FAULT DIAGNOSIS IN ROTATING MACHINERY USING FUZZY MEASURES AND FUZZY INTEGRALS

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Abstract: In the fault diagnosis of rotating machinery using fuzzy measures and fuzzy integrals, the optimization of membership functions and identification of fuzzy measures are important for accurate diagnosis. Herein, a method for optimizing membership functions is proposed based on the statistical properties of vibration spectra and identifying fuzzy measures based on interaction levels using partial correlation coefficients between spectra. The possibility of a given fault is obtained from fuzzy integrals using membership degrees determined by the membership function, and the fuzzy measures for the set of spectra. The method is also evaluated using the example of diagnosis of misalignment and unbalance faults.

1 INTRODUCTION

Due to the widespread use of rotating machinery and the growing demand for reliability and cost efficiency, condition based maintenance (CBM) is being more widely used in many industries. CBM has proved effective in accurately diagnosing faulty machinery. Vibration based diagnosis is often used in CBM because it requires less expensive equipment, can diagnose a variety of faults, and vibration data may easily be obtained. However, the technique requires highly skilled engineers to make an accurate diagnosis.

Several diagnostic techniques have been proposed (Liu 2007) for automatic diagnosis or to aid diagnostic engineers. Some of the techniques use fuzzy measures and fuzzy integrals to encompass the existing knowledge of skilled engineers (Tsunoyama 2008). However, constructing a membership function and identifying fuzzy measures is difficult and time consuming.

A method for diagnosis of rotating machinery based on fuzzy measures and fuzzy integrals is proposed herein. In this method, first the membership function is optimized using the statistical properties of the vibration spectra. Then fuzzy measures are identified using the partial correlation coefficients of the spectra and importance factors identified by skilled engineers. The possibility of a fault existing in the machinery is determined by fuzzy integrals using the membership degrees of the vibration spectra and fuzzy measures.

2 VIBRATION SPECTRA AND MEMBERSHIP FUNCTION

2.1 Faults in Rotating Machinery and Associated Vibration Spectra

Several kinds of faults occur in rotating machinery including abnormal vibration and fluid leaks. As a large number of these faults are accompanied by vibration, the method proposed herein focuses on the diagnosis of such faults through analysis of the associated vibrations.

Vibration diagnosis uses membership degrees for spectra determined from the root-mean-square (RMS) values. However, the RMS values of spectra associated with a fault may vary depending on the position of the fault or the degree of damage. Herein, the normal probability distribution for the RMS values of spectra is based on the statistical properties.

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The parameters, μ and σ are average and standard deviation of the normal probability distribution, respectively.

2.2 Membership Function and its Optimization

Several types of membership functions exist such as triangular, exponential, and trapezoidal. Herein, the trapezoidal type is used.

In fault diagnosis, diagnosed results are classified into four cases, shown in Table 1.

Table 1: Diagnoses.

Case	Cause of fault	Diagnosed result
1	F_α	Not Fα
2		F_α
3	F_β	Fα
4		Not F_α

When F_α is diagnosed, Cases 2 and 4 are correct but Cases 1 and 3 are not. Moreover, Cases 1 and 2 are exclusive, and Cases 3 and 4 are also exclusive. Therefore, the membership function is optimized by maximizing the mean value of the membership degree for Case 2 and minimizing that for Case 3. Figure 1 shows the membership function and normal distribution for F_α for Case 2. In the figure, h(x) is the trapezoidal membership function and f(x) is the normal probability distribution for F_α. The optimum values of the parameters are obtained by solving Eq. (1). These equations are obtained by the integral of the normal distribution and the membership function.

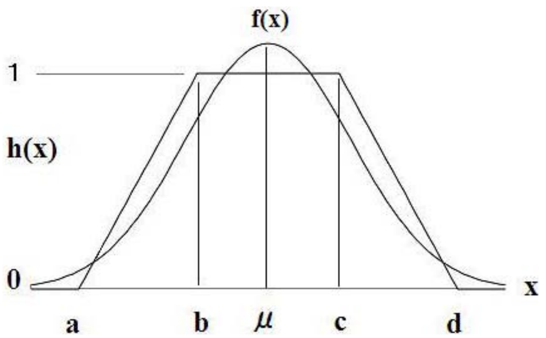

Figure 1: Membership function and probability distribution for Case 2.

$$\begin{aligned}
\int_a^d h(x)dF(x) &= \int_a^b h(x)dF(x) + \int_b^c h(x)dF(x) + \int_c^d h(x)dF(x) \\
&= \frac{(\mu-a)}{2(b-a)}\left(\sqrt{1-e^{-\frac{2(a-\mu)^2}{\pi\sigma^2}}} - \sqrt{1-e^{-\frac{2(b-\mu)^2}{\pi\sigma^2}}}\right) \\
&\quad + \frac{\sigma}{\sqrt{2}\pi(b-a)}\left(e^{-\frac{(a-\mu)^2}{2\sigma^2}} - e^{-\frac{(b-\mu)^2}{2\sigma^2}}\right) \\
&\quad + \frac{1}{2}\left(\sqrt{1-e^{-\frac{2(b-\mu)^2}{\pi\sigma^2}}} + \sqrt{1-e^{-\frac{2(c-\mu)^2}{\pi\sigma^2}}}\right) \\
&\quad + \frac{(d-\mu)}{2(d-c)}\left(\sqrt{1-e^{-\frac{2(d-\mu)^2}{\pi\sigma^2}}} - \sqrt{1-e^{-\frac{2(c-\mu)^2}{\pi\sigma^2}}}\right) \\
&\quad - \frac{\sigma}{\sqrt{2}\pi(d-c)}\left(e^{-\frac{(c-\mu)^2}{2\sigma^2}} - e^{-\frac{(d-\mu)^2}{2\sigma^2}}\right)
\end{aligned} \tag{1}$$

Subsequently, the mean value of the membership degree is minimized for Case 3. Figure 2 shows the membership function and the normal probability distribution for F_β for Case 3 when μ of the normal distribution for F_β is larger than the average of F_α.

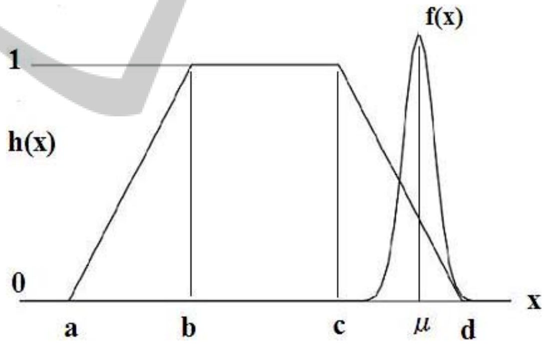

Figure 2: Membership function and probability distribution for Case 3.

The mean value of the membership degree is:

$$\begin{aligned}
&\int_c^\mu h(x)dF(x) + \int_\mu^d h(x)dF(x) \\
&= \frac{1}{d-c}\left\{\left(\sqrt{1-e^{-\frac{2(c-\mu)^2}{\pi}}} + \sqrt{1-e^{-\frac{2(d-\mu)^2}{\pi}}}\right)\frac{d-\mu}{2}\right. \\
&\quad \left. - \frac{\sigma}{\sqrt{2\pi}}\left(2 - e^{-\frac{(c-\mu)^2}{2\sigma^2}} - e^{-\frac{(d-\mu)^2}{2\sigma^2}}\right)\right\}
\end{aligned} \tag{2}$$

Conversely, when μ of F_β is less than the average of F_α, the mean value of the membership degree is:

$$\int_a^\mu h(x)dF(x)+\int_\mu^b h(x)dF(x)$$
$$=\frac{1}{b-a}\left\{\frac{\sigma}{\sqrt{2\pi}}\left(2-e^{-\frac{(a-\mu)^2}{2\sigma^2}}-e^{-\frac{(d-\mu)^2}{2\sigma^2}}\right)\right. \quad (3)$$
$$\left.+\frac{\mu-a}{2}\left(\sqrt{1-e^{-\frac{2(a-\mu)^2}{\pi}}}+\sqrt{1-e^{-\frac{2(b-\mu)^2}{\pi}}}\right)\right\}$$

3 FUZZY MEASURE AND FUZZY INTEGRAL

3.1 Fuzzy Measure for the Spectra and the Fuzzy Integral

A fuzzy measure g is a set function on X satisfying the following conditions:

$$g: 2^X \to [0,1], g(\phi)=0,$$
$$A \subset B \subset X \Rightarrow g(A) \le g(B) \quad (4)$$
$$X = \{s_1, s_2, \cdots s_n\},$$

The fuzzy measure can cope with the following three interactions between the sets A and B.

(1) No interaction between A and B.

(2) Positive synergy between A and B.

(3) Negative synergy between A and B.

Several fuzzy integrals have been proposed such as Sugeno's and Choquet integrals(Grabisch 2000). In this paper, the Choquet integral is used. The Choquet integral of a non-negative function h on $X = \{s_1, s_2, \cdots, s_n\}$ with respect to g is defined:

$$(C)\int_X h(s)dg = \sum_{i=1}^{n}[h(s_i)-h(s_{i-1})]\cdot g(A_i). \quad (5)$$
$$A_i = \{s_i, s_{i+1}, \cdots, s_n\}$$

In the definition, it may be assumed, without loss of generality, that $h(s_1) \le h(s_2) \le \cdots \le h(s_n)$.

3.2 Identification of the Fuzzy Measure

3.2.1 Fuzzy Measure based on Interaction Level

Several methods for fuzzy measure identification have been proposed (Wang 1992). However, they are difficult to apply fault diagnosis of rotating machinery, since several parameters must be assigned experimentally before identification. In this paper, the fuzzy measure based on interaction level(Taya 2006) is used and is defined:

$$g(A) = \omega_0 \cdot \alpha_A + \omega_p \cdot \beta_A + \omega_n \cdot \gamma_A$$
$$\omega_0 > 0,\ \omega_p \ge 0,\ \omega_n \ge 0 \quad (6)$$
$$\alpha_A = \sum_{i \in I_A} w_i,\ \beta_A \sum_{\substack{k_{ij} \ge 0 \\ \{i,j\} \le I_A \\ i \ne j}} k_{ij} \cdot \min\{w_i, w_j\}$$
$$\gamma_A = \sum_{\substack{k_{ij} < 0 \\ \{i,j\} \le I_A \\ i \ne j}} k_{ij} \cdot \min\{w_i, w_j\}$$
$$I_A = \{i \mid s_i \in A\}$$
$$W = \{w_1, w_2, \cdots, w_n\}$$
$$\sum_{i=1}^{n} w_i = 1$$

where: $\omega_0, \omega_p, \omega_n$ are the coefficients for interaction; $w_i (1 \le i \le n)$ are importance factors of the spectra, as identified by skilled engineers; coefficient $k_{i,j}$ is a partial correlation coefficient between s_i and s_j excluding the effects of other spectra (Sipley 2000).

3.2.2 Determining

$\omega_0, \omega_p, \omega_n$

Let $h(s_i)(1 \le i \le n)$ satisfy $h(s_1) \le \cdots \le h(s_i) \le \cdots \le h(s_n)$. Then the fuzzy measure must satisfy the conditions:

$$g(A_1) = 1$$
$$g(A_i) \ge g(A_{i+1}),\ 1 \le i \le n-1$$
$$\omega_o \ge \omega_p + \omega_n \quad (7)$$

where:

$$A_1 = X$$
$$A_i = \{s_i, \cdots, s_n\}.$$

We can obtain $\omega_0, \omega_p, \omega_n$ by maximizing Z in Eq. (8) under the conditions in Eq.(7) using linear programming such as the Simplex method.

$$Z = \omega_p + \omega_n \quad (8)$$

4 EXAMPLE DIAGNOSIS

In this example, we evaluate the proposed method by looking at the possibility of a Case 2 or Case 3 fault (Table 1). Here, fault F_α is misalignment and

F_β is imbalance. The spectra used for fault diagnosis of misalignment are 1N, 2N, and 3MN where 1N, 2N, and 3MN are the fundamental frequency, second harmonic, and third harmonic and over, respectively. The importance factors given by skilled engineers for the spectra are:

$$w_{1N} = 0.3, w_{2N} = 0.6, w_{3MN} = 0.1$$

The RMS values and membership degrees obtained from the optimized membership function are shown in Table 2.

Table 2: RMS value and membership degree for misalignment and unbalance.

		Misalign-ment	Unbalance
RMS value	1N	0.457	0.911
	2N	0.457	0.019
	3MN	0.037	0.013
Membership degree	1N	0.8	0.6
	2N	1.0	0.2
	3MN	0.7	0.3

The partial correlation coefficients of vibration spectra obtained from field data are:

$$k_{1N,2N} = 0.73, k_{2N,3MN} = 0.41, k_{1N,3MN} = 0.24$$

4.1 Fuzzy Measure

The conditions for a fuzzy measure for misalignment are:

$$g(A_1) = 1, g(A_2) = \omega_0 (w_{1N} + w_{2N}) + \omega_p k_{1N,2N} w_{1N}$$

$$g(A_3) = \omega_0 w_{1N}$$

$$g(A_1) > g(A_2) > g(A_3)$$

Maximizing Eq. (8) under the above conditions, we obtain:

$$\omega_0 = \omega_p = 0.78, \omega_n = 0.$$

The fuzzy measures are composed for the above value and the importance factors for the spectra. The fuzzy measures for misalignment are:

$$g(A_1) = 1,$$

$$g(A_2) = \omega_0 (w_{1N} + w_{2N}) + \omega_p k_{1N,2N} w_{1N} = 0.87$$

$$g(A_3) = \omega_0 w_{1N} = 0.23$$

The fuzzy measures for imbalance are:

$$g(A_1) = 1,$$

$$g(A_2^{'}) = \omega_0 (w_{1N} + w_{3MN}) + \omega_p k_{1N,3MN} w_{3MN} = 0.33$$

$$g(A_3^{'}) = \omega_0 w_{1N} = 0.24$$

4.2 Fuzzy Integral

The fuzzy integral for misalignment is obtained using the fuzzy measures and membership degree using the following equation:

$$(C)\int_X h(s)dg = \sum_{i=1}^{n} [h(s_i) - h(s_{i-1})] \cdot g(A_i)$$
$$= h(3MN) \times g(A_1) + (h(1N) - h(3MN)) \times g(A_2)$$
$$+ (h(2N) - h(1N)) \times g(A_3) = 0.88$$

The fuzzy integral for imbalance is obtained in the same manner:

$$(C)\int_X h(s)dg = \sum_{i=1}^{n} [h(s_i) - h(s_{i-1})] \cdot g(A_i)$$
$$= h(2N) \times g(A_1) + (h(3MN) - h(2N)) \times g(A_2^{'})$$
$$+ (h(1N) - h(3MN)) \times g(A_3^{'}) = 0.30$$

From the above fuzzy integrals, the possibility of misalignment (Case 2 in Table 1) was determined as 0.88 and the possibility of imbalance (Case3 in Table 1) was determined as 0.3.

5 CONCLUSIONS

Herein, a method for diagnosing faults in rotating machinery using fuzzy measures and fuzzy integrals is proposed. The membership function giving the membership degree of the spectra is optimized based on the statistical properties. The fuzzy measures are based on the interaction level using the importance factor of the spectra and partial correlation coefficients between spectra.

The results of the evaluation show that misalignment (correct result) is about three times more probable than imbalance (wrong result). In future work, the authors will apply this method to other fault diagnoses and evaluate the method using extensive field data.

REFERENCES

Liu, X., Ma, L. and Mathew, J., 2007. Rotating machinery fault diagnosis on fuzzy data fusion techniques, *2nd World Congress on Engineering Asset Management and the 4th International Conference on Condition Monitoring*, pp. 1309-1318, Harrogate England.

Tsunoyama, M., Jinno, H., Ogawa M. and Sato, T., 2008. An Application of Fuzzy Measure and Integral for Diagnosing Faults in Rotating Machines, *Tools and Applications with Artificial Intelligence*, pp. 121-133, Springer Berlin.

Taya, M. and Murofushi, T., 2006. Fuzzy measure identification for bootstrapped Choquet integral model in multicriteria decision making. *International Conference on Soft Computing and Intelligent Systems and International Symposium on advanced Intelligent Systems 2006*, pp.1402-1407, Tokyo, Japan.

Sipley, B., 2000. *Cause and correlation in Biology*. Cambridge University Press.

Grabisch, M., Murofushi, T. and Sugeno, M., 2000. *Fuzzy Measures and Integrals: Theory and Applications*, Springer.

Wang, Z. and Klir, G. J., 1992. *Fuzzy Measure Theory*, Plenum Press.