0.4567	0.3263	0.5112
Oil spill	0.5137	0.4579	0.4497	0.5683	0.4576	0.5199

Table 2. Failure mode tables.

State / Failure mode	F1	F2	F3	F4	F5	F6
Normal	0	0	0	0	0	0
Cylinder wear	1	0	0	0	0	0
Anomaly oil temperature	0	1	0	0	0	0
Oil distribution disc wear	0	0	1	0	0	0
Swash plate wear	0	0	0	1	0	0
Too much noise	0	0	0	0	1	0
Oil spill	0	0	0	0	0	1

To verify the effectiveness of the fault diagnosis of hydraulic power components, introduce PARD-BP algorithm for network structure.

3. Fault Diagnosis of Plunger Pump Based on PARD-BP

3.1 Fault Detection Diagnosis Design

Because of the plunger pump work disturbance by external factors such as dust, moisture, to curb its impact on the state monitoring, the following monitor is designed [2, 8].

$$\dot{V} = T_O V + G_O B_1 I + K_O Y$$
$$\hat{E} = V + H_O Y ,$$

where V is the state vector of monitor; $\hat{E}$ is the state estimation vector of hydraulic pump. Defining state error $\bar{E} = E - \hat{E}$, output residuals $o = Y - \hat{Y}$, Combining with the plunger pump model

$$\dot{E} = AE + B_1 I + B_2 W$$
$$Y = C_y E + D_{y1} I$$

Trouble-free plunger pump status is stable working performance, in combination with the acceleration dynamic parameter extraction and optimization of plunger pump fault diagnosis, and the algorithm is studied. The network model of the hydraulic pump fault diagnosis is shown in Fig. 2.

3.2. PARD-BP Genetic Algorithm

With the algorithm convergence properties of the network structure, simplified pruning and implication of its reviewing random event selection problem, PARD-BP genetic algorithm is better than ordinary genetic algorithms. To illustrate the availability of PARD-BP genetic algorithm, axial plunger pump fault data samples are input, fault mode goal matrix are output, and BP algorithm is trained.

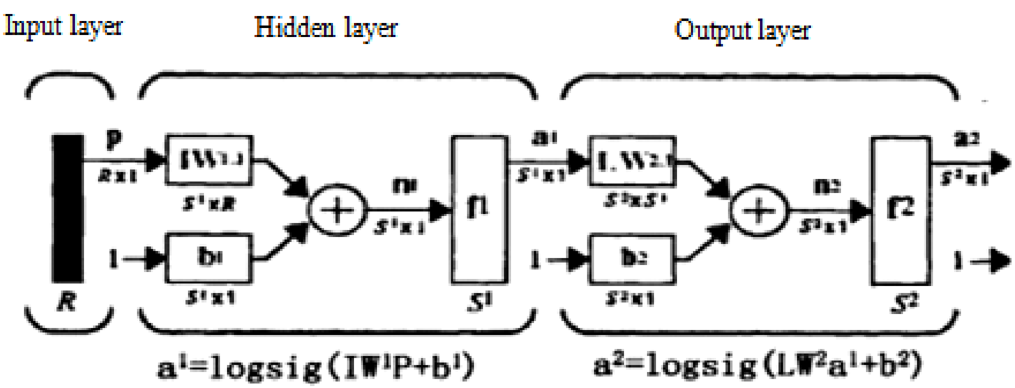


Fig. 2. Network model of the hydraulic pump fault diagnosis.

First of all, the output goals matrix is $a^2 = \text{logsig}(LW^2 * (\text{logsig}(IW^1 P + b^1)) + b^2)$ among this formula:

$$W^1 = \begin{bmatrix} w_{1,1}^1 & w_{1,2}^1 & \cdots & w_{1,10}^1 \\ w_{2,1}^1 & w_{2,2}^1 & \cdots & w_{2,10}^1 \\ \cdots & \cdots & \cdots & \cdots \\ w_{k,1}^1 & w_{k,2}^1 & \cdots & w_{k,10}^1 \end{bmatrix} \quad b^1 = \begin{bmatrix} b_1^1 \\ b_2^1 \\ \cdots \\ b_k^1 \end{bmatrix}$$

$$W^2 = \begin{bmatrix} w_{1,1}^2 & w_{1,2}^2 & \cdots & w_{1,k}^2 \\ w_{2,1}^2 & w_{2,2}^2 & \cdots & w_{2,k}^2 \\ \cdots & \cdots & \cdots & \cdots \\ w_{9,1}^2 & w_{9,2}^2 & \cdots & w_{9,k}^2 \end{bmatrix} \quad b^2 = \begin{bmatrix} b_1^2 \\ b_2^2 \\ \cdots \\ b_9^2 \end{bmatrix}$$

To set up the network, setting goals choose-training error and the initial learning rate to 0.008, the initial weights of the random number interval (1, 1), learning function is not set, initializing networks, and collecting fault diagnosis sample data of hydraulic pump.

3.3. Fault Diagnosis of Plunger Pump Based on the Algorithm

The fault diagnosis model of plunger pump based on genetic algorithm consists of two parts – genetic algorithm optimization calculation and plunger pump failure integration of numerical simulation. Compared with other traditional optimization algorithm, genetic algorithm does not require derivative or other auxiliary information, can realize the process of evolution in nature to approximation problem of the optimal solution only by imitating screening successful gene, can deal with fault diagnosis and optimization problems of the working process hydraulic pump.

The algorithm has strong robustness and good global search ability [9, 10].

Through the PARD-BP network, testing fault data samples of the hydraulic pump, have taken history fault samples vibration signal collection of X-direction normalize processing. As the network input matrix, taking cylinder wear (F1), the oil distribution disc wear (F3), a set of each, and swash plate abrasion (F4) two sets of fault data, input matrix is sorted out, as shown in Table 3.

Table 3. Fault data samples (horizontal/X-direction).

Cylinder wear (Sample 1)	0.3125	0.3097	0.4765	0.5261	0.4201	0.3845	0.3652	0.5643
Oil distribution disc wear (Sample 2)	0.3085	0.2876	0.4236	0.4011	0.3173	0.3065	0.2937	0.6767
Swash plate wear (Sample 3)	0.2389	0.2673	0.2543	0.2306	0.3502	0.2876	0.2645	0.6473
Swash plate wear (Sample 4)	0.5291	0.5627	0.5864	0.5683	0.3092	0.4563	0.4785	0.3557

The structural parameters of the level (X-direction) vibration after the neural network training are shown in Table 4, thus it can be seen that the object after pruning, number of hidden layer nodes by 18 down to five. Adopting the trained network structure of fault data samples for testing, the results as shown in Table 5. The output results of the table for further processing, take its output matrix, the table of fault diagnosis model, and diagnosis conclusion. What can be seen from Table 6, network diagnosis result of PARD-BP are in complete accord with actual test results. Through the analysis, we can see that PARD-BP network can identify the different forms of faults, and can make accurate fault diagnosis. To confirm that the method is effective, the test and simulation test will be given.

Table 4. Vibration parameters simplification (level/X-direction).

Initial value of level/X-direction
-0.3226 -0.2828 0.1027 0.1271 -0.1165 0.085 -0.073 -0.4238 -0.4653 -0.1578 -0.4764 -0.1089 0.1783 -0.3895 -0.4563 0.1124 0.1016 -0.4329
Value of the training
-7.055463 5.182612 -1.837596 2.587431 3.758632

Table 5. Sample data.

Cylinder wear (Sample 1)	0.1564	0.1453	0.9836	0.0000	0.0000	0.0125
Oil distribution disc wear (Sample 2)	0.0021	0.9964	0.1382	0.0000	0.0009	0.0000
Swash plate wear (Sample 3)	0.0003	0.1469	0.0005	0.9894	0.0000	0.0059
Swash plate wear (Sample 4)	0.0890	0.0000	0.0002	0.9952	0.0007	0.0017

Table 6. Network diagnosis of PARD-BP.

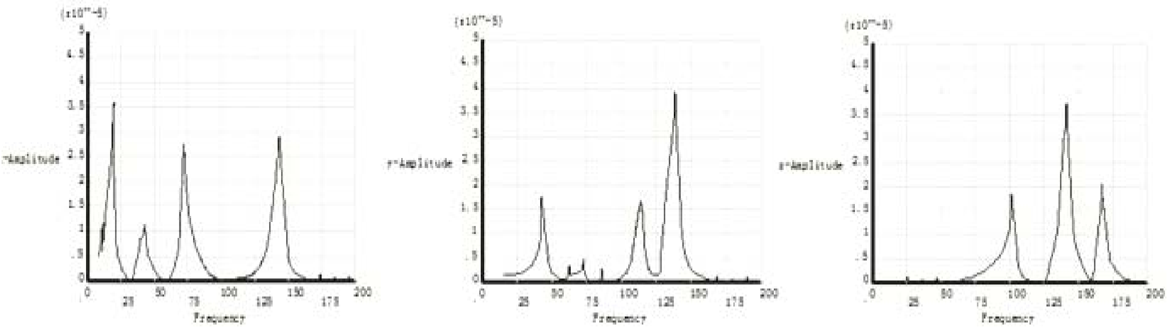
Sample No.	Failure mode						Diagnosis conclusion
Sample 1	0	0	1	0	0	0	Cylinder wear
Sample 2	0	1	0	0	0	0	Oil distribution disc wear
Sample 3	0	0	0	1	0	0	Swash plate wear
Sample 4	0	0	0	1	0	0	Swash plate wear

4. Optimization Analysis of Experimental Result

To test and verify the reliability of algorithm, using the single-point excitation vibration picking method [11], modal analysis test was carried out on the hydraulic pump, through experiment decorate 900 points (six test points, each test point is the X-direction, Y-direction and Z-direction, partial test 50 times every direction) to collect data [11, 12]. In addition to the modal test of hydraulic pump under static condition, continuous incentives in the corresponding points of hydraulic pump were adopted to acquire respective vibration signal. ANSYS Harmonic Response module was chosen, hydraulic pump model was imported, and equivalent harmonic force was applied to X-direction, Y-direction and Z-direction of hydraulic pump, which only affects the size of the exciting force amplitude, have no effect on the frequency response curve of distribution. Analysis of frequency range of 0-200 Hz, in order to make the simulation of the vibration is more approximate to the actual situation.

There is an obvious peak value of X-direction relative amplitude frequency curve between 18-23 Hz, the order modal is that the hydraulic pump swings along X-direction. There is a peak around 40 Hz, which shows the pump reverse with X-direction and swings along the Y-direction. There is an obvious peak between 65-70 Hz when the hydraulic pump swings along Y-direction and turns around Y axis.

There is an obvious peak between 135 Hz, using the same loading mode and optimizing harmonic response analysis of the hydraulic pump finite element model [11], and extracting the relative displacement amplitude frequency curves of X-direction, Y-direction and Z-direction (Fig. 3).



(a) X direction (b) Y direction (c) Z direction

Fig. 3. Relative displacement amplitude frequency curve after the optimization.

Data in the Table 7 shows that the frequency values of basic were improved by optimizing all directions of frequency values corresponding to amplitude-frequency curve peak, and the largest increase was 9.37 %. Optimized amplitude-frequency curve peak of all directions also have different amplitude reduced, the largest peak of X-direction, Y-direction and Z-direction has fallen by 30.49 %, 21.13 % and 18.73 % respectively, to illustrate that the dynamic performance of hydraulic pump are improved.

Table 7. Relative displacement amplitude frequency change of hydraulic pump.

Relative displacement amplitude frequency curve of X-direction				**Frequency variation (%)**	**Variation of largest peak (%)**
Original value		**Optimal value**			
Frequency (Hz)	**Peak (m)**	**Frequency (Hz)**	**Peak (m)**		
21.45	4.27×10^{-5}	23.46	3.68×10^{-5}	9.37%	-13.82 %
40.59	1.64×10^{-5}	40.59	1.14×10^{-5}	0	-30.49 %
66.49	3.18×10^{-5}	70.13	2.80×10^{-5}	5.47%	-11.95 %
137.43	3.65×10^{-5}	140.21	2.97×10^{-5}	2.02%	-18.63 %
Relative displacement amplitude frequency curve of Y-direction				**Frequency variation (%)**	**Variation of largest peak (%)**
Original value		**Optimal value**			
Frequency (Hz)	**Peak (m)**	**Frequency(Hz)**	**Peak (m)**		
40.02	2.12×10^{-5}	40.02	1.76×10^{-5}	0	-16.98 %
117.69	1.94×10^{-5}	119.35	1.53×10^{-5}	1.41%	-21.13 %
138.80	4.52×10^{-5}	140.43	3.96×10^{-5}	1.17%	-12.39 %
Relative displacement amplitude frequency curve of Z-direction				**Frequency variation (%)**	**Variation of largest peak (%)**
Original value		**Optimal value**			
Frequency (Hz)	**Peak (m)**	**Frequency (Hz)**	**Peak (m)**		
98.26	2.19×10^{-5}	98.26	1.82×10^{-5}	0	-16.89 %
137.71	4.35×10^{-5}	140.40	3.73×10^{-5}	1.95%	-14.25 %
167.61	2.51×10^{-5}	170.30	2.04×10^{-5}	1.60%	-18.73 %

5. Conclusion

There are many factors that could influence the hydraulic press work. With its power element swash-plate axial piston pump as the research object in this paper, according to the theory of algorithms and test methods of data information extraction, to prove the validity of the method of hydraulic pump fault diagnosis algorithm. This method can also be applied to the diagnosis of similar components, even form a system, establish RZU2000HM hydraulic fault diagnosis model. But subsequent work needs a further study: expecting search optimization from the multiple method fusion, and experiencing the experiment verification.

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