ベイジアンネットワークによる回転機械の状態診断法

Diagnosis method for Rotating Machinery Using Bayesian Network

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In order to effectively identify faults of a rotating mechanics, a new kind of symptom parameter-----Relative Ratio Symptom Parameter (RRSP) is proposed in this paper. Moreover, combined with Bayesian Network, the corresponding fault diagnosis system is built. In the paper, the vibration signals are monitored and measured and the relative ratio symptom parameter is calculated, of which the parameters whose identification index is bigger are chosen as the input of Bayesian Network, by observing and analyzing the output that is the probability of normal state and abnormal states, Bayesian Network in the mechanical fault diagnosis is proved to be effective by real data measured in each state of a rotating machine.

Key Words: Bayesian Network, Rotating machine, Symptom parameter, Fault diagnosis

1. INTRODUCTION

With the development of the intelligence and complexity in the rotating machinery, the monitoring and fault diagnosis for rotating machinery are becoming more and more important to prevent accidents and financial loss. Furthermore, when developing intelligent condition diagnosis system by computer, symptom parameters (SPs) are required to express the feature of vibration signals measured for distinguishing machine states. If we can find good symptom parameters which sensitively reflect the feature of the machine states, automatic diagnosis for machine faults is possible^[1]. However, in many cases of the condition diagnosis for rotating machinery, especially in an early stage of a fault, the effect of noise in the signal measured for the diagnosis is so strong that the symptom of the fault is not evident and there are a lot of ambiguous relationships between symptom parameters and failure types of plant machinery, so failure types of plant machinery cannot be easily identified^{[2][3][4]}.

In order to resolve these problems, this paper proposes a novel intelligent method of condition diagnosis for plant machinery by using Relative Ratio Symptom Parameters (RRSPs) and Bayesian Network. The RRSPs in low- frequency area are defined for reflecting the feature of vibration signals measured in each state. Moreover, Discrimination Index (DI) has also been defined to evaluate the applicability of

RRSPs. Practical example of fault diagnosis for diagnosing structural faults of rotating machinery, such as misalignment unbalance and loose states which are often accruing in a rotating machine are shown to verify that the proposed method is effective^[5].

2. SYMPTOM PARAMETER AND

DISCRIMINATION INDEX

In this paper ten new symptom parameters called "Relative Ratio Symptom Parameters (RRSPs)" in low- frequency area for diagnosing structural faults of rotating machinery, such as misalignment, loose and unbalance state, are defined and given as follows.

$$R_1 = \frac{A_{ad} / A_{rd}}{A_{an} / A_{rn}} \quad (1)$$

Here, A_{an} and A_{rn} are the vibration level in shaft direction and radial direction in normal state respectively, A_{ad} and A_{rd} are the vibration level of shaft direction and radial direction in abnormal state respectively. (Vibration level is standard deviation or root mean square value .etc.)

$$R_2 = \frac{P_d(f_r) / P_n(f_r)}{|N_d - N_n| / 100} \quad (2)$$

Here, $P_n(f_r)$ and $P_d(f_r)$ are the spectrum value at f_r in normal state and abnormal state

respectively, N_n and N_d are the rotation speed of the machine in normal state and abnormal state respectively.

$$R_3 = \frac{P_d(f_r) / \sum_{i=2}^{20} P_d(i \cdot f_r)}{P_n(f_r) / \sum_{i=2}^{20} P_n(i \cdot f_r)} \quad (3)$$

$$R_4 = \frac{P_d(2f_r)/P_d(f_r)}{P_n(2f_r)/P_n(f_r)} \quad (4)$$

$$R_5 = \frac{P_d(3f_r)/P_d(f_r)}{P_n(3f_r)/P_n(f_r)} \quad (5)$$

$$R_6 = \frac{\sum_{i=4}^{10} P_d(i \cdot f_r) / P_d(f_r)}{\sum_{i=4}^{10} P_n(i \cdot f_r) / P_n(f_r)} \quad (6)$$

Here, f_r is the rotating frequency. $P_n(i \cdot f_r)$ and $P_d(i \cdot f_r)$ are the high-order harmonic value at $i \cdot f_r$ in normal and abnormal state respectively.

$$R_7 = \frac{A_{vd} / A_{hd}}{A_{vn} / A_{hn}} \quad (7)$$

Here, A_{vn} and A_{hn} are the vibration level in vertical direction and horizontal direction in normal state respectively, A_{vd} and A_{hd} are the vibration level of vertical direction and horizontal direction in abnormal state respectively.

$$R_8 = \frac{\sum_{\substack{<1.5kHz \\ >0.6kHz}} P_d(f) / \sum_{<0.6kHz} P_d(f)}{\sum_{\substack{<1.5kHz \\ >0.6kHz}} P_n(f) / \sum_{<0.6kHz} P_n(f)} \quad (8)$$

$$R_9 = \beta_d - \beta_n \quad (9)$$

Here, β_n and β_d are the skewness in normal state and abnormal state respectively.

$$R_{10} = \frac{\sum_{\substack{f_i > 6f_r \\ i \neq i \cdot f_r}} P_d(f_i) / \sum_{i=1}^6 P_d(i \cdot f_r)}{\sum_{\substack{f_i > 6f_r \\ i \neq i \cdot f_r}} P_n(f_i) / \sum_{i=1}^6 P_n(i \cdot f_r)} \quad (10)$$

The Discrimination Index (DI) is defined to

evaluate the diagnosing sensitivity of RRSP. The quality of a symptom parameter (SP), which will be used to distinguish two states, such as normal and abnormal state, is evaluated by Discrimination Rate (DR) and Discrimination Index (DI) [1] [3]. Supposing that x_1 and x_2 are the SP values calculated from the signals measured in state 1 and state 2 respectively, and their average and standard are μ and σ . The DR and DI are calculated by

$$DR = 1 - \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{-DI} \exp\left(-\frac{\mu^2}{2}\right) d\mu \quad (11)$$

$$DI = \frac{|\mu_2 - \mu_1|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \text{ or } DI = \frac{|\bar{x}_2 - \bar{x}_1|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad (12)$$

3. BAYESIAN NETWORK

Bayesian Network (BN) is a kind of probability network used to describe the relationship between variables, and it is also acyclic graph with probability label which can visually show the distribution function of joint probability between corresponding variables. Bayesian Network structural model can be combined by the network nodes (discrete or continuous), sets of directed edges which connect the network nodes with special relationships and that conditional probability is used to describe the interaction between nodes.

Bayesian Network(BNC) can be described in detail and clearly as follows: Bayesian Network is combined by n nodes, expressed by $B(G, P)$, which is made of two parts:

(1) G is the structure of Bayesian Network, and it is also a directed acrylic graph showing the dependence and independence among the nodes. Every node in the graph is a random variable and the directed edges between nodes represent the relation of each other. Moreover, the nodes can be the abstract of any problems, such as diagnosis assumption, test value, monitoring phenomenon, etc. Bayesian Network regulates that every node X_i is independent with other nodes. That is, if $A(X_i)$ is sets of any nodes which is not filial generation of X_i , and $D(X_i)$ is the direct parent nodes, then $I(X_i, A(X_i) / \pi(X_i))$ means: $P(X_i / A(X_i), \pi(X_i)) = P(X_i / \pi(X_i))$

(2) P is a conditional probability table of every node, depicting the dependence between nodes and their parent nodes rationally which can be written as $P(X_i | D(X_i))$. The conditional probability of nodes without parent nodes is

called prior probability. Based on the nodes, directed edges and conditional probability, Bayesian Network can be used to describe the joint probability between nodes. We can obtain the joint distribution by applying the conditional dependence in chain rules:

$$P(U) = P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i / \pi(X_i))$$

Furthermore, the joint probability distribution of the variables in the following graph can arrive at:

$$P(X_1, X_2, \dots, X_6) = \prod_{i=1}^6 P(X_i / \pi(X_i))$$

$$= P(X_1)P(X_2 / X_1)P(X_3 / X_1)P(X_4 / X_2)P(X_5 / X_2, X_3)P(X_6 / X_5)$$

According to the above analysis, we know Bayesian Network is kind of decomposed expression of joint probability distribution that is Bayesian Network can simplify the joint probability of variables.

Figure1. General model of Bayesian Network for fault diagnosis

Figure2. Experimental equipment for fault diagnosis

4 . BAYESIAN NETWORK MODEL FOR ROTATING MACHINERY DIAGNOSIS

A. Rotating machine for fault diagnosis

The rotating machine for the diagnosis is shown in Fig.2. The subject of the diagnosis is to distinguish shaft misalignment, unbalance and loose state, which are called “structural faults on rotating machine” and are often occurring in rotating machinery. The accelerometer is used to measure vibration signals of the rotating machine. The sampling frequency of signal measurement is

5000Hz, and the sampling time is 20s. Raw vibration signals in the normal, misalignment, unbalance and loose states are shown in Figure.3, respectively.

Figure3.Original vibration signals of all states

B. Establishment and verification of Bayesian Network in the fault diagnosis

In this paper the five Bayesian Network models for the condition diagnosis based on Bayesian Network theory are constructed, and through the comparison of the diagnosis results, the most suitable model of Bayesian Network for the condition diagnosis is selected.

Figure 6-8 show the Bayesian Network model 1-3 for the condition diagnosis respectively, which consist of four layers. The first layer is normal state and abnormal state. The second layer is combinations of misalignment, unbalance and loose states. The third layer is misalignment, unbalance and loose states, and the last layer is ten Relative Ratio Symptom Parameters (RRSPs) calculated by formulae 1-10 and the signals shown in Figure 3, from which the possibility grades of each state can be obtained.

Table1-4 show the names and values of each layer node respectively.

Table1. The names and values of the first layer

State	Values of each state
Normal state (N)	0, 1 (0 : abnormal; 1 : normal)
Abnormal state (UN)	0, 1 (0 : normal; 1 : abnormal)

Figure 6. Bayesian Network Model

Figure 7. Bayesian Network Model 2

Figure 8. Bayesian Network Model 3

Figure 9. Bayesian Network Model 4

Table 6. The diagnosis results of model 1-4

	Model 1	Model 2	Model 3	Model 4
Probability of normal state	0.6634	0.6589	0.6754	0.6984
Probability of misalignment state	0.9982	0.9994	0.9999	0.9472
Probability of loose state	0.9990	0.9991	0.9983	0.9994
Probability of unbalance state	0.0229	0.2460	0.3332	0.2169

From the above table, we know the probability of normal state of model 1-4 is near 0.7. The probability of unbalance state is near 0.3, and probabilities of misalignment and loose state are near 1. The results in table 6 show that ten symptom parameters (RRSPs) shown in formulae (1)-(10) are suitable for effectively distinguishing normal state and tow faults (misalignment state and loose state). However, because the probability of unbalance state is not high, the symptom parameters inputted into the Bayesian Network should be analyzed and selected by DI shown in formula (12), in order to raise the diagnosis sensitivity of unbalance state. The model 4 is improved to model 5.

Table 7 lists the DI of each RRSP for normal state and abnormal state, and loose state, misalignment state and unbalance state calculated using formulae (1)-(10) and the signals shown in Figure 3.

Table 8 lists the RRSPs selected on the basis of the DIs. Since all of DIs are larger than 2.9, all of the detection rates (DR) are larger than 99%.

By the same verification method as used in model 1-4, the test data and the relationship between nodes were input in the learned Bayesian Network model 5, and the Bayesian Network correctly and quickly judged the states. The diagnosis results show that the probability of normal state, misalignment, loose and unbalance state are 0.9601, 0.9603, 0.9999, 0.5930 respectively. The accuracy is greatly improved.

Table 7 DI of RRSP for each state

RRSP	DI _(N-UN)	DI _(M-L)	DI _(M-U)	DI _(L-U)
R1	2.66	3.28	0.05	3.16
R2	5.00	5.01	0.36	5.01
R3	1.04	1.71	1.80	0.30
R4	0.05	1.22	0.46	1.50
R5	0.02	0.62	0.62	0.01
R6	0.10	1.18	1.29	0.30
R7	1.41	1.39	0.02	1.39
R8	0.61	2.15	1.05	2.91
R9	0.03	0.12	0.89	0.07
R10	2.70	3.16	3.81	0.69

Table 8.The RRSP for each state

State	Symptom parameter
Normal state	R ₁ ,R ₂ ,R ₁₀
Misalignment state	R ₁ ,R ₂ ,R ₁₀
Loose state	R ₁ ,R ₂ ,R ₈ ,R ₁₀
Unbalance state	R ₁ ,R ₂ ,R ₈ ,R ₁₀

Table 9.The relationship between nodes for model 5

N					
UN	*U	*L	*M		
U					
M					
L					
R1	*N	*UN	*M	U	*L
R2	*N	*UN	*M	U	*L
R3	N	UN	M	*U	L
R4	N	UN	M	U	L
R5	N	UN	M	U	L
R6	N	UN	M	U	L
R7	N	UN	M	U	L
R8	N	UN	M	U	L
R9	N	UN	M	U	L
R10	*N	*UN	*M	U	*L

5 CONCLUSIONS

In order to improve the efficiency of the condition diagnosis for plant rotating machinery and distinguishing fault types at an early stage,

this paper proposed a novel intelligent condition diagnosis method for rotating machinery using Relative Ratio Symptom Parameters (RRSPs) and Bayesian Network, by which the state of machinery can be automatically judged on the basis of the possibility grades of normal state and each abnormal state. The ten RRSPs in low-frequency area were defined, which can reflect the characteristics of time signal measured for the fault diagnosis of rotating machinery. The Discrimination Index (DI) was also used to evaluate the sensitivity of RRSPs for detecting and distinguishing faults. Moreover, in this paper five Bayesian Network models for the condition diagnosis are constructed, and through the practical example of diagnosis of rotating machinery for detecting and distinguishing structural faults states, such as misalignment unbalance and loose states which often occur in rotating machinery, the most suitable model of Bayesian Network for the condition diagnosis was decided.

REFERENCE

- [1] Peng Chen, Toshio Toyota and Zhengjia He, Automated Function Generation of Symptom Parameters and Application to Fault Diagnosis of Machinery under Variable Operating conditions; IEEE TRANSACTIONS ON SYSTEMS '01, No.6, p.775-781.
- [2] P. CHEN, T. TOYOTA, Fuzzy Diagnosis and Fuzzy Navigation for Plant Inspection and Diagnosis Robot, Proc. of FUZZ-IEEE/IFES'95, Vol.1, p.185-193.
- [3] H. Wang, P. Chen, Condition diagnosis of blower system using rough sets and a fuzzy neural network, WSEAS TRANSACTIONS ON BUSINESS AND ECONOMICS'08, Vol. 5, Issue 4, p. 58-63.
- [4] H. Matuyama, Diagnosis Algorithm, JOURNAL OF JSPE, Vol.75, 1991.No.3, p.35-37.
- [5] Jianghua Luo. The application of Bayesian Network in the mechanical fault diagnosis, Chongqing University [D],2006.
- [6] Songqing Peng, Yousheng Zhang. Research on the theory of Bayesian Network and Its implication in Image Analysis. Hefei industrial university[D],2005
- [7] Jianchuan Li, Huniao Qing,etc. Bayesian Network theory in the equipment fault device, CHINA MECHANICAL ENGINEERT, Vol.10,2003
- [8] Wilson Quansheng Wang, Rotary machinery health condition monitoring, fault diagnosis [D], Waterloo University,2002