Fault Diagnosis System for Rotary Machine Based on Fuzzy Neural Networks*

Sheng ZHANG**, Toshiyuki ASAKURA***, Xiaoli XU**** and Baojie XU****

This paper is concerned with the application of fuzzy neural networks to fault diagnosis systems for rotary machines. In practical fault diagnosis, it is very difficult to improve the recognition rate of pattern recognition, especially when the sample data are similar. To solve these difficulties, a fault diagnosis system using fuzzy neural networks is proposed in this research. A fault diagnosis system with fuzzy neural networks is based on a series of standard fault pattern pairings between fault symptoms and fault. Fuzzy neural networks are trained to memorize these standard pattern pairs. Unlike other neural networks, fuzzy neural networks adopt bi-directional association. They make use of information from both the fault symptoms and the fault patterns, which can improve recognition rate greatly. When an unknown sample becomes the input for a trained fault diagnosis system, the fault diagnosis system can make fault diagnosis by bi-directional association of fuzzy neural networks. Through experiments with a rotor testing table and applications in monitoring and fault diagnosis of water pump sets of oil plant, it is verified that fuzzy neural networks have a well distinguished ability and are effective to perform fault diagnosis of rotary machines.

**Key Words:** Fuzzy Neural Networks, Fault Diagnostics, Rotary Machine, Vibration, Pattern Recognition, Bi-directional Association

1. Introduction

In the fault diagnosis of rotary machines, the basic method of diagnosis is pattern recognition. From historical data, experiments, expert knowledge and common sense, standard fault patterns are extracted. And then, these standard patterns are put combined to establish a fault diagnosis system. The process of fault diagnosis is to compare unknown input data with the standard fault patterns. With the most similar standard pattern, the fault pattern of input sample data is decided. This fault diagnosis method seems very simple. However, in practical applications, it is difficult to design the way comparing unknown samples with standard patterns. Two reasons are considered(1)(2). One is that the standard patterns often have some common characteristics. Another reason is that the practical input sample data are often very similar. To improve the recognition rate of fault diagnosis systems, fuzzy neural networks are proposed. Unlike other neural networks, fuzzy neural networks adopt bi-directional association. They make use of information from both fault symptoms and fault patterns. The result is that it can improve recognition rates greatly.

In this paper, first the structure of water pump sets is introduced. Second, a fault diagnosis system is proposed which includes a series of parallel fuzzy neural networks. And then, the algorithms for the fuzzy neural networks are discussed. Fuzzy neural networks include a feedforward fuzzy relation matrix and a feedback matrix. They can memorize standard
fault patterns in the fuzzy relation matrix and associate them according to standard patterns. Third, experiments are performed. Experimental data are used to extract standard fault patterns and to test the fault diagnosis system. Fuzzy neural networks have a great ability to distinguish similar samples. To demonstrate this advantage, a fault diagnosis system with distance function and a fault diagnosis system with back propagation neural networks are examined with the same sample data. The comparison shows that fuzzy neural networks have the best recognition rate among these three methods. The fault diagnosis system by fuzzy neural networks is applied in the monitoring and fault diagnosis of water pump sets of oil plants. It is verified that fuzzy neural networks are effective for fault diagnosis.

2. Rotary Machine System

2.1 Rotary machine system

The research objects of our fault diagnosis are water pump sets of an oil plant. Figure 1 shows a photo of a water pump set and Fig. 2 shows a brief chart. The water pump sets mainly include an electrical motor and a water pump. The water pump sets are key equipments of an oil plant, therefore it is important to monitor the working condition of them.

![Photo of water pump set](image)

**Fig. 1** Photo of water pump set

![Brief chart of the water pump set](image)

**Fig. 2** Brief chart of the water pump set

2.2 Vibration sensors

To monitor the working condition of water pumps, six vibration sensors are installed on a water pump set. As shown in Fig. 2, one sensor is installed on the body of the gearbox, one sensor on the body of the pump, two sensors on the front bearings and two sensors on the back bearings. Two sensors on the bearings, one is in the horizontal direction and another in the vertical direction.

2.3 Six major fault patterns

As a rotary machine, water pump sets have six major fault patterns, which are listed in Table 1. More than 80 percent of rotary machine faults belong to these six fault patterns. Therefore it is appropriate to consider that the fault diagnosis of a rotary machine should be fulfilled for these six main fault patterns.

3. Fault Diagnosis System For Water Pump Sets

3.1 Standard fault patterns

In fault diagnosis systems with fuzzy neural networks, a standard fault pattern is described by a fuzzy vector pair. The fuzzy vector pair includes a fuzzy symptom vector and a fuzzy fault vector.

Vibration signals obtained from vibration sensors should be normalized to vibration intensity values. The normalization process is shown as Fig. 3. The vibration velocity signal is converted into the vibration intensity value, and then normalized to values between 0 and 1. The calculation of the vibration intensity is shown as Eq. (1).

\[
V_{int} = \sqrt{\frac{1}{N\Delta t} \sum_{i=0}^{N-1} V(t)}
\]  

(1)

- \(\Delta t\): sampling interval (0.166 ms)
- \(N\): sampling number per second (1024/second)
- \(V(t)\): vibration velocity (mm/s)
- \(V_{int}\): vibration intensity (mm/s)

The alarm vibration intensity values \(V_{max}\) are different according to the position of a sensor. They are set according to ISO 2372 and ISO 3965. In this

<table>
<thead>
<tr>
<th>ID</th>
<th>Fault Pattern</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Unbalanced rotor</td>
<td>36%</td>
</tr>
<tr>
<td>2</td>
<td>Cracked rotor</td>
<td>4%</td>
</tr>
<tr>
<td>3</td>
<td>Misaligned joint</td>
<td>14%</td>
</tr>
<tr>
<td>4</td>
<td>Cracked gear</td>
<td>14%</td>
</tr>
<tr>
<td>5</td>
<td>Front bearings</td>
<td>8%</td>
</tr>
<tr>
<td>6</td>
<td>Back bearings</td>
<td>8%</td>
</tr>
</tbody>
</table>

![Normalization process of vibration signal](image)

**Fig. 3** Normalization process of vibration signal
way, from the six vibration sensors, six normalized vibration intensity values are obtained. These normalized values constitute a fuzzy symptom vector. For example there is fuzzy symptom vector \( A \) which is shown in Eq. (2).

\[
A = [0.2, 0.2, 0.6, 0.8, 0.6, 0.2]
\] (2)

Here, the fuzzy vector \( A \) means vibration intensity to be 0.2 in sensors 1, 2 and 6, 0.6 in sensors 3 and 5, and 0.8 in sensor 4.

Another fuzzy vector \( B \) is used to describe degree of all kinds of fault types. To make use of fuzzy neural networks, fault degrees are roughly described by four values such as 0.2, 0.4, 0.6, 0.8. The value of 0.2 means that there is no fault, 0.4 means that the fault degree is slight, 0.6 means the fault degree is mild and 0.8 means that the fault degree is serious. In our research of fault diagnosis for rotary machines, six most common fault types such as unbalanced rotor, cracked rotor, misalignment joint, cracked gear, front bearings fault and back bearings fault are considered. The values of fuzzy vector correspondingly represent fuzzy degrees of six faults above. For example, there is a fuzzy vector \( B \) of fault shown in Eq. (3).

\[
B = [0.8, 0.2, 0.2, 0.2, 0.2, 0.2]
\] (3)

It means that fault degree of unbalanced rotor is 0.8, degree of cracked rotor is 0.2, misalignment joint is 0.2, cracked gear is 0.2, front bearings fault is 0.2 and back bearings fault is 0.2. A fuzzy symptom vector and a fuzzy fault degree vector construct a standard fault pattern vector pair \((A, B)\).

### 3.2 Structure of fault diagnosis system

The structure of a fault diagnosis system is shown as Fig. 4. It includes a series of standard fault pattern pairs \((A_k, B_k)\), \(k = 1, 2, \ldots, n\). Here, \(A_k\) is \(i\)-dimensional fuzzy vector of symptoms and \(B_k\) is \(j\)-dimensional fuzzy vector of fault. For every standard fault pattern pair, a fuzzy neural network is trained to memorize and associate them. To do fault diagnosis, a subset function is defined as in Eq. (4):

\[
\text{subset}[k] = 1 - \frac{|A_k^* - A_k|}{i} + |B_k^* - B_k|/j
\]

\(k = 1, 2, \ldots, n\) (4)

As shown in Fig. 4, it is supposed that there is an unknown fuzzy vector input \( A \). According to the standard patterns, a series of associated results \((A_1^*, B_1^*, A_2^*, B_2^*, \ldots, A_n^*, B_n^*)\) are obtained. And then, a series values of subset value as subset [1], subset [2], \(\ldots\), subset [\(n\)] is obtained. The maximum of subset decides the fault pattern for input sample vector.

However, if the maximum subset is less than 0.8, then the associated result is not accepted and the input sample is regarded as a normal condition.

### 3.3 Fuzzy neural networks

In this fault diagnosis system, the fuzzy neural networks are used to memorize standard patterns and diagnoses by association. Fuzzy neural networks are bi-directional associative memories \(^{[3]-[5]}\). They include a feedforward fuzzy relation matrix and a feedback one. The topologic structure of fuzzy neural networks is shown as Fig. 5. The layer LA has \(i\) fuzzy cells and the layer LB \(j\) fuzzy cells. Each fuzzy cell in layer LB is connected to all fuzzy cells in layer LA. The connection weight matrix from layer LA to layer LB is the fuzzy relation matrix \( W \). Each fuzzy cell in layer LA is connected to all fuzzy cells in layer LB. Fuzzy cells in the same layer are not connected to each other. The connection weight matrix from layer LB to the input layer is the fuzzy relation matrix \( R \).

The fuzzy neural networks are often described by the fuzzy relations of Eqs. (5) and (6):

\[
A^T W = B
\] (5)

\[
B^T R = A
\] (6)

The fuzzy relation matrix \( W \) is an \(i \times j\) matrix and the fuzzy relation matrix \( R \) is a \( j \times i \) matrix. The symbol “*” is called synthesis relation, the synthesis calculation of Eq. (5) can be expressed in Eq. (7) and Eq. (6) can be expressed in Eq. (8).

\[
b_i = \max \left\{ \min \left\{ a_n, w_{ni} \right\} \right\}
\] (7)

![Fig. 5 Topologic Structure of fuzzy neural network](image)
\[ a_i = \max \left\{ \min_{j=1} b_{nj}, r_{mi} \right\} \quad (8) \]

It is supposed that the vector \( A_\ast \) can be expressed by an \( i \)-dimensional vector as in Eq. (9):
\[ A_\ast = [a^{(1)}_\ast, a^{(2)}_\ast, \ldots, a^{(n)}_\ast], \quad a^{(i)}_\ast \in [0, 1] \quad (9) \]

Similarly, it is supposed that the vector \( B_\ast \) can be expressed by an \( j \)-dimensional vector as in Eq. (10):
\[ B_\ast = [b^{(1)}_\ast, b^{(2)}_\ast, \ldots, b^{(j)}_\ast], \quad b^{(j)}_\ast \in [0, 1] \quad (10) \]

To memorize a fuzzy standard pattern \((A_\ast, B_\ast)\), the feedforward fuzzy relation matrix \( W_\ast \) and feedback fuzzy relation matrix \( R_\ast \) are calculated by the following Eqs. (11) and (12). This is often called the training of fuzzy neural networks.
\[ w^{(ij)} = \min (a^{(i)}_\ast, b^{(j)}_\ast) \quad (11) \]
\[ r^{(ij)} = \min (b^{(i)}_\ast, a^{(j)}_\ast) \quad (12) \]

The association process of fuzzy neural networks is a bidirectional associative process. For example, it is supposed that there is an unknown fuzzy set \( A^0 \) to be input, according to Eq. (5), \( B^0 \) is obtained by the association:
\[ (A^0)^{\ast} \bullet W_\ast = B^0 \quad (13) \]

Then, by feedback, \( B^0 \) is used to associate \( A^1 \) applying Eq. (6).
\[ (B^0)^{\ast} \bullet R_\ast = A^1 \quad (14) \]

And then, \( A^1 \) is used to associate \( B^1 \) according to Eq. (5). And then \( B^1 \) is used to associate \( A^2 \) using Eq. (6).
\[ (A^1)^{\ast} \bullet W_\ast = B^1 \quad (15) \]
\[ (B^1)^{\ast} \bullet R_\ast = A^2 \quad (16) \]

This bi-directional association is continued until the \( A^\ast \) and \( B^\ast \) remain constant. Then the obtained \((A^\ast, B^\ast)\) are regarded as the best associative results of \((A_\ast, B_\ast)\). It can be proved that the associative process of fuzzy neural networks has global stability (10)-(12).

4. Experiments

4.1 Experimental apparatus

Fault sample data from practical running water pump sets are very difficult to obtain. To solve this difficulty, a rotor testing table is designed for experiments. The structure of this rotor testing table completely resembles that of the water pump set.

Figure 6 shows a picture of the full view of the rotor testing table. To make it clear, an explanatory graph is added. Figure 7 is the rotor testing table. An explanatory graph is added. The positions of the vibration sensors are the same as the positions on a water pump set.

4.2 Experiments

Fault sample data are obtained from experiments. Six experiments have been performed to produce six groups of fault sample data. These six faults are imitations of the fault patterns listed in Table 1. For example, in experiment 1, a bias mass is put on the flier of the rotor to produce an unbalanced rotor fault. 100 samples are taken and they are shown by the following normalized vectors.
\[ S_1 = [0.6, 0.6, 0.4, 0.8, 0.2, 0.2] \]
\[ S_2 = [0.4, 0.2, 0.2, 0.8, 0.4, 0.6] \]
\[ \ldots \ldots \]
\[ S_{100} = [0.8, 0.2, 0.6, 0.8, 0.2, 0.4] \]

These sample data are divided into two groups. One group of 50 samples is used to produce standard fault pattern and then train fuzzy neural networks. The other group of 50 samples is used to test the fault diagnosis system. The fuzzy symptom vector for fault pattern of an unbalanced rotor is calculated by Eq. (17).
A_i = \frac{1}{n} \sum_{j=1}^{n} S_i \quad (17)

Here, \( n \) is 50 and \( A_i = [0.2, 0.4, 0.6, 0.8, 0.6, 0.2] \) and with this condition, the fault degree for an unbalanced rotor fault is 0.8 and the fault degree of other faults is 0.2, so \( B_i = [0.8, 0.2, 0.2, 0.2, 0.2, 0.2] \). This way the standard fault pattern vector pair \((A_i, B_i)\) for an unbalanced rotor is obtained. From the experiments, 6 kinds of standard fault patterns are obtained. They are listed in Table 2.

4.3 Learning of fuzzy neural networks

The next step is to train a fuzzy neural network to memorize these fault patterns. As an example, fault pattern 1 in Table 2 is used to demonstrate the training process. According to Eqs.(11) and (12), the feedforward fuzzy relation matrix \( W_1 \) of Eq.(18) and the feedback fuzzy relation matrix \( R_1 \) of Eq.(19) are obtained:

\[
W_1 = \begin{bmatrix}
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.4 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.6 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.8 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.6 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.4 & 0.6 & 0.8 & 0.6 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
\end{bmatrix} \quad (18)
\]

\[
R_1 = \begin{bmatrix}
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.4 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.6 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.8 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.6 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.4 & 0.6 & 0.8 & 0.6 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
\end{bmatrix} \quad (19)
\]

Here the fuzzy matrix \( W_1 \) and the fuzzy matrix \( R_1 \) construct fuzzy neural networks to memorize the pattern pair \((A_i, B_i)\). In the same way, five other fuzzy neural networks are trained. The fault diagnosis system by fuzzy neural networks is therefore established.

4.4 Fault diagnosis with fuzzy neural networks

The effectiveness of the fault diagnosis system with fuzzy neural networks is examined by experiments. The example is shown to demonstrate the fault diagnosis process. Sample data \( S_i = [0.6, 0.6, 0.4, 0.8, 0.2, 0.2] \) is from fault pattern 1. This sample is used as input for fault diagnosis system by fuzzy neural networks. As shown in Fig. 4, from six fuzzy neural networks, six associated results and six subset values are obtained. They are listed as following.

\[
\begin{align*}
A^r_i &= [0.2, 0.4, 0.6, 0.8, 0.6, 0.2] \\
B^r_i &= [0.8, 0.2, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [1]} = 0.100000 \\
A^r_i &= [0.2, 0.4, 0.4, 0.6, 0.6, 0.4] \\
B^r_i &= [0.2, 0.6, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [2]} = 0.966667 \\
A^r_i &= [0.6, 0.6, 0.4, 0.2, 0.2, 0.2] \\
B^r_i &= [0.2, 0.2, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [3]} = 0.966667 \\
A^r_i &= [0.6, 0.4, 0.4, 0.2, 0.2, 0.2] \\
B^r_i &= [0.2, 0.2, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [4]} = 0.966667 \\
A^r_i &= [0.2, 0.8, 0.6, 0.8, 0.2, 0.2] \\
B^r_i &= [0.2, 0.2, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [5]} = 0.966667 \\
A^r_i &= [0.2, 0.2, 0.2, 0.2, 0.4, 0.4] \\
B^r_i &= [0.2, 0.2, 0.2, 0.2, 0.2, 0.2] \\
&\quad \text{Subset [6]} = 0.916667
\end{align*}
\]

The maximum subset value decides the fault pattern of the input sample. Therefore this sample belongs to fault pattern 1.

In this way, all the test samples are input into the fault diagnosis system. The fault patterns of the test sample data are actually known. If the diagnosis result is in accordance with the original fault pattern of the test sample, the diagnosis result is regarded as correct. Here, six groups of sample data, every group with 50 samples, are examined. The diagnosis results with fuzzy networks are shown as Table 3. From Table 3, it can be seen that the fault diagnosis system with fuzzy neural networks has high recognition rates.

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Sample number</th>
<th>Correct diagnosis</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>48</td>
<td>96%</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>49</td>
<td>98%</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>48</td>
<td>96%</td>
</tr>
<tr>
<td>4</td>
<td>50</td>
<td>49</td>
<td>98%</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>48</td>
<td>96%</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>50</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 3: Diagnosis results with fuzzy neural networks
5. Application to Fault Diagnosis of Water Pump Sets

The fault diagnosis with fuzzy neural networks is installed in the water pump sets of an oil plant, monitoring the working condition of the water pump sets. Two practical cases of water pump sets are examined. As a result, it was verified that fault diagnosis results are in accordance with practical faults.

Case 1: The fault diagnosis system indicates that the machine is in an abnormal working condition, the front bearings are over worn. The input vector from the sensors is

\[ A = [0.2, 0.6, 0.8, 0.6, 0.2, 0.2] \]

The associated vector of the fuzzy neural networks is:

\[ B = [0.2, 0.2, 0.2, 0.2, 0.6, 0.2] \]

The workers checked the front bearings of the pump, verifying that some of the rollers of the bearings are indeed over worn. The diameter of one roller was 0.4 mm smaller than the normal size.

Case 2: The fault diagnosis system indicates that the machine is in an abnormal working condition, the gearbox suffered abnormal vibration. The input vector from the sensors is

\[ A = [0.6, 0.2, 0.4, 0.2, 0.2, 0.2] \]

The associated vector of the fuzzy neural networks is:

\[ B = [0.2, 0.2, 0.2, 0.6, 0.2, 0.2] \]

The workers checked the gearbox, verifying that the high speed gear had a crack of 3 mm length.

6. Comparison with Other Methods of Fault Diagnosis

In order to show the advantage of fuzzy neural networks, a fault diagnosis system with distance function and with back propagation neural networks are examined by the same test data.

6.1 Comparison with diagnosis results with distance function

The structure of the fault diagnosis system with distance function is the same as that of the fault diagnosis system as shown in Fig. 4. The difference is that the fault diagnosis with distance function makes its diagnosis directly by calculating the distance between the sample data and standard fault patterns. The distance function is defined as Eq. (20):

\[
\text{distance } [k] = |A - A_k| / k = 1, 2, \ldots, n \tag{20}
\]

The standard pattern parameters are listed in Table 2. For an unknown input sample, distance [1], distance [2], \ldots, distance [n] are obtained. From the minimum of distances, the fault type of input sample is decided. However, if the distance is greater than 0.4, then associated result is not accepted and the input sample is regarded to be of normal condition. The diagnosis results by distance function are shown in Table 4. Table 4 shows that the recognition rate by distance function is much less than those of fuzzy neural networks.

6.2 Comparison with diagnosis result of BP neural networks

The structure of the fault diagnosis system with BP neural networks is the same as that of Fig. 4. The difference is that six parallel BP neural networks are used to memorize the six standard patterns. BP neural networks for the fault diagnosis consist of an input layer with 6 input cells, a hidden layer with 3 cells and an output layer with 1 cell, as shown in Fig. 8.

The learning input data are 50 sample data for each of the six fault pattern data and all output teacher signals are set as 1. When unknown samples are used as input from the fault diagnosis system, the six BP neural networks yield six output values. The maximum value decides the fault type of the unknown sample. If the output is less than 0.7, then this sample does not belong to this fault type. The diagnosis results using fuzzy networks are shown as Table 5. From Table 5, it can be seen that, although BP neural networks are capable to implement nonlinear mapping, the recognition rate is still lower than that of fuzzy neural networks.

Comparing with the results of Tables 3, 4 and 5, it can be seen that fuzzy neural networks have the highest accuracy among these three methods. This is because fuzzy neural networks can make use of infor-
Table 5 Diagnosis results with BP neural networks

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Sample number</th>
<th>Correct diagnosis</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>19</td>
<td>38%</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>28</td>
<td>56%</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>29</td>
<td>58%</td>
</tr>
<tr>
<td>4</td>
<td>50</td>
<td>28</td>
<td>56%</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>23</td>
<td>46%</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>45</td>
<td>90%</td>
</tr>
</tbody>
</table>

mation of both fault symptoms and fault types. Bi-directional association deduces fault patterns from fault symptoms and then verifies fault symptoms from the fault patterns. This two-way deduction is better than the one-way deduction from fault symptoms to fault patterns.

A standard fault pattern is in fact a fuzzy rule. Fault diagnosis by fuzzy neural networks is the deduction process according to the fuzzy rule. This process is similar to the thinking process of the human beings. When a symptom vector $A^0$ is input, fuzzy neural networks start to associate bi-directionally according to the fuzzy rule. The result of association is $(A^*, B^*)$. Compared with original $(A^0, B^0)$, this $(A^*, B^*)$ has been optimized according to the fuzzy rule. And then calculating the distance between $(A^*, B^*)$ and standard pattern is better than calculating distance between $(A^0, B^0)$ and standard pattern. This is the reason why the fuzzy neural networks can improve recognition rate. Bi-directional association acts as a filter and an amplifier, not just as linear mapping between fault symptom and fault.

Consider human judge process in fault diagnosis, usually first from symptoms the fault type is deduced, and then if it is of this fault type, the symptoms are once more to be checked to confirm the diagnosis. Often a repetition of deduction is needed to make the final fault diagnosis. The association process of fuzzy neural networks is similar.

7. Conclusion

In this research, the application of fuzzy neural networks is proposed to the fault diagnosis of rotary machines of the plants. The results are summarized as following:

1. The fuzzy neural network can memorize fault patterns and associate them. The advantage of fuzzy neural networks is that they make use of information from both the fault symptoms and the fault type. This bi-directional association deduces fault patterns from fault symptoms and then associates fault symptoms from fault patterns. Then, the results become much better than mere one-way deduction from fault symptoms to fault patterns.

2. The same data are used to examine fault diagnosis system with both distance function and back propagation neural networks. It was shown that the recognition rates of fuzzy neural networks are much better than that of the other two methods.

3. The fault diagnosis with fuzzy neural networks was installed in the water pump sets of an oil plant, monitoring the working condition of pump sets. Through practical cases of fault diagnosis, it was verified that the fault diagnosis systems are effective to make fault diagnosis.

Through this research, it can be concluded that fuzzy neural networks are very effective in making practical fault diagnosis.

References


