Fault Diagnosis for Chain Circulating Conveyor Based on Standard State Model Verifying and BP Neural Network

ZHAO Qiangqiang\(^1\), Gao Xuexing\(^2\), Hou Baolin\(^3\), Yao Laipeng\(^4\), Wang Xi\(^5\)
School of Mechanical Engineering, Nanjing University of Science and Technology
Nanjing, P. R. China

Abstract: A standard state model verifying fault diagnosis method is proposed to overcome the problem in which it is hard to acquire enough samples for intelligent fault diagnosis. Firstly, the motion parameters of the system are acquired by standard state test. Then the test data is used as the standard, the simulation model of the conveyor is verified by changing the selected uncertain variables. Finally, a large number of samples are generated from the simulation model for training the neural network model so as to get a diagnostic machine. This method is used in chain circulating conveyor’s fault diagnosis, and the diagnosis results are very effective.

Keywords: BP neural network, Standard state model verifying, Fault diagnosis, Chain circulating conveyor

I. Introduction

Fault diagnosis is a new technique which is developed since 1960s, America is the earliest country to study fault diagnosis technology, US Naval Research Laboratory started to develop and research fault diagnosis technology of mechanical systems for the first time on the initiative of National Aeronautics and Space Administration (NASA) in 1967, and they have made a great success in fault mechanism research, fault detection, fault diagnosis and fault prediction. The paper published in Automatic by Mehra and Peschon\(^1\) is regarded as one of the origin of fault diagnosis technology. Willsky\(^2\) published the first review article about fault detection and diagnosis in Automatic in 1976, Himmelblau\(^3\) published the first monograph about fault detection and diagnosis in 1978, International Federation of Automatic Control (IFAC) established the Fault Detection, Supervision and Safety for Technical Processes in 1993 and hold an international conference to discuss the technology about fault diagnosis every three years.

England and Japan started to research fault diagnosis in early 1970s and a lot of achievements have been made on boiler, pressure vessel, nuclear power plant, nuclear reactor and railway vehicles. According to former information, when fault diagnosis technology is exploited, the cost for devices maintenance reduces by an average of 15%-20%, the cost for fault diagnosis accounts for as much as 7.2% of the total cost of production in America, and the rate in Japan and Germany is about 5.6% and 9.4% respectively\(^4\).

Since 1980s, fault diagnosis technology enters into intelligent diagnosis stage, as a feature, expert system, neural network, fuzzy inference and support vector machine are used in fault diagnosis\(^5-8\), which have a capacity of logical inference, self-learning, self-diagnosis and self-processing. Zhu\(^9\) built a fault diagnosis model for a forklift by BP neural network and the model’s convergence can meet the diagnosis requirements. Feng\(^10\) proposed a fuzzy neural network based on fault tree for variable amplitude hydraulic system, this method trains the neural network by Levenberg-Marquardt optimization algorithm, and this system has a fast inference speed and a strong fault tolerance. Mahanty\(^11\) researched the application of RBF neural network in transmission line’s fault classification and fault location.

For complex electromechanical system, usually it cannot find the analytical expressions among the measurable parameters and uncertain variables, but this kind of problem often can be solved by machine learning method well represented by neural network methodology. Machine learning method can be used to estimate the dependency relationship among the data by using the
known samples to predict or judge the unknown data which cannot be directly measured. It is a black box or grey box which can give the correct answer by probability.

However, for a diagnostic machine, when the training method is confirmed, the parameters of a neural network can be determined by the training samples. An actual experiment can provide high-quality samples, but restricted by experiment numbers and experimental objects, it is hard to get enough samples from actual experiment. On the contrary, virtual simulation method can obtain samples easily, but the simulation results usually exist unexpected errors.

This paper proposes a fault diagnosis method in which the virtual simulation model is verified by standard state experiment. It means that some high-quality samples are acquired from an actual experiment, then the simulation models are debugged until simulation outputs are coincident with the samples from the actual experiment, finally a lot of samples are get from the simulation model to train the neural network diagnostic machine. At last, this method is applied in the fault diagnosis of a circulating conveyor, and the diagnosis results are satisfied.

II. The Model of Chain Circulating Conveyor

A1 The dynamic model of the chain circulating conveyor

The chain circulating conveyor is a very complex electromechanical system, in order to reduce the man-made errors during the process of modelling and solution and to increase the computational efficiency, the conveyor dynamic model need to be simplified. The simplified conveyor dynamic model is shown in Fig.1. This model consists of two driving chain wheels, two driven chain wheels, a support frame, 25 workpiece tubes, 100 rollers and a gear reducer, the reducer consists of a small gear, a big gear, a worm gear and a worm. Because there is only one workpiece in the test, there is also only one workpiece in the dynamic model.

A2 The control system of the chain circulating conveyor

The chain circulating conveyor is driven by two parallel DC series motors, the equations of the motors are listed as follows:

\[
U = E + R_mI_a + L \frac{dI_a}{dt} \\
\Phi = K_fI_a \\
E = C_e \Phi \omega_w \\
T = C_T \Phi I_a
\]

Here, \( U \) is the motor’s input voltage, \( E \) is counter electromotive force, \( I_a \) is armature current, \( L \) is electric inductance, \( \Phi \) is magnetic flux, \( K_f \) is excitation coefficient, \( C_e \) is counter electromotive force coefficient, \( \omega_w \) is the rotating speed of the motor, \( T \) is the motor’s output torque, \( C_T \) is electromagnetic torque coefficient. According to these equations, the control system built in Simulink is shown in Fig.2.
A3 Model verifying based on test data

There are many fault types of the chain circulating conveyor and the cause of faults are not all the same, so in this paper, just three typical faults are chosen to be diagnosed, the corresponding uncertain variables are the efficiency of the worm and worm gear transmission, the voltage of the motors, and the sensitivity of the tachometer generator respectively, here the sensitivity of the tachometer generator means the output of the tachometer generator is voltage instead of rotating speed, the scale coefficient between the voltage and rotating speed is the sensitivity factor.

When verifying the dynamic model of the conveyor, the selected uncertain variables are adjusted until the simulation outputs of the conveyor dynamic model are basically consistent with the test data. As shown in Fig.3, after the model is verified, the workpiece’s displacement curve of actual experiment is very close to the corresponding simulation result.

![Fig.3. Workpiece’s displacement of simulation result and actual experiment](image)

Although the model verifying is just for standard state, but from a statistical standpoint, the accuracy of nonstandard state dynamic model will increase correspondingly.

A4 Uncertain variables sampling and dynamic simulation

The efficiency of the worm and worm gear transmission, the sensitivity of the tachometer generator and the voltage of the motor are selected as the uncertain variables in this paper.

The efficiency equations of worm and worm gear transmission is:

$$\eta = \eta_1 \eta_2 \eta_3$$  \hspace{1cm} (1)

When the worm gear is active,

$$\eta_1 = \frac{\tan y}{\tan (y + \rho_v)}$$  \hspace{1cm} (2)

When the worm is active,

$$\eta_1 = \frac{\tan (y - \rho_v)}{\tan y}$$  \hspace{1cm} (3)

Here, $\eta_1$ is meshing efficiency of the worm and worm gear transmission, $\eta_2$ is the efficiency considering lubrication, the range of $\eta_2$ is [0.94 0.99], in this paper, $\eta_2 = 0.98$. $\eta_3$ is the efficiency of the bearings, the range of $\eta_3$ for rolling bearing is [0.98 0.99], and for sliding bearing is [0.97 0.99], in this paper, $\eta_3 = 0.98$.

In the system of chain circulating conveyor, worm and worm gear transmission is the last reducing transmission, worm is the driving part, so $\eta_1 = \frac{\tan y}{\tan (y + \rho_v)}$.

<table>
<thead>
<tr>
<th>Sliding speed/ m·s⁻¹</th>
<th>$\rho_v$/°</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>6.28</td>
</tr>
<tr>
<td>0.05</td>
<td>5.15</td>
</tr>
<tr>
<td>0.1</td>
<td>4.57</td>
</tr>
<tr>
<td>0.25</td>
<td>3.72</td>
</tr>
<tr>
<td>0.5</td>
<td>3.15</td>
</tr>
<tr>
<td>1</td>
<td>2.58</td>
</tr>
<tr>
<td>1.05</td>
<td>2.28</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2.8</td>
<td>1.72</td>
</tr>
</tbody>
</table>

Table.1. The relationship between $\rho_v$ and sliding speed

In equation (2), $\rho_v$ is the equivalent friction angle, its value is related with the sliding speed between worm
and worm gear, the specific relationship is shown in Table 1.

In this paper the range of $\rho_v$ is considered in $[1.72^\circ, 6.28^\circ]$ because of the sliding speed between worm and worm gear is uncertain. Thus the upper limit of the efficiency of the worm and worm gear is:

$$\eta = \eta_1 \eta_2 \eta_3 = \frac{\tan \gamma}{\tan(\gamma + \rho_v)} $$

$$\eta_1 \eta_2 \eta_3 = \frac{\tan 5.71}{\tan(5.71 + 1.72)} = 0.7667$$

The lower limit is:

$$\eta = \eta_1 \eta_2 \eta_3 = \frac{\tan \gamma}{\tan(\gamma + \rho_v)} $$

$$\eta_1 \eta_2 \eta_3 = \frac{\tan 5.71^\circ}{\tan(5.71^\circ + 6.28^\circ)} = 0.4710$$

The sensitivity of the tachometer generator will directly influence accuracy of the control system, the ideal value is 0.1, in this paper it is considered in $[0.075, 0.12]$. The motor’s nominal voltage is 26V, its range is $[24, 28]$.

III. Fault Diagnosis Based on BP Neural Network

A1 Process of developing fault diagnosis system development

The whole process of developing fault diagnosis system is shown in Fig. 5. Firstly, the initial dynamic simulation model of the chain circulating conveyor is built, and the failure mechanism of the common faults are analyzed which are chosen as the faults need to be diagnosed, then the uncertain variables are selected for the dynamic simulation model. At the same time, the standard state test experiment is done, and the test data is processed to acquire the test curves. Secondly, the dynamic simulation model is verified according to test data iteratively until the data curves from simulation model are close to the data curves from the test. Thirdly, after the dynamic simulation model is verified, the uncertain variables are sampled, and the sampling results are used for dynamic simulation. According to the simulation results, the data curves from simulation are analyzed to extract some characteristic points as response parameters. Finally, the response parameters are set as the inputs of the training samples, and the characteristic points are set as the outputs of the training samples to train the neural network model for acquiring the diagnostic machine.

BP neural network is applied in this paper for fault diagnosis. BP neural network was proposed by Rumelhart and McClelland in 1986, structurally, it is a typical multilayer feed forward neural network, it has one input layer, several hidden layers (maybe one layer, maybe two or more layers) and one output layer. Neurons between different layers are fully connected and neurons in the same layer do not connect with each other. Theory has proved that three layers network which has one hidden layer can approach any nonlinear functions.
of the whole curve, the method for choosing and extracting characteristic values will influence the capacity of the diagnostic machine directly.

When choosing characteristic values in this paper, it follows the principles below.

1. Sensitive, characteristic values should reflect the change of the uncertain variables sensitively.
2. Characteristic values should use the changing characteristics of the data curves sufficiently.
3. The number of characteristic value should bigger than the number of uncertain variables to ensure the uniqueness of the solution.
4. The data parameters should be effective, the parameters which are chosen should not be influenced by noise and simulation step size.

As shown in Fig.6, the selected characteristic values are ordinate of point D (E), horizontal axis of point A, B, D, E and slope of line EG. The extraction steps are as follows:

1. Median filtering method is used to denoise the noise in the curves.
2. Calculate the distributed density curve of the speed value, find out the speed which is the biggest distributed density, which is the ordinate of point D (E), and it is the first characteristic value.
3. Search from the front end of the curve, find out the values which are 40% and 70% of the ordinate of point D (E), they are point A and B, the horizontal axis of point A and B are the second and third characteristic values.
4. Search from the front end of the curve, find out the values which are the horizontal axis of point D and E, it is the fourth and fifth characteristic values.
5. Search from the back-end, find out the values which are 5 smaller than the ordinate of point E and 70% of the ordinate of point E, there are point F and G, fit the data between point F and point G in a line, and the slope of the fitted line is the sixth characteristic value.

These six selected characteristic values are fully taking advantage of the curve’s piecewise-linear characteristics, and summarizing the change characteristic of the curve according to the uncertain variables.

Notice that the characteristic values from standard state simulation data and standard state test data are a little different, consider the rigorous of the diagnosis method, when train the neural network, the samples are the difference between the characteristic valves from standard state simulation and variation state simulation.

A3 The results of fault diagnosis

During the training process, only 24 samples are used, the other six samples are never used, they are new to the diagnostic machine to test the generalization ability of the diagnostic machine.

The result of fault diagnosis are shown in Fig.7.-Fig.9. Symbol △ stands for the original samples, symbol ✗ stands for diagnostic results. Horizontal axis in the three figures is the serial number of the points, the distance between △ and ✗ is the diagnosis error in every point, the distance is greater, the error is greater.

As shown in Fig7-Fig9, the diagnosis for motor’s voltage is not very well, the possible reason is the number of the sample is not enough and the data used in this paper is just speed curve, the curve’s useful information is not enough to distinguish all the uncertain variables.
Fig.8. Diagnosis result for the sensitivity of the tachometer generator

Fig.9. Diagnosis result for motor’s voltage

IV. Conclusions

A standard state model verifying fault diagnosis method is proposed in this paper, first, the system’s fault mechanism and its corresponding uncertain variables are analyzed, then an actual experiment is done in standard state to acquire the motion parameters of the chain circulating conveyor, based on the test data, the dynamic model of the system is verified until the outputs of the dynamic model are close to the test data. After that, the selected uncertain variables are sampled by LHS, several simulation are done according to the sampling, and the simulation results are used to train the BP neural network model to get a diagnostic machine. This method discusses the problem that it is hard to get training samples and the number of samples is usually not enough in intelligent fault diagnosis. At last, this method is used in a chain circulating conveyor’s fault diagnosis and the diagnosis results are very effective.

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References