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Combination of Fault Tree and Neural Networks in Excavator Diagnosis

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Abstract

By using the theory of artificial intelligence fault diagnosis of hydraulic excavator of several basic problems are discussed in this paper, the artificial intelligence neural network model is established for the fault diagnosis of hydraulic system; the combined application of fault diagnosis analysis (FTA) and artificial neural network is evaluated. In view of the hydraulic excavator failure symptom of dispersion and fuzziness, the fault diagnosis method was presented based on the fault tree and fuzzy neural network. On the basis of analysis of the hydraulic excavator system works, the fault tree model of hydraulic excavator was built by using fault diagnosis tree. And then, utilizing the example of hydraulic excavator fault diagnosis, the method of building neural network, obtaining training samples and neural network learning in the process of intelligent fault diagnosis are expounded. And the status monitoring data of hydraulic excavator was used as the sample data source. Using fuzzy logic methods the samples were blurred. The fault diagnosis of hydraulic excavator was achieved with BP neural network. The experimental result demonstrated that the information of sign failure was fully used through the algorithm. The algorithm was feasible and effective to fault diagnosis of hydraulic excavator. A new diagnosis method was proposed for fault diagnosis of other similar device.

Keywords: *intelligent fault diagnosis, artificial neural network (ANN), hydraulic excavator, fault tree analysis (FTA), fuzzy logic*

1. Introduction

With the development of the great modern production and the progress of science and technology, the hydraulic excavator became more and more complex, increasingly automated and intelligent. It is gradually the integration of organic whole. The event of failure is often caused troubleshooting very difficult. The faults of hydraulic excavator may not only cause the interruption of hydraulic excavator operation but also increase costs, decrease machine quality and affect the safety of operators. Early detection of incipient faults can minimize breakdown and reduces maintenance time. Furthermore, the availability and reliability of hydraulic excavator will be also increased. Consequently, fault diagnosis for detection of faults in hydraulic excavator has been the subject of considerable research in recent years to avoid stoppage of hydraulic excavator operation. For increased productivity and safety reason, there has been an increasing demand for automated predictive maintenance and fault diagnosis system.

Consequently, intelligent fault diagnosis technology have extensive research and attention, such as fault diagnosis expert system method, fault tree diagnosis method, fault diagnosis method of pattern recognition, fault diagnosis method based on fuzzy logic, diagnosis method based on neuro network. The advantages of these methods are not to need to accurate mathematical models, but theirself have the respective existing limitation, so a variety of combining intelligent diagnosis method become one of the hottest research point. In the field of fault diagnosis, fault tree model and its corresponding processing method with its graphical, simple and intuitive characteristics is widely applied in the mechanical fault ananlysis. In each level of fault tree, all the direct reasons of the fault are expressed as input events. And the root causes of the fault are expressed as bottom events or bottom events combination. The

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intelligent fault diagnosis systems based on fault tree is better able to express different levels of the logical relationship between the fault and the relevance between them. But when the system is complex, the rules numbers extracting from the fault tree increasing in progression growth, resulting in slow reasoning speed according to the rules [1].

Artificial neural networks (ANNs) have been proven as a reliable technique to diagnose and have good learning capability. However, ANNs are not interpretable and understandable, and are incapable of explaining a particular decision to the user in a human-comprehensible form. Fuzzy logic is another method, which has been used for fault detection and diagnosis. It has the ability of modeling human knowledge using easily understandable linguistic term. It has the capability of transforming linguistic and heuristic terms into numerical values for use in complex machine computation via fuzzy rules and membership functions. Thus, fuzzy logic requires fine-tuning in order to obtain acceptable rule base and optimize parameters for available data. The individual problems from fuzzy logic or ANN alone can be solved by the integration of both methods [2].

For the characteristics of these methods, a combination method of fault tree and fuzzy neuro network is presented to solve the fault diagnosis of hydraulic excavator. Fistly, the whole fault patterns of hydraulic excavator are concluded by fault tree analysis and the training samples of neuro network are extracted. Secondly, the method of combining fuzzy logic and neuro network is used to diagnose the faults of hydraulic excavator.

2. Structure of BP Neural Network

The diagnose application of BP (Back Propagation) neural network is using BP network of nonlinear mapping to sign collection to the failure of monitoring nonlinearly related. The input parameter of neural network is a failure, and the output is the type of failure. In use of neural network to diagnose, the neural network is trained to meet the demand by a lot of failure sample. And then it is used to failure diagnosis. When the failure symptom is inputted to the neural network, the failure mode can be acquired by the failure diagnosis of neural network. If a new sign of failure patterns is entered, the corresponding new patterns of failure are learned from the experience of failure patterns by the neural network [3].

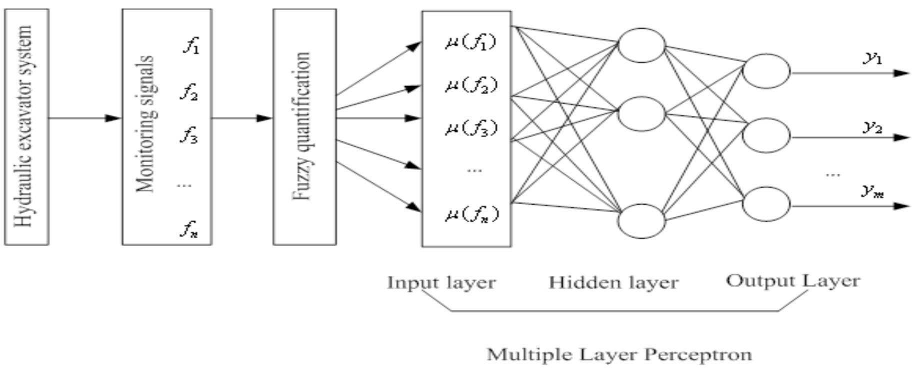

Figure 1. Structure of BP Neural Network

BP neural network is consisting of input layer, output layer and a number of implied layers. Information beginning from the input layer to one-way communication between the layers in passing is transmitted to the implied layer nodes and finally reaches the output layers. Each layer contains a number of nodes and each node represents a neuron, with a floor of no ties between the nodes to connection. The structure of neural network is shown as Figure 1 [4].

The input parameter of neural network is a failure, and the output is the type of failure. The input and output vectors of BP neural network are expressed as x and y, that is:

$$x = [x_1, x_2, ..., x_n]^T \tag{1}$$

$$x = [y_1, y_2, ..., y_m]^T \tag{2}$$

Corresponding respectively to the neural network node numbers of n and m. BP neural network serves as a nonlinear mapping from n dimension input space into m dimension output space, as follow:

$$f : R^n \to R^m, f(x) = y \tag{3}$$

The layers of network are determined by the map existing theorem. f can be built accurately by a three storied (input layer, output layer and implied layer) sensor network or any continuous functions are represented by a three ranks sensor. Therefore, each layer of neural network parameters can determined by the numbers: neural node n of input layer corresponding to numbers of fault symptoms, neural node m of output layer corresponding to numbers of fault causes, neural node number of implied layer is described by experience formula (4).

$$h = \sqrt{n+m} + l(l : 1 \sim 10) \tag{4}$$

Choosing of study rate α, in order to hold the iterative process of oscillating and overcome the disadvantage of getting into local minimum. A study rate α is used according to Rumelhart's suggestion. And it is usually 0≤α≤1 [5].

3. Fault Analysis of PC 200-7 Hydraulic Excavator

3.1 Fault Tree Analysis of PC 200-7 Hydraulic Excavator

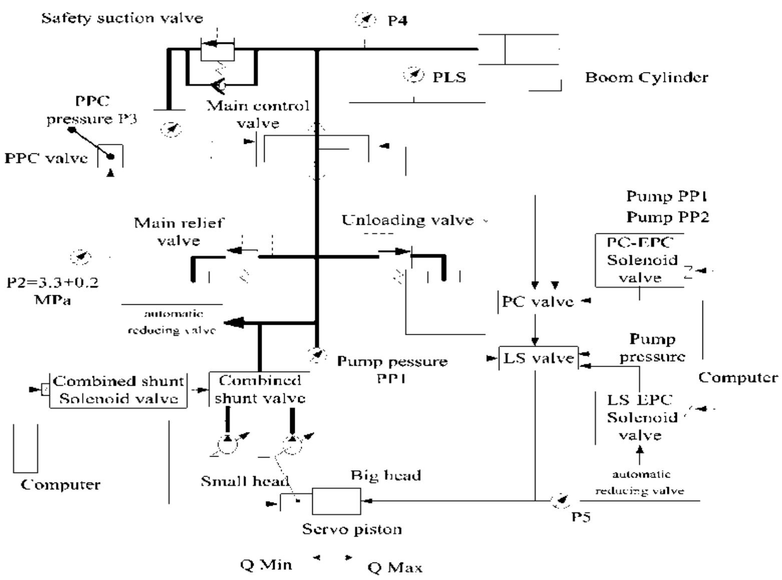

Figure 2. Principle of Boom Hydraulic System

The boom hydraulic principle of PC200-7 excavator is shown in Figure 2. The hydraulic system includes two parts: major loop and control loop. In the picture the bold lines and relevant components are major loop. The high pressure oil from the main pump to the boom is expressed clearly by the figure: main pump → main control valve → boom cylinder. The control loop is relatively complex and basically consisted of PPC loop, pump control loop, safety loop and electrical control loop [6].

The setting pressure of hydraulic system for PC200-7 excavator is 32.5MPa. Less than the pressure, the system pressure is low. According to analysis result of hydraulic working operation for excavator and fault tress analysis, the hydraulic system fault is broken down into two subsystem fault: major loop fault (E_{11}) and control loop fault (E_{12}). The major loop fault is brought up into main pump fault (E_{21}), main control valve fault (E_{22}), boom cylinder fault (E_{23}). And the control loop fault is resolved into boom PC loop fault (E_{24}), pump control loop fault (E_{25}), safety loop fault (E_{26}, including major spillover valve fault, unloading valve fault, safety inlet valve fault). And then the sub-loop fault is continued analyzing until the fault types of hydraulic components are determined, as shown in the Figure 3 [7]. The bottom events of fault tree are expressed as $X_i = [x_1, x_2, ..., x_{21}]$, that is x_1 = {Main pump plunger wear serious}, x_2 = {Main pump valve plate wear serious}, x_3 = {Main Control valve spool of serious wear and tear}, …, x_{21} = {Unloading valve spool are no objects resting }. These bottom events are shown in Table 1.

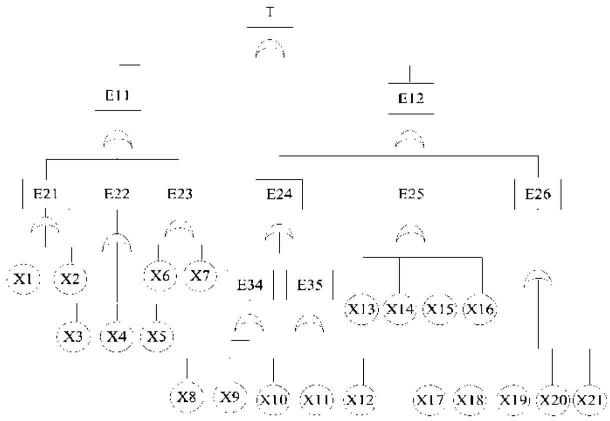

Figure 3. Fault Tree Model of Excavator Boom Hydraulic System

Table 1. Bottom Events of Boom Hydraulic System

Numbers	Bottom events	Numbers	Bottom events
x_1	Main pump plunger wear serious	x_{12}	Since the cone valve and valve housing between the stolen goods
x_2	Main pump valve plate wear serious	x_{13}	PC spool stuck
x_3	Main Control valve spool of serious wear and tear	x_{14}	PC-EPC valve internal coil burned out
x_4	Main control valve spool stuck	x_{15}	LS spool valve orifice plug
x_5	Main control valve spool O-ring damage	x_{16}	LS-EPC valve internal coil burned out
x_6	Serious leakage of hydraulic cylinder	x_{17}	Improper pressure adjustment
x_7	Damage to the hydraulic cylinder seals	x_{18}	Material surface badly worn valve cone
x_8	PPC valve spool stuck	x_{19}	Valve orifice obstruction
x_9	PPC severe valve wear	x_{20}	Spring break
x_{10}	PPC valve spool movement is not normal	x_{21}	Unloading valve spool are no objects resting
x_{11}	From improper pressure adjustment valve		

3.2. Fault Diagnosis Analysis of Hydraulic System

Komatsu PC200-7 type of mechanics-electronics-hydraulics integration excavator is a complex whole [8]. In the course of excavator operation, the regular fault types of hydraulic system are mainly engine overload, revolution drop, working slow speed of whole machine, lack of cutting force, traveling off, turning slow and so on. Its failure status can be divided into two states: normal and fault, with quantitative values of 0.1, 1.0.

The main reasons causing fault are lower of operating oil pressure. And the primary causes of lower pressure mare the blockage and leakage. According to the principle of excavator hydraulic system and the results of fault analysis tree, the actual problems to eliminate these failures are to solve the hydraulic element faults for hydraulic pump, main control valve, hydraulic cylinder, hydraulic motor, major spillover valve, PPC valve, safety valve and unloading valve. The fault categories are expressed as follow: $D = \{D_0, D_1, D_2, ..., D_7\}$ =

{Normal, Major pump fault, Safety valve or unloading valve fault, Main control valve fault, Major spilover valve, Hydraulic cylinder fault, Hydraulic motor fault, PPC valve fault}. These fault categories are shown in Table 2.

Table 2. Fault Categaries of Hydraulic System

Fault numbers	Fault causes
D_0	Normal,
D_1	Major pump fault
D_2	Safety valve or unloading valve fault
D_3	Main control valve fault
D_4	Major spilover valve
D_5	Hydraulic cylinder fault
D_6	Hydraulic motor fault
D_7	PPC valve fault

In order to accurately locate the fault position of excavator hydraulic system, the running parameters of hydraulic systems, such as engine water temperature C_1 (^{0}C), hydraulic oil temperature C_2 (^{0}C), engine oil pressure C_3 (MP_a), main pump pressure C_4 (MP_a), the pilot control pressure C_5 (MP_a), engine speed C_6 (r/min), excavators noise C_7, and hydraulic oil level C_8 are needed to detect. Therefore, the inputting fault symptoms of neural network is 8, the input layer nodes is the number of fault symptom = 8, denoted as C = {C_1, C_2, ..., C_8}. The correspondences of the failure symptom and failure cause for hydraulic system are shown in Table 3 [9].

Table 3. Corresponding Relation between Fault Reason for Excavator Hydraulic Systems

Numbers	Fault syptoms								Fault
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	categories
1	111	104	0.30	10	0.8	414	noise	nomal	D_1
2	96	72	0.29	17	3.2	1860	normal	nomal	D_2
3	98	81	0.31	32	1.3	1920	normal	nomal	D_3
4	85	92	0.32	24	2.1	1940	noise	nomal	D_4
5	80	90	0.30	20	2.2	1860	noise	nomal	D_4
6	90	70	0.22	19	3.0	1920	normal	nomal	D_2
7	101	84	0.31	32	1.5	2100	noise	nomal	D_3
8	105	86	0.32	32	1.4	1970	noise	nomal	D_3
9	102	97	0.31	16	3.2	1810	noise	nomal	D_5
10	109	96	0.30	17	2.9	1820	noise	nomal	D_6
11	106	87	0.31	32	1.6	1960	noise	nomal	D_3
12	112	103	0.30	12	1.2	620	noise	nomal	D_1
13	98	80	0.25	20	3.2	1860	normal	nomal	D_2
14	74	52	0.32	31	0.5	1950	normal	nomal	D_7
15	111	104	0.30	10	0.8	414	normal	nomal	D_1
16	96	72	0.29	17	3.2	1860	normal	nomal	D_2

Based on the needs of binary coded, the output layer nodes of neural network are designed to m=3, expressing the eight kinds of fault type. The neural network is built by fault symptom and possible cause. By the formula (4), different l is selected in the range of 1 to 10, and the neural network is trained.

Finally the hidden layer nodes are determined 8. α is taken to be 0.7. In conclusion n=8, m=3, h=8, α =0.7. At this point the fault diagnosis of hydraulic excavators of BP neural network is built up.

4. Fault Diagnosis for Hydraulic Excavators of Fuzzy Sample

As the system failure information environment is more uncertain, the value of various signs and fault value is fuzzy, and test data for diagnostic reflect the operation of the system, so the data must be translated into fuzzy data, in line with the knowledge base needs. Reasons for each failure C_i, the fault symptoms that may occur are extracted, and the establishment of a sign may be set: X_i=[x_1, x_2,..., x_n]. Fault symptoms fuzzy vector are found as input to each neuron value xi. The characteristic of information fault symptoms can be quantified by the form of fuzzy membership function, where F is 0.1, 0.25, 0.5, 0.75, 1.0, indicating respectively the characteristic information of symptoms, such as normal, slight, plurality, obvious and serious.

The parameters of the component fault condition are accomplished as the points of the maximum values. The quantifications of fault characteristic information increase the gap between the failure parameter value s and normal values.

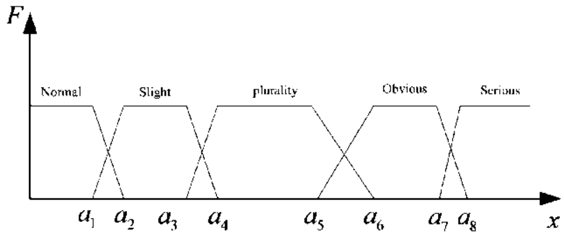

Figure 4. Membership Function of Testing Variable

Shown in Figure 4, the fuzzy method is used to determine the distribution of the membership function of each test variable. Information based on fault tree and some experience is employed to determine the form and parameter a_i of membership function. According to the determining the actual operation process parameters of hydraulic excavator, the test data is translated into fuzzy data by the use of fuzzy logic membership function [10].

1) The state variable domain is "normal". A lower semi-trapezoidal distribution is used to expressed the conversion and the weight factor is determined as 0.1, as shown in the formula 5.

$$\mu_A(x) = \begin{cases} 1 & x \le a_1 \\ \dfrac{a_2 - x}{a_2 - a_1} & a_1 < x \le a_2 \\ 0 & a_2 \le x \end{cases} \tag{5}$$

2) The state variable field is high (severe). The conversion is a half-liter trapezoidal distribution, and the weight factor is determined as 0.9, as shown in the formula 6.

$$\mu_A(x) = \begin{cases} 0 & x \le a_7 \\ \dfrac{x - a_7}{a_8 - a_7} & a_7 < x \le a_8 \\ 1 & a_8 \le x \end{cases} \tag{6}$$

3) The state variables are "normal, slight, plurality, obvious". The conversions are trapezoidal distribution and the weight coefficient points are determined as 0.25, 0.5 and 0.75. The membership function of “slight” is below, as shown in the formula 7.

$$\mu_A(x) = \begin{cases} 0 & x \le a_1 \\ \dfrac{x - a_1}{a_2 - a_1} & a_1 < x \le a_2 \\ 1 & a_2 < x \le a_3 \\ \dfrac{a_3 - x}{a_4 - a_3} & \mathrm{a}_3 < x \le a_4 \\ 0 & a_4 \le x \end{cases} \tag{7}$$

The setting weight values are used to deal with the test data between two states. Using the method of the membership function of the weighted average, the data between the two states is turned into the input data of neural network.

Based on the above methods, the detection variables of C_1-C_6 are faintly quantified, such as C_4 in Figure 5 for the detection variable of fuzzy membership function. For Komatsu PC 200-7 hydraulic excavator, the main pump of the standard pressure is 32.5MPa. And the common fault conditions based on pump pressure are four states: " serious low, low, obvious low, slight low". If the measured variable C_4 is 12 MPa, belonging to "low" degree of membership is 0.786, belonging to "Plurality low" degree of membership is 0.357, then $x_4 = u(C_4) = 0.786*0.75+0.357*0.5=0.768$. Using the same method, each of detection signals is fuzzy and then input into the neural network for diagnosis.

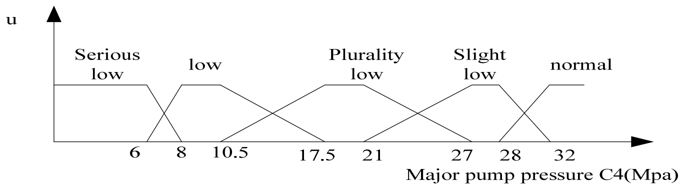

Figure 5. Detection variable memberships function of C_4

And then all possible causes are analyzed, reasons for the failure are established. The appropriate set is Y= {y_1, y_2, y_3, ..., y_m}. The membership value of fault cause is used to explain the likelihood size of failure y_i. Its range is [0, 1]. Fault level categories are shown in Table 4 [11].

Table 4. Fault Level Categories

Fault grade	Membership value y_i	Meaning
Fatal	0.75-1	Endanger the personal safety, causing assembly scrap, result in significant
Serious	0.5-0.75	Cause the main components, assembly severely damaged, can not be excluded by spare parts and vehicle tools in the short term
General	0.25-0.5	Mining operations do not affect the major components of non-damaged; can be ruled out in a relatively short period of time
Normal	0-0.25	Excavator working properly

Based on the above analysis of the results shown in Table 1, the fuzzy samples of excavator hydraulic system failure are acquired. The neural network input and output training samples shown in Table 5 is established. The cause of the fault fuzzy set isX={x_1, x_2, x_3, ..., x_8}. Because it is the fault information for fault diagnosis, fault type is therefore all kinds of failure. That is D = {D_1, D_2, D_3, ..., D_7}, respectively encoded as {000}, {001}, {010}, {011}, {100}, {101}, {110}, {111}. Indicating the reasons for the failure set is Y= {y_1, y_2, y_3} [12].

Table 5. Fault Diagnosis Training Samples of Neural Network

Numbers	Neural network input x_i								Neural network output y_i			Fault Categories
	1	2	3	4	5	6	7	8	1	2	3	
1	0.50	0.45	0.10	0.75	0.75	1.00	1.0	0.1	0	0	1	D_1
2	0.13	0.10	0.18	0.52	0.10	0.10	0.1	0.1	0	1	0	D_2
3	0.17	0.10	0.10	0.10	0.67	0.10	0.1	0.1	0	1	1	D_3
4	0.10	0.16	0.10	0.38	0.33	0.10	1.0	0.1	1	0	0	D_4
5	0.10	0.25	0.10	0.50	0.25	0.10	1.0	0.1	1	0	0	D_4
6	0.10	0.10	0.10	0.50	0.10	0.10	0.1	0.1	0	1	0	D_2
7	0.25	0.10	0.25	0.10	0.50	0.10	1.0	0.1	0	1	1	D_3
8	0.50	0.10	0.10	0.10	0.58	0.10	1.0	0.1	0	1	1	D_3
9	0.25	0.25	0.10	0.56	0.10	0.10	1.0	0.1	1	0	1	D_5
10	0.45	0.25	0.10	0.52	0.10	0.10	1.0	0.1	1	1	0	D_6
11	0.30	0.10	0.10	0.10	0.50	0.10	1.0	0.1	0	1	1	D_3
12	0.50	0.40	0.10	0.77	0.75	1.00	1.0	0.1	0	0	1	D_1
13	0.19	0.10	0.25	0.50	0.10	0.10	0.1	0.1	0	1	0	D_2
14	0.10	0.25	0.10	0.14	1.00	0.10	0.1	0.1	1	1	1	D_7
15	0.10	0.25	0.10	0.18	0.25	0.10	0.1	0.1	1	1	1	D_7
16	0.10	0.25	0.10	0.10	0.10	0.10	0.1	0.1	0	0	0	D_0

5. Training of Neural Network

BP algorithm flow is shown in Figure 6.The traditional BP algorithm is used in the neural network training, that is, the error back-propagation algorithm. Its essence is the gradient descent algorithm. The output error function, which is the difference between the actual output and requirements, is employed to amend the weighted space of the link strength so that the error function is declining.

The main steps of algorithm are as follows [13]:

0. Initialization of network state: the network weights and threshold values are given initial values by -1 to 1 with a random number.

1. A sample is removed from the training sample set and the input information is import to the network. That is the input vector x_p and the teacher vector d_p, (p = 1, 2 ... P).

$$x_p = \{x_{p1}, x_{p2}, \ldots, x_{pL}\} \tag{8}$$

$$d_p = \{d_{p1}, d_{p2}, \ldots, d_{pN}\} \tag{9}$$

2. Learning begins: for each sample as follows: Calculate the output values of network hidden layers and output layer neurons.

$$y^l_{pj}(n) = f_j\left(v^l_{pj}(n)\right) = f_j\left(\sum_{i \in c} w^{(l)}_{ji}(n) x^{(l-1)}_i(n) - x^{(l)}_{j0}(n)\right) \tag{10}$$

Calculate the training errors $\delta_{pj}(n)$:

$$\delta_{pj}(n) = e_{pj}(n)\varphi'_{pj}(v_{pj}(n)) \quad \text{(Output layer)} \tag{11}$$

$$\delta_{pj}(n) = \varphi'_{pj}(v_{pj}(n))\sum_{k \in c}\delta_{pk}(n)w_{pkj}(n) \quad \text{(Hidden layer)} \tag{12}$$

Modify the weights and thresholds

$$w^{(l)}_{ij}(n+1) = w^{(l)}_{ji}(n) + \eta\delta^{(l)}_{pj}(n)x^{(l-1)}_{pi}(n) + \alpha(w^{(l)}_{ji}(n) - w^{(l)}_{ji}(n-1)) \tag{13}$$

3. If it satisfies Equation (14):

$$\left|y^l_{pj}(n+1) - y^l_{pj}(n)\right| < \zeta \tag{14}$$

If it is satisfied, step 5 is implemented, else returning to step 0.

4. If it satisfies Equation (15):

$$\left|y^l_{pj}(n+1) - d_{pj}(n)\right| < \beta \tag{15}$$

If it is satisfied, step 5 is implemented, else returning to step 0.

5. Stop.

BP algorithm is intended to find connection weights $w^{(l)}_{ji}$ (l=1.i =1 ,2 ,... ,L, j=0, 1, 2, ..., M-1; l=2, i= 0, 1, 2, ..., M, j=0, 1, 2, ..., N-1, L, M, N) for the neurons of input layer, output layer and hidden layer so that equation(16) becomes the global minimum.

$$E(n) = \frac{1}{2}\sum_{j \in c} e^2_j(n) = \frac{1}{2}\sum_{j \in c}[d_j(n) - y_j(n)]^2 \tag{16}$$

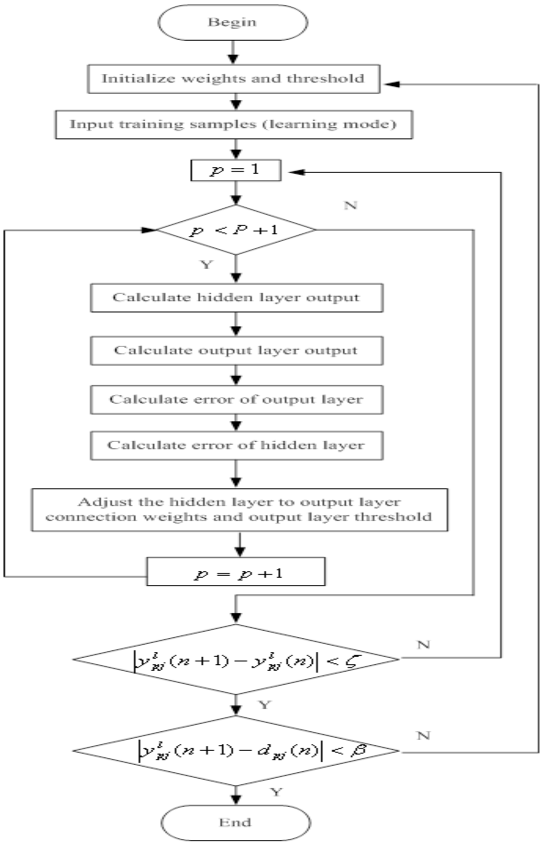

Figure 6. BP Algorithm Flow

In practice, the network often converges to a local minimum, which is not to obtain the global minimum of E, but a relatively larger E value. How to avoid in the learning process into a local minimum is a major problem of BP algorithm. When the network is into local characteristics, characteristics shown that the weights converge to a stable value and the error value is not the smallest. The equation requirements of (14) and (15) are meeting and from step 5) to determine whether the network can fall into local minimum [14].

Table 6. Test Results of Samples

Numbers	Neural network output			Desired output		
	y_1	y_2	y_3	y_1	y_2	y_3
1	0.00183	0.00210	0.99818	0	0	1
3	0.00176	0.99175	0.99875	0	1	1
5	0.99925	0.00178	0.00168	1	0	0
8	0.00270	0.99890	0.99823	0	1	1
11	0.00015	0.99864	0.99746	0	1	1
16	0.00085	0.00025	0.00056	0	0	0

Percent 70 of hydraulic excavator training samples shown in Table 3 are input to the BP neural network training program compiled by MATLAB, and the remaining 30% are the test samples. When the error of 10-3 is required, the network training is completed. Six samples randomly selected from the 17 samples, such as a test sample 1, 3, 5, 8,10,16, are used as the testing samples to test the neural network, the test results are shown in Table 6 [15].

As can be seen from Table 8 the actual output and desired output results of neural network are corresponded. The maximum error of test samples is 0.27%. Maximum error represents a network of diagnostic accuracy. The network diagnostic accuracy error is 0.27

percent. The results show that using the network running status of the excavator fault diagnosis is feasible; the common failure of the hydraulic excavator is accurately diagnosed.

6. Conclusions

The two diagnosis technology based on fault tree model or based on neural network is different diagnosis technology. It has its own advantages and disadvantages. And this is a research hot spot of intelligent diagnosis technology. This paper presents a new combination method based on fault tree model and neural network used in hydraulic excavator fault diagnosis. Firstly the working principle of hydraulic excavator is analyzed. And then fault tree analysis method is used to determine the cause of the fault symptoms and fault correlation. Next troubleshooting information of the sample is fuzzy. Lastly neural network inference is employed for diagnosis, and algorithms used in fault diagnosis of hydraulic excavators acquire a very good application effect. Through specific applications, the following conclusions are made:
1) The algorithm is highly relevant to the failure to study samples together to improve diagnostic accuracy.
2) The algorithm of failure not only considers the relevance of the sample, but also takes into account the ambiguity of the fault sample.
3) Through specific engineering applications, it shows that the algorithm has good performance, high accuracy of fault diagnosis. According to the test samples, the early failure of the hydraulic excavator hidden diagnosis and disposal can be achieved.

The result suggests that this method is effective for hydraulic excavator fault diagnosis. And the overall scheme is feasible. So, the application prospect of using many intelligent fault diagnosis methods is quite optimistic. And this technology is worth further research and discussion.

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