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VIBEX: an expert system for vibration fault diagnosis of rotating machinery using decision tree and decision table

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Abstract

This paper proposes an expert system called VIBEX (VIBration EXpert) to aid plant operators in diagnosing the cause of abnormal vibration for rotating machinery. In order to automatize the diagnosis, a decision table based on the cause-symptom matrix is used as a probabilistic method for diagnosing abnormal vibration. Also a decision tree is used as the acquisition of structured knowledge in the form of concepts is introduced to build a knowledge base which is indispensable for vibration expert systems. The decision tree is a technique used for building knowledge-based systems by the inductive inference from examples and plays a role itself as a vibration diagnostic tool. The proposed system has been successfully implemented on Microsoft Windows environment and is written in Microsoft Visual Basic and Visual C++. To validate the system performance, the diagnostic system was tested with some examples using the two diagnostic methods.
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Keywords: Expert system; Diagnosis; Decision tree; Decision table; Rotating machinery; Vibration

1. Introduction

Rotating machinery is widely used in industry and is a critical machinery. Due to the high operating speed, large load and severe working conditions, when a fault occurs it needs to be identified for possible causes and conduct remedical action immediately. Condition monitoring has been used to detect an abnormality of the machine and use to detect incipient failures in rotating machinery and plays a significant role in preventing dangerous accidents from occurring and in improving economic efficiency. To detect an abnormal condition, vibration information is widely used, since vibration signals contain the dynamic characteristics of the machine condition and therefore early detection of incipient failure can be easily detected (Kanki, Yasuda & Umemura, 1993).

Diagnosis is a process of locating the exact cause(s) of a failure or a fault. Once a failure has been detected, the maintenance engineer is to identify the symptoms, analyze the symptomatic information, interpret the various error messages and indications and come up with the right diagnosis of the situation in terms of which components may have caused the fault and the reasons for the failure of the components. Since a machine has many components and is highly complex, diagnosis of a machine fault usually requires technical skill and experience. It also requires extensive understanding of the machine's structure and operation, and some general concepts of diagnosis. This requires an expert engineer to have a domain specific knowledge of maintenance and knows the 'ins-and-outs' of the system. In a normal situation, the expert is either too busy with some other tasks or a specific component expert is not available at all (Patel & Kamrani, 1996).

In order to better equip with a non-expert to carry out the diagnosis operations, it would be wise to present the cause-symptom relationship in a tabular form for quick comprehension and a coincise representation. However, advanced knowledge and experience of an expert are required to analyse the causes, since the vibration signals from the machine are the results from changes of various conditions and are very complex and complicated. Due to high performance and complexity of the system, an approach to define the relationship between the causes and the resulting

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symptoms is needed. For examples, decision table (DTA) (Baesens, Setiono, Mues & Vanthienen, 2003), decision tree (DT) (Kim & Koehler, 1995; Quinlan, 1993; Yang, Part, & Kim, 2000) and decision graph (Kohavi & Li, 1995; Oliveira & Sangiovanni-Vincentelli, 1996) are some of the practical and popular approaches to meet the objectives of clarity, conciseness, and comprehensibility. These techniques lend themselves to computerized analysis and evaluation and can be easily incorporated into the expert system (ES). Many researchers have tried to establish ways for using them in vibration diagnostics. Consequently, vibration diagnostics expert systems have recently been developed to represent knowledge of human experts in a structured manner (Gemmell, MacDonald & Stewart, 1998; Kuhnell, Mingfei & Anvar, 1991; Liu & Chen, 1995).

An ES consists of a knowledge base and a reasoning engine. Many methods have been proposed to date. The combination of probabilistic and statistic method is one of the most popular methods adopted in ES. This method consists of a modeling system which uses the expert's reasoning process, since knowledge and experience of the expert is the result obtained from many cases resulting in practical field.

This study presents an integrated diagnostic expert system VIBEX (VIBration EXpert) that can be applied to fault diagnosis of rotating machinery using vibration signal. The proposed system combines two techniques; a DTA which is constructed on known cases and a DT which is constructed to make classification modeled by the inductive acquiring process.

2. Expert system (ES)

The proposed VIBEX is a consultation program based on computer system which approaches certain problem area based on practical knowledge (Gemmell, MacDonald, & Stewart 1998). VIBEX is an expert system which supports various functions and the schematic of the system is shown in Fig. 1. The system consists of two programs, VIBEX-TBL and VIBEX-DT. VIBEX-TBL is used to query the diagnostic process using DTA with cause-result matrix which represents the causes of vibration and machine

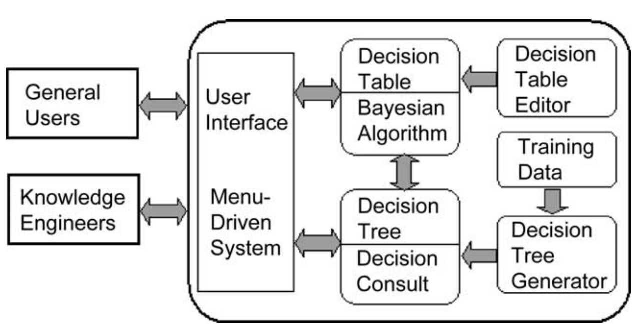


Fig. 1. Schematic of VIBEX.

conditions. Also, this system contains a DTA editor which is used to input, modify and delete the vibration information. Since VIBEX-TBL has 42 embeded abnormal causes of vibration and 31 vibration symptoms according to five vibration information groups, it can be directly applied to diagnosis a problem. VIBEX-DT is used to query the process using a DT which is constructed by training the data. In the VIBEX-DT, a DT generator can be used directly and easily to construct the DT to diagnose the rotating machinery with an intuitive and conversational method.

VIBEX-TBL has an advantage when use to diagnose complicated vibration causes because VIBEX-DT can grasp the causes of vibration and narrows the criteria. The combined systems complement each other. The system program runs on Windows platform and has a convenient user interface. Visual Basic and Visual C++ were used for developing the diagnostic system.

2.1. VIBEX-TBL

2.1.1. Construction of DTA

An expert builds an association (such as DTA) between the causes of fault and symptoms from an empirical knowledge gained either by direct experience with the system or through another expert in the field. This tabulation of causes-symptoms is usually expressed in the form of IF (symptom) and THEN (cause). A set of rules is then built to serve as a knowledge base of the expert system. Based on the embedded knowledge base, the diagnostic process is conducted using the information from Table 1. The users can select the information on a predominant frequency, direction and location of the predominant amplitude, and the amplitude response during starting up and shutdown from the symptom information as shown in Table 1. The Bayesian algorithm is then used to obtain the confidence factors *cf*. It can be used in conjunction with the decision tree system since it is possible to determine the probabilities of the causes of vibration rather than designating one or two causes.

2.1.2. Bayesian algorithm

Bayesian algorithm is adopted in the expert system. This algorithm is based on the probabilistic theory (Bley, 1996) which calculates the probability of an accident occurring based on the known information and cases.

When a vibration cause B_j occurs, there are n symptoms, A_i ($i=1,2,\ldots,n$), which can induce B_j. The probability that the vibration symptom A_k occurs relative to the cause B_j is given as follows.

$$P(A_k|B_j) = \frac{P(B_j \cap A_k)}{P(B_j)} = \frac{P(B_j \cap A_k)}{\sum_{i=1}^{n} P(B_j \cap A_i)} \tag{1}$$

where n is the number of symptoms about one item of a cause.

If the number of the symptoms is two, we combine the confidence factor using the Eq. (2). When $P(A_k|B_j)$

Table 1
Symptom information

Symptom domain	Descriptor
Predominant frequency	0–40% of running frequency
	40–50% of running frequency
	50–100% of running frequency
	1/2*X* of running frequency
	1/4*X* of running frequency
	Running frequency (1*X*)
	Twice running frequency (2*X*)
	Lower multiples
	Higher multiples
	Very high frequencies
	Odd multiples
Direction of vibration	Vertical
	Horizontal
	Axial
Location of vibration	Shaft
	Bearings
	Casing
	Foundation
	Piping
	Coupling
Amplitude response (start-up)	Amplitude remains constant
	Amplitude increases
	Amplitude decreases
	Amplitude fast maximum
	Amplitude increases suddenly
	Amplitude decreases suddenly
Amplitude response (shutdown)	Amplitude remains constant
	Amplitude increases
	Amplitude decreases
	Amplitude increases suddenly
	Amplitude decreases suddenly

corresponds to each item of the symptom, cf_1 and cf_2, the combined confidence factor $C(cf)$ is given as follows.

$$C(cf) = cf_1 + cf_2 - (cf_1 \times cf_2) \tag{2}$$

if we combine the n confidence factors and the final equation is given as follows.

$$C(cf) = C(cf) + cf_i - (C(cf) \times cf_i)\ (i = 1, 2, \ldots, n) \tag{3}$$

if $i=1$ then $C(cf)=cf_i$.

Repeating this process for the vibration cause B_j, we will get each confidence factor relative to the causes of vibration.

Table 2 shows part of the tabulation of causes-symptoms introduced by Sohre (1968) which considered only the initial unbalance and misalignment. The data in each category are percentages of possibilities based on experience. For example, with an initial unbalance there is a 90% probability that this will occur at the running frequency (1*X*) and 5% possibility it will appear at twice the running frequency (2*X*) and other higher multiples. If the 'pre-predominant frequency' is 1*X*, the confidence factor of the symptom, predominant frequency is 0.86 from Eq. (1). With this one can calculate the confidence factors of other symptoms. Therefore, we can calculate the confidence factor of 'initial unbalance' using Eq. (3). In the same way, the final confidence factor of each vibration cause is calculated. This process can be repeated for other causes of vibration, for example 'misalignment'.

2.2. VIBEX-DT

VIBEX-DT adopts the DT which is a typical algorithm used for construction of model of knowledge used by a human expert (Yang, Park & Kim, 2000). Among the data mining techniques, DT is one of the most frequently used methods for knowledge discovery. DT is used to discover rules and relationships by systematically breaking down and subdividing the information contained in data (Chen, Hsu & Chou, 2003). Some of the popular algorithms used for the classification tree are CART (Breiman, Friedman, Olshen & Stone, 1984), ID3 (Quinlan, 1986) and C4.5 (Quinlan, 1993). The latter algorithm (C4.5) is adopted in the present work.

2.2.1. Construction of DT

To generate the DT for machine diagnosis, it requires definition of classes which represents vibration causes; and attributes which represents the vibration phenomena required for sets of samples for machine learning. The cause-symptom matrix (Jackson, 1990) introduced by Sohre (1968) was regenerated inversely and the training data was used to generate the DT. At first, the DT generating routine was tested on Unix and then transported to PC platform using Visual C++ and connected to Visual Basic 5.0. In order to obtain reasonable results, the training data was

Table 2
Part of the decision table (Jackson, 1990)

Symptoms	Items of a symptoms	Vibration causes: Initial unbalance	Misalignment
Predominant frequency	0–0.48*X*	0.05	
	1*X*	0.90	0.40
	2*X*	0.05	0.50
	Higher multiples	0.05	0.10
	1/2*X*		
	1/4*X*		
	Lower multiples		
Direction and location of predominant amplitude	Vertical	0.40	0.20
	Horizontal	0.50	0.30
	Axial	0.10	0.50
	Shaft	0.90	0.80
	Bearing	0.10	0.10
	Casing		0.10
	Foundation		
	Piping		
	Coupling		
Amplitude response to speed variation	Stays same		0.20
	Increase	1.00	0.30
	Decrease		0.10
	Peaks		
	Comes suddenly		0.20
	Drops out suddenly		0.20

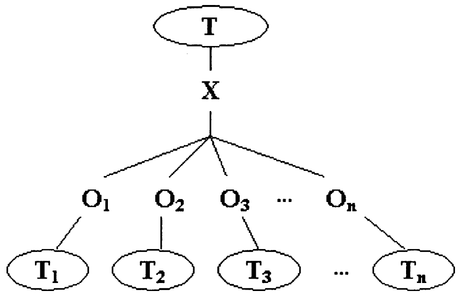


Fig. 2. Structure of a decision tree from training set *T*.

constructed using a trial-error method. When data required by the DT were not known, probabilistic results were used to obtain the process of unknown attributes. In the diagnostic phase, querying method based on Kuhnell et al. (1991) was adopted.

Since DT conducts supervised learning, a case represents a set which describes its characteristics. Therefore, the capacity of the decision tree depends on its ability to resolve a complex process of determination into a set of simple processes of determination. When generating the DT, a training set is divided into more detailed observation by following decision rules until one subset corresponds to a certain class. This is very similar to displaying a hard disk directory structure, which is shown in Fig. 2.

When T is a training set and if T is a null set or a set having only one class, the simplest DT is a tree having a leaf of that class. However, when X is a decision rule and having output O_1, O_2,…, O_n; each data of T include one of these outputs. Therefore X generates a subsets $\{T_1, T_2, \ldots T_n\}$ representing data having O_n. When each subset T_i replaces a DT relative to T_i in the above process, the result is the final of the entire DT.

2.2.2. Selection criterion of attribute

The structure of DT depends very much on how a test X is selected. Therefore the selection criterion of test X becomes highly significant. In the present work, one attribute is taken as the test and the values of attribute as output. We then use information entropy evaluation function based on the information theory (Quinlan, 1993) as the selection criteria. This entropy evaluation function is calculated in the following way.

Step 1: Calculate info(T) necessary to identify the class in the training set T.

$$\text{info}(T) = -\sum_{j=1}^{k} \left\{ \frac{\text{freq}(C_j, T)}{|T|} \times \log_2 \left(\frac{\text{freq}(C_j, T)}{|T|} \right) \right\} \tag{4}$$

where $|T|$ is the number of cases in the training set. C_j is a class, k is the number of classes and freq(C_j, T) is the number of cases included in T.

Step 2: Calculate the expected information value, $\text{info}_X(T)$ for test X to divide into T.

Table 3
Class of the decision tree

No.	Class (cause of vibration)
1	Mechanical unbalance
2	Misalignment
3	Partial rub
4	Crack
5	Mechanical looseness
6	Ball bearing damage
7	Foundation distortion
8	Critical speed (1*X* resonance)
9	Subharmonic resonance
10	Oil whip/oil whirl
11	Vane passage vibration
12	Clearance induced vibration
13	Static eccentricity of airgap or stator damage
14	Dynamic eccentricity of airgap or rotor damage

$$\text{info}_X(T) = \sum_{i=1}^{n} \left\{ \frac{|T_i|}{|T|} \times \text{info}(T_i) \right\} \tag{5}$$

where n is the number of outputs for test X and T_i is a subset of T corresponding to output i.

Step 3: Calculate the mutual information value acquired from division according to test X.

$$\text{gain}(X) = \text{info}(T) - \text{info}_X(T) \tag{6}$$

Step 4: Calculate the dividing information value split info(X) acquiring for T and divide into n subsets.

$$\text{split info}(X) = -\sum_{i=1}^{n} \left\{ \frac{|T_i|}{|T|} \times \log_2 \left(\frac{|T_i|}{|T|} \right) \right\} \tag{7}$$

Step 5: Calculate the ratio of gain(X) over split info(X).

$$\text{GR}(X) = \text{gain}(X)/\text{split info}(X) \tag{8}$$

Table 4
Attribute of the decision tree

No.	Attribute
1	What is the predominant frequency?
2	Is there a natural frequency?
3	Is the 0.4–0.48*X* component predominant?
4	Is the 0.5–1*X* component predominant?
5	Is the bearing damage frequency predominant?
6	Is the vane passage frequency predominant?
7	Is the subharmonic predominent?
8	Is there harmonics of 1/2*X* component?
9	Is there intense noise at the high frequency area?
10	Is there a line frequency?
11	Is the two times frequency as large as the line frequency?
12	Is there a pulsation component, $2sf_o$?
13	Do phase and amplitude of 1*X* component change?
14	Do phase and amplitude of 2*X* component change?
15	Does runout vector change?
16	Is the axial amplitude larger than lateral amplitude?
17	Is the orbit shape leaning to one side or has eight figure shapes?
18	What is the direction of orbit?
19	How is amplitude change during shutdown?
20	What is the predominant location of vibration?

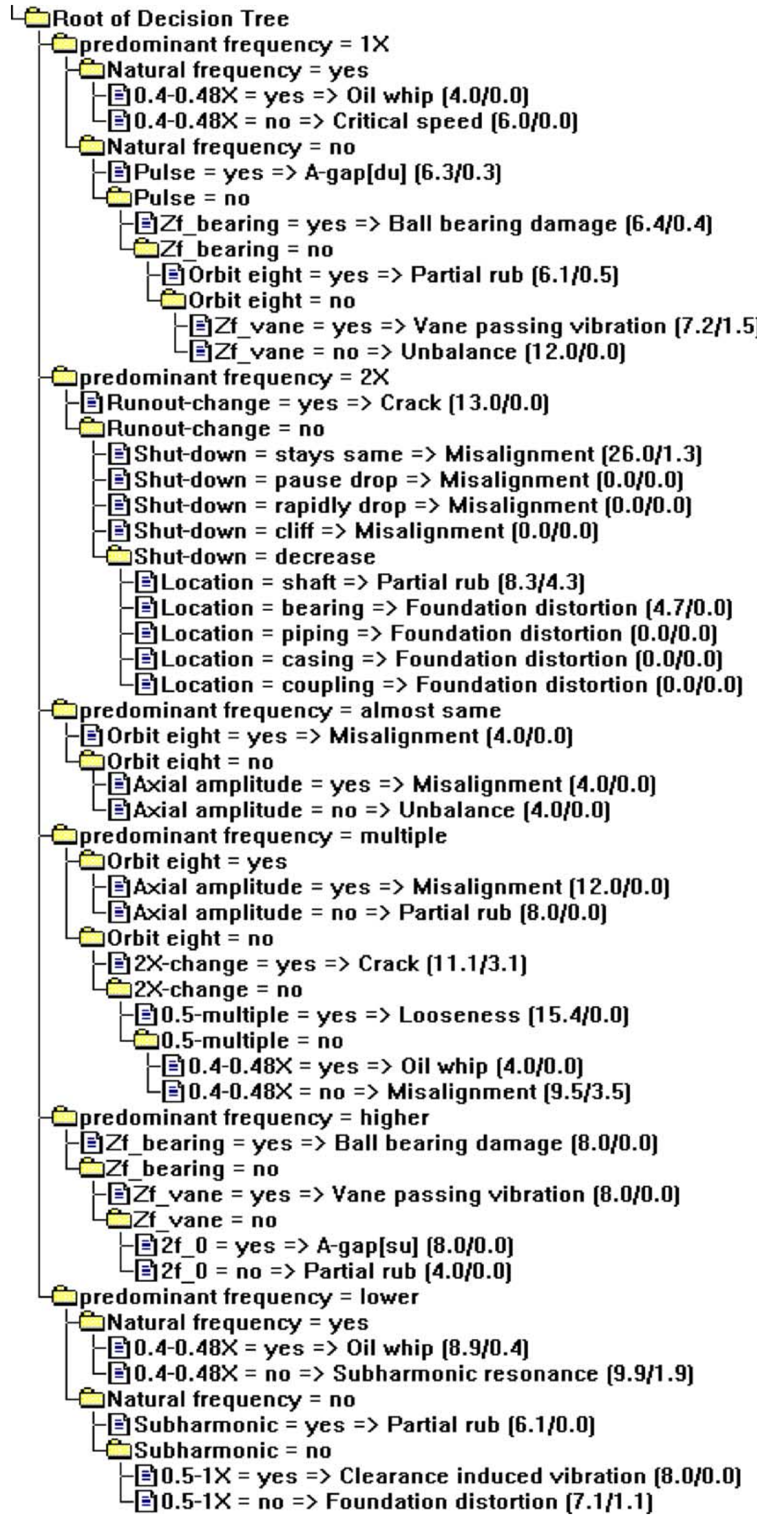


Fig. 3. An example of final decision tree.

The GR(X) compensates for the weak point of gain(X) which represents the quantity of information provided by X in the training set. Therefore, an attribute with the highest GR(X) is taken as the root of the DT.

2.2.3. Evaluating unknown attribute

An attribute of an unknown attribute value incurs shortage of usable information, since cases with such attribute do not provide any useful information.

Hence a generalized gain ratio must be calculated taking into account the shortage of information.

If F is the ratio of cases with known attribute values relative to the entire cases for attribute A, the generalized gain(X) and the split info(X) are calculated according to Eqs. (9) and (10), respectively.

$$\text{gain}(X) = F \times \{\text{info}(T_{\text{known}}) - \text{info}_x(T_{\text{known}})\} \tag{9}$$

$$\text{split info}(X) = -\sum_{i=1}^{n+1} \left\{ \frac{|T_i|}{|T|} \times \log_2\left(\frac{|T_i|}{|T|}\right) \right\} \tag{10}$$

where T_{known} is a set of cases with known outputs.

Therefore, the generalized gain ratio GR(X) is calculated as follows.

$$\text{GR}(X) = \text{gain}(X)/\text{split info}(X) \tag{11}$$

2.2.4. Definition of classes and attributes

In VIBEX-DT, 14 classes (vibration causes) and 20 attributes (vibration phenomena) were used. The classes and attributes used in this paper are shown in Tables 3 and 4, respectively. If more classes and attributes are required, these can be easily extended by updating the training set.

2.2.5. Final decision tree

Fig. 3 shows part of the final decision tree generated by DT. In this figure, a folder icon implies a tree (or subtree), while a note icon implies a leaf (vibration cause).

2.2.6. Querying algorithm about unknown data

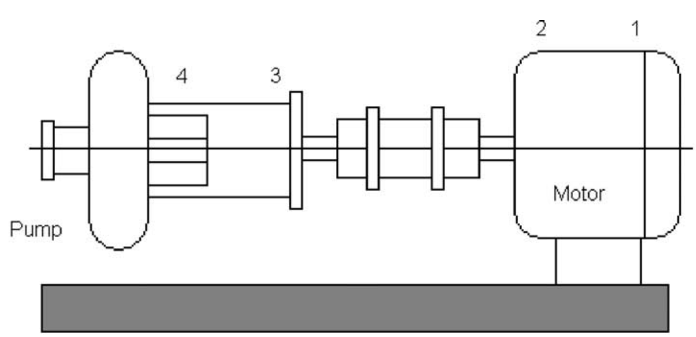
In Fig. 3, 'multiple' is selected from predominant frequency menu. The system requires the shape of orbit whether is 'orbit eight' or not. In this work we assume that this information cannot be acquired. Then, VIBEX-DT needs to know the condition of 'axial amplitude'. In this way, all possible causes are registered by the internal function 'register', whereas ambiguous ones depend on user's selection. All processes are conducted by the 'consult' function in this system. The numerical values within the bracket of each leaf are; the left value represents the number of cases (Info1_i) included in the entire training data, while the second one is the number of cases (Info2_i) which is not included in the data. If the number of possible causes is n, then the probability of each item, $p(\text{Info}_i)$ is given by Eq. (12).

$$p(\text{Info}_i) = \frac{\text{Info1}_i - \text{Info2}_i}{\sum_{k=1}^{n}(\text{Info1}_k - \text{Info2}_k)} \tag{12}$$

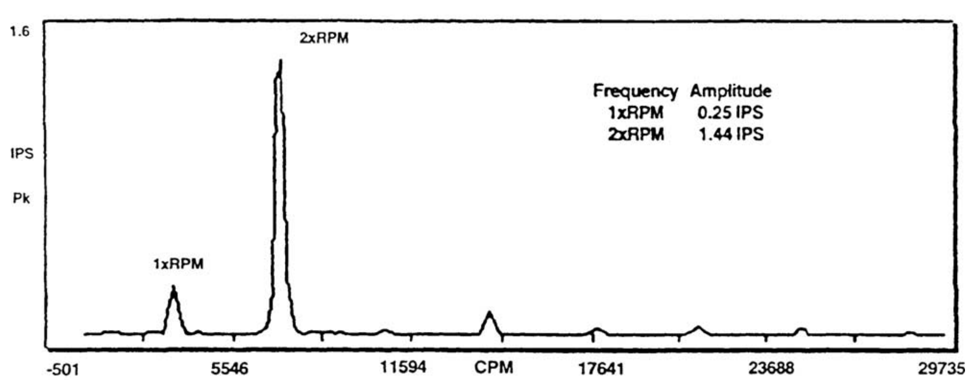
The above value is displayed in a descending order.

3. Example

Fig. 4 shows a case history of high vibration amplitude of a centrifugal pump due to misalignment. The pump runs at 3600 rpm. In Table 5 shows the overall vibration amplitudes for each location and direction of measurement.



(a) Measuring points



(b) Vibration spectrum at the location 3H

Fig. 4. Vibration spectrum of misalignment vibration signal.

Table 5
Overall vibration level

Location	Direction	Velocity (mm/s)
1	Vertical	2.210
1	Horizontal	3.175
2	Vertical	3.429
2	Horizontal	3.912
2	Axial	3.175
3	Vertical	27.203
3	Horizontal	40.665
4	Vertical	19.355
4	Horizontal	15.443

The vibration amplitude is highest at the horizontal direction of inner bearing (position 3) with 40.665 mm/s. The predominant frequency component is 120 Hz, i.e. 2× revolution vibration, as shown in Fig. 4(b). In this case, from the measured information, the direction, location and predominant frequency and amplitude were acquired to diagnose the pump vibration (Yang, 1998).

3.1. Application of VIBEX-TBL

In this example the predominant frequency is twice the running speed and the amplitude was measured in the horizontal direction at the axial bearing.

In VIBEX-TBL, the predominant frequency was first selected. Next, two times the normal running frequency (2*X*) was selected. This was followed by selecting the 'horizontal' from the second menu 'direction of vibration'. Finally 'bearing' was selected from the 'location of vibration' menu. If the inputting process is over, the user then select 'show result' from the main menu. The final result, associated with the confidence factor, was displayed on the screen, as shown in Fig. 5. The figure shows five causes with 42 total causes are recommended as candidate for causes of vibration.

3.2. Application of VIBEX-DT

In VIBEX-DT, assuming that the predominant frequency equals to two times the rotating speed is selected, then

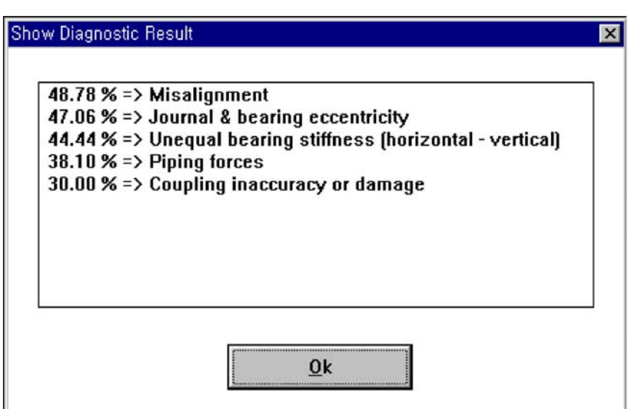


Fig. 5. Diagnostics result of VIBEX-TBL.

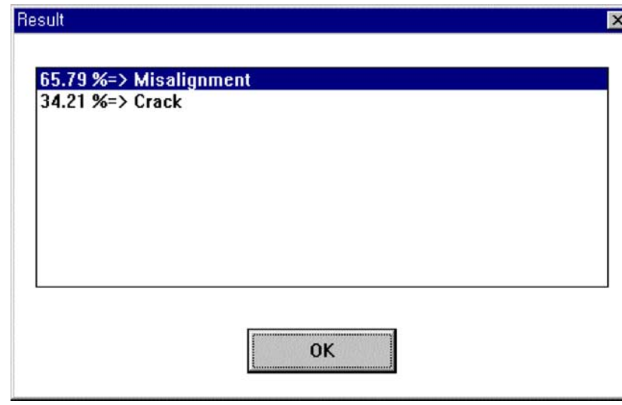


Fig. 6. Diagnostics result of VIBEX-DT.

'runout-change' is displayed. However, that information is not available and therefore need to select 'please select this, if you have insufficient data'. In the following 'shut-down' menu, since the information is not available, the same as in the runout-change menu is done. Finally, we select 'bearing' from the 'location of vibration' menu. The diagnostic result then is displayed on the screen as shown in Fig. 6. We can then decide the cause of vibration is due misalignment.

4. Conclusions

This paper describes the development a vibration diagnostics expert system, VIBEX, which enables operators of rotating machinery to solve vibration problems, when they cannot access the expert's knowledge. The expert system is used to provide information possible to replace the expert's advice. Since VIBEX embeds the cause-result matrix containing 1800 confidence factors, it is suitable to monitor and diagnose the rotating machinery. Furthermore this system can be applied to other rotating machinery such as turbo-machinery. Comparing VIBEX-TBL and VIBEX-DT, the two systems well performed in machine diagnostics and are robust even for cases when information are not available. VIBEX-DT diagnoses more efficiently than VIBEX-TBL. VIBEX-DT deals with 14 vibration causes and the probability are higher then other causes. The system will be upgraded and developed with higher efficiency and accuracy and specialized knowledge base in the system for specific machines.

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