Development of a System for Diagnosing Faults in Rotating Machinery using Vibration Signals

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It is widely recognized that increasing the accuracy and diversity of rotating machinery necessitates an appropriate diagnostic technique and maintenance system. Until now, operators have monitored machinery using their senses or by analyzing simple changes to root mean square output values. We developed an expert diagnostic system that uses fuzzy inference to expertly assess the condition of a machine and allow operators to make accurate judgments. This paper describes the hardware and software of the expert diagnostic system. An assessment of the diagnostic performance for five fault phenomena typically found in pumps is also described.

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1. Introduction

Many general plants such as power plants contain pressurized vessels, piping equipment, and moving facilities. The major component of a moving facility is its rotating machinery, which moves or compresses fluid using a motor. Rotating machinery can consist of a pump, compressor, engine, turbine, generator, gear set, and other components, and is unstable and vulnerable to breakdowns due to the high pressures and speeds at which the components operate. Breakdowns of rotating machinery occur often and are generally associated with major economic losses. Increases in the speed and precision at which rotating machinery operates, brought about by continued industrial development, have accentuated these losses.

There are several methods that can be used to perceive abnormal conditions in rotating machinery.[1,2] These include visual inspections, vibration monitoring, tribology-based monitoring, process parameter monitoring, nondestructive testing techniques, and ultrasonic monitoring. Vibration monitoring has been shown to be the most sensitive and reliable testing method.

Predictive maintenance is necessary to avoid costly machinery breakdowns. This consists of vibration root cause and signal analyses, and provides periodic reliability and stability inspections without the over-maintenance associated with general inspections.[3] Rotary machinery, in particular, requires predictive maintenance due to the cumulative damage that moving parts sustain over their lifetime.

An accurate diagnosis of vibrations in rotating machinery must consist of data measurement, acquisition, and analysis, followed by a judgment. Previous research has focused on diagnostic algorithms that use signal processing techniques, neural networks, and fuzzy inference to assess measured vibrations and noise signals.[4,5]

However, additional hardware and sensors for measuring vibration signals must be developed in addition to these diagnostic algorithms. An expert-level diagnostic system integrates principal software and hardware suitable for diagnosing vibration signals in rotating machinery with artificial intelligence-based signal processing and determination techniques.

This study proposes an expert-level diagnostic system for early measurement and predictive maintenance of abnormal vibration phenomena in rotating machinery. The proposed diagnostic system was tested on a pump, which is a common fixture in industry. Abnormal fault phenomena were detected, the measuring point was determined, and a measurement system was constructed to analyze the vibration signals from the test pump. The diagnostic system was constructed by developing a hardware interface, data monitoring, signal processing, and user interface modules. The diagnostic performance of the complete system was the evaluated through simulations.

2. Facility Expert Diagnostic System

2.1 Facility diagnosis of rotating machinery

Rotating machinery generally consists of a shaft, couplings, and bearings. The diagnosis of faulty behavior in rotating machinery has been well researched, primarily by assessing the vibration and noise signals of the machinery. Abnormal phenomena that cause assessable vibration and noise signals can be classified into the following five categories.

2.1.1 Unbalanced shaft

An unbalanced shaft is the most vexing abnormal phenomenon. This occurs when the center of mass and the geometric center of the shaft are not coincident. When the shaft is in an unbalanced state, it vibrates with an amplitude that increases rapidly with increasing rotating frequency.

2.1.2 Misalignment

Misalignment is a common abnormal phenomenon of rotating machinery. Misalignment generally occurs when two coupled shafts are not aligned, and the phenomenon results in the machinery vibrating at twice its operating frequency. The vibration caused by misalignment has a high axial component rather than a radial component.

2.1.3 Oil whip

Oil whip occurs when a shaft wears or slips due to an oil edge phenomenon that occurs in the journal bearing. When machinery operates at low frequencies that are less than twice the fractional frequency of the system, an oil whip may cause a dramatic increase in the amplitude of the vibration.

2.1.4 Bearing fault

As principal construction elements, bearings support shafts and maintain their smooth rotation. The mechanical failure of a bearing, such as that caused by the cracking of a ball or race, has a negative impact on the rotating machinery. Therefore, bearings with abnormal attributes, such as wear, need to be replaced. Bearing failures result in a specific, abnormal frequency in the shaft rotation that leads to an unbalancing of the shaft, resulting in the formation of a side band. A side band is a region of wear on the shaft that occurs because a pair of defective frequencies is centered about the running frequency. Most bearing faults are accompanied by some shock and abnormal noise.

2.1.5 Mechanical looseness

Mechanical looseness occurs when nonrotating connections, such as bearing caps, bearing mounts, or base mounts, are out of order. The phenomenon also occurs when an unbalanced or misaligned shaft is neglected. Mechanical looseness is likely to cause a vibration problem because the bearings and mounts are the devices that constrain the shaft to its rotational centerline. When the connective force of the connection parts becomes weak, a shock vibration may occur at a high-order harmonic frequency that, if maintained, can result in resonance.

2.2 Fuzzy inference method

Fuzzy inference is a method that is used to consider uncertainty. It quantifies the subjective assessment made by a human into a real value between 0 and 1.[6,7] The fuzzy inference method can be particularly effective when the weighting values used in an assessment are subject to variation or when the exact information on the conditional probability distribution of a subject is not available.[8]

Facility diagnosis can be problematic due to the obscurity of the data or diagnostic information obtained from a mechanism experiencing an abnormal condition. In this study, the diagnostic readability of obscure data is enhanced by the fuzzy inference method. The vibration signal is processed and the diagnostic index is extracted using a signal processing technique. Subsequently, fuzzy inference is used as the judgment method for assessing the diagnostic index.

In fuzzy inference, the general form of a rule is "IF A and B THEN C", where A, B, and C are linguistic variables. In the diagnostic method, the correlation matrix for inputs A and B and output U is obtained through the maximum–minimum synthetic law using the membership function of each linguistic variable, as shown in Equation (1):

$$\mu_R(x_1, x_2, u) = max[min\{\mu_A(x_1), \mu_B(x_2), \mu_U(u)\}] \tag{1}$$

Defuzzification is required to determine the weighting value of the operative variation from the output membership function. The mass center method is used:

$$u^* = \frac{\sum_{i=1}^{M}[\mu_U(u)\cdot u]}{\sum_{i=1}^{M}\mu_U(u)} \tag{2}$$

where $u^{\ddagger}$ represents the defuzzification value.

3. Development of the Expert Diagnostic System

3.1 Construction

A schematic diagram of the expert diagnostic system developed in this study is shown in Fig. 1. The expert diagnostic system can be divided into hardware and software. The hardware consisted of input signal components, which changed the physical signal into an electrical signal; an A/D converter, which changed the electrical signal to numerical data; and the memory, which temporarily stored the numerical data. The hardware is currently constructed with one channel, but its fundamental structure can be adapted for use with multiple channels in the future. Because the physical signal used by the diagnostic algorithm is a vibration signal, a suitable accelerometer and amplifier were selected by investigating the frequency tendency. An A/D converter with 16 channels was selected to accommodate multiple input channels for future use. The number of channels can be modified according to the measurement system being used. The software consisted of a hardware control component; a signal processing component, which extracted the desired information from the measured signals; and a signal decision component, which judged, stored, and managed the processed signal.

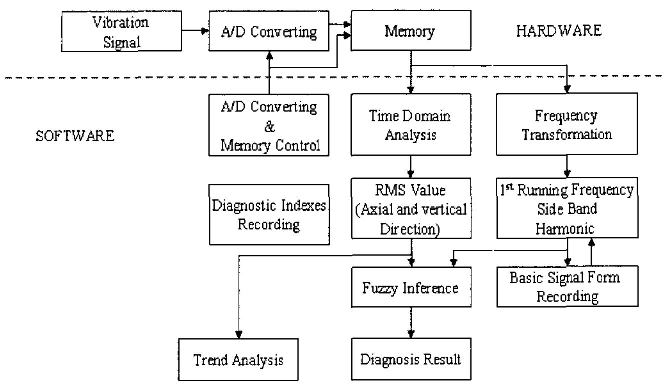


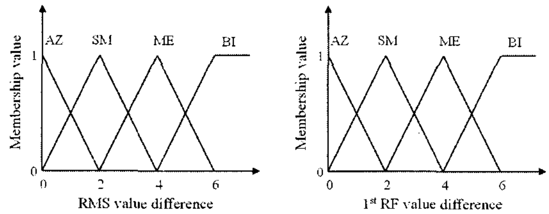
Fig. 1 Schematic diagram of the developed system

Recorded vibration data were transformed to RMS values within the time domain, and to multiple diagnostic indices within the frequency domain. Using fuzzy inference, the transformed data were printed as the diagnostic results of the present facility. A RMS variance trend was also generated.

A Windows-based laptop computer was used for the data analysis. The software was constructed using the LabWindows/CVI building program by National Instruments.

3.2 Diagnostic algorithm

The measured vibration data were transformed into useful information by extracting diagnostic indices using a signal processing technique. Several fundamental diagnostic indices were selected, including the RMS values of the vibration signal, which were established with a conventional diagnostic method, and the amplitude of the first running frequency. The fundamental indices also included assistance indices, such as a side band, a high-order harmonic frequency, and the vibration level in the axial direction. The membership function that constituted the difference between the normally distributed vibration RMS value and the measured RMS value is shown in Fig. 2(a). Membership functions use fundamental information for fuzzy inference and are modeled after the sensitive standard of judgment of a human expert. Such modeling is achieved by graphing the RMS value differences on an x-axis and noting the triangular region of values that apply in a conventional diagnosis. In addition, four linguistic variables (approximately zero or AZ, small or SM, medium or ME, and big or BI) were plotted on the y-axis as normalized values between 0 and 1. Fig. 2(b) shows a similar membership function plotted about the amplitude difference of the measured first running frequency of the rotating machinery. The region of the x-axis or the linguistic variable was equal to a functional expression of the RMS difference.[9]



(a) Membership function of RMS value difference

(b) Membership function of 1st RF value difference

Fig. 2 Membership function of the diagnostic index

Fig. 3 shows the membership function about the diagnostic results of each output. The values on the x- and y-axes have been normalized to values between 0 and 1. The linguistic variables are normal (NO), caution (CA), fault (FA), and alarm (AL).

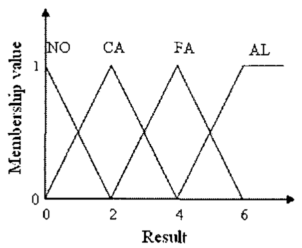


Fig. 3 Membership function of the output

A variety of rules were required to draw inference from the membership function constructed about the fundamental diagnostic indices. For this, a judgment table of RMS values and first running frequency amplitudes was constructed, as shown in Table 1. Sixteen rules for diagnosing rotating machinery were extracted from the table.

IF RMS is AZ and 1st RF is AZ THEN output is NO

IF RMS is AZ and 1st RF is SM THEN output is CA

⋮

IF RMS is BI and 1st RF is BI THEN output is AL

Table 2 was constructed from RMS difference values and the number of indices detected by the assistance diagnostic index. A total of 16 rules were extracted, similar to Table 1. The results inferred by each judgment table were integrated.

Table 1 Judgment table for the RMS and first RF differences

1st RF / RMS	AZ	SM	ME	BI
AZ	NO	CA	FA	AL
SM	CA	CA	FA	AL
ME	FA	FA	AL	AL
BI	AL	AL	AL	AL

Table 2 Judgment table for RMS difference and the number of indices

Index / RMS	0	1	2	3
AZ	NO	NO	CA	FA
SM	CA	CA	FA	AL
ME	FA	FA	AL	AL
BI	AL	AL	AL	AL

3.3 Construction of the hardware and software

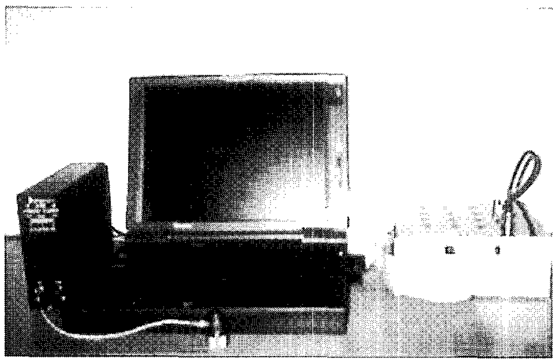


Fig. 4 Hardware of the expert diagnostic system

The hardware of the expert diagnostic system was developed as shown in Fig. 4. A voltage vibration accelerometer with a power source and an amplifier was used as the fundamental sensor for the prototype of the diagnostic system. The sensor worked as follows. An amplified vibration signal passed through the connector block and was inputted into the A/D converter. To use a microphone, which is the fastest form of sensor, the A/D converter must be able to measure more than two channels of audio frequency at 20 kHz, and when measuring vibration, must be able to measure more than three channels at 1 kHz. Therefore, we used a PCMCIA A/D converter, which is suitable for use with a laptop computer and capable of processing 16 input channels at 250 kHz. The driver file, which controls the A/D converter, used a double buffer to avoid interfering with the data collection while performing other diagnostic tasks on the computer. The diagnostic software processed the data acquired from the accelerometer using a signal processing method and outputted the diagnostic results using the fuzzy inference method.

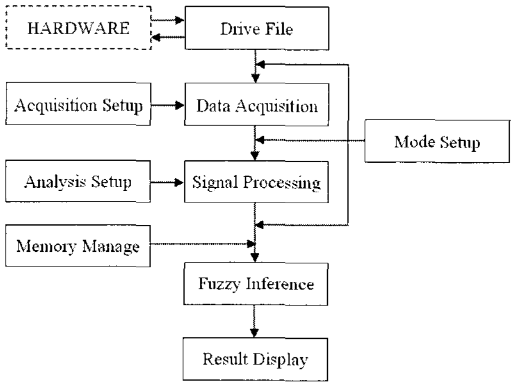


Fig. 5 Schematic diagram of the expert diagnostic system software

The diagnostic system software was developed by modulating each program. Therefore, it was straightforward to delete unnecessary processes and upgrade or add new functions. Additionally, the use of the fuzzy inference method improved the reliability of the outputted diagnostic results. The modulation of each program made the system management easier for field workers without expertise in the vibration field while still providing users with expert vibration analysis results. Figs. 6–7 outline and highlight the features of the diagnostic system.

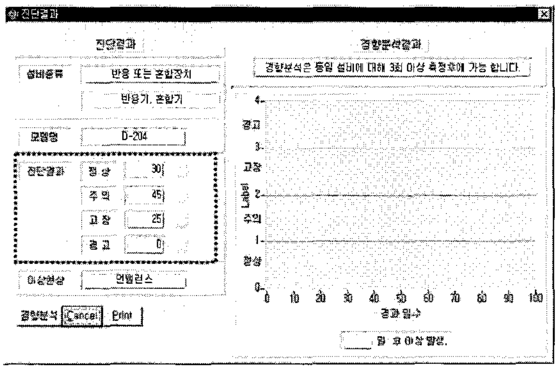


Fig. 6 Diagnostic results panel

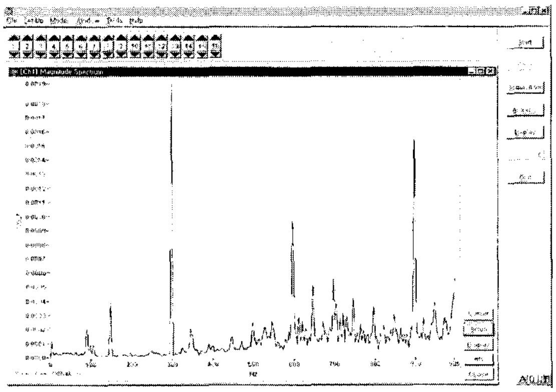


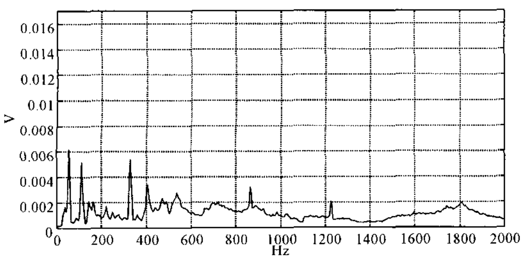
Fig. 7 Monitoring panel

4. Diagnostic Simulation

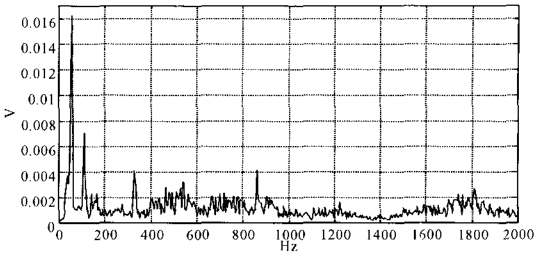
The vibration signal from the test pump was measured and assumed to be steady to verify the reliability of the diagnostic algorithm on which the expert system was based. The vibration signal had to be measured under the five types of abnormal conditions noted in Section 2. The diagnostic simulation was performed as described below.

4.1 Simulated diagnosis of an unbalanced pump

The acceleration signal indicative of an unbalanced pump is shown in Fig. 8. Fig. 8(a) gives the normal acceleration signal of a pump, and Fig. 8(b) represents the vibration signal of an unbalanced pump. In Fig. 8(b), the amplitude of the accelerometer measuring the first running frequency increased 2.6 times at 60 Hz and the RMS value increased 1.2 times due to the random noise associated with the imbalance. Fig. 9 shows the newly developed diagnostic system analysis of the accelerometer signal. The system was not able to diagnose a lack of "normality" unless it continuously monitored the frequency shape of the normal condition in the field and compared that to the present condition.



(a) Normal pump



(b) Unbalanced pump

Fig. 8 Change in vibration signal caused by an unbalanced pump

However, the RMS value was 1.2 times that of the original RMS value of the first running frequency and several diagnostic indices. Thus, the diagnostic system noted that the machinery was sustaining "unbalance," and the system was judged as being in the "warning" condition.

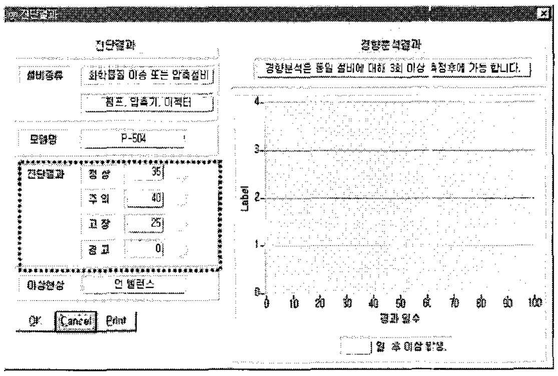
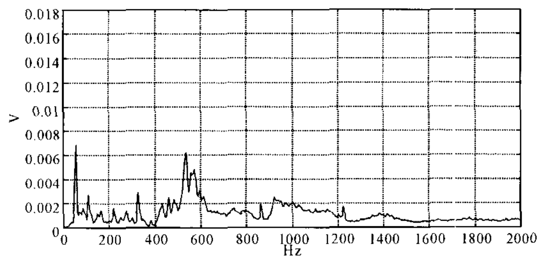


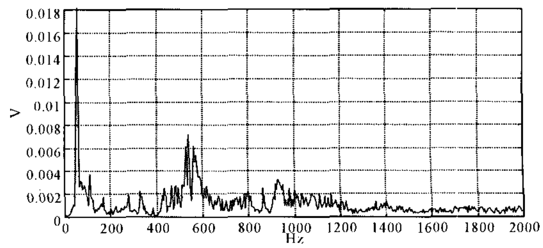
Fig. 9 Diagnostic results for an unbalanced pump

4.2 Simulated diagnosis of misalignment

To represent the misalignment phenomenon, the amplitude of the first running frequency in the axial direction of the measured normal accelerometer signal was increased threefold at 58 Hz. Random noise was also added to the RMS value so as to increase it 1.2 times. Finally, the normal accelerometer signal was modified to have more than two times its original RMS vibration level in the vertical direction. The normal and modified signals are shown in Fig. 10.



(a) Normal pump



(b) Pump with a misalignment

Fig. 10 Change in vibration signal caused by a misalignment

A general diagnosis, which considers only RMS values, will recognize the 1.2-fold increase in the RMS of the axial vibration and attribute it to changes that occurred in the field. However, the newly developed diagnostic system recognized the signal shown in Fig. 10(b) as being caused by "misalignment," and the system thus judged the machinery to be in a "warning" condition, as shown in Fig. 11.

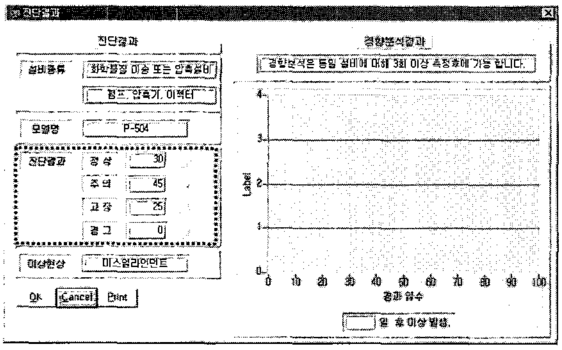
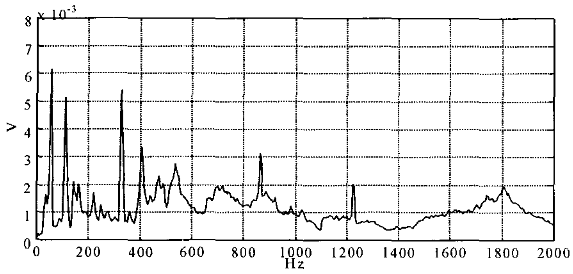
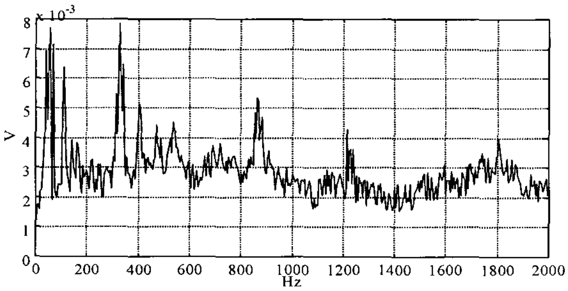


Fig. 11 Diagnostic results for a misalignment

4.3 Simulated diagnosis of a bearing fault



(a) Normal pump



(b) Pump with a bearing fault

Fig. 12 Change in vibration signal caused by a bearing fault

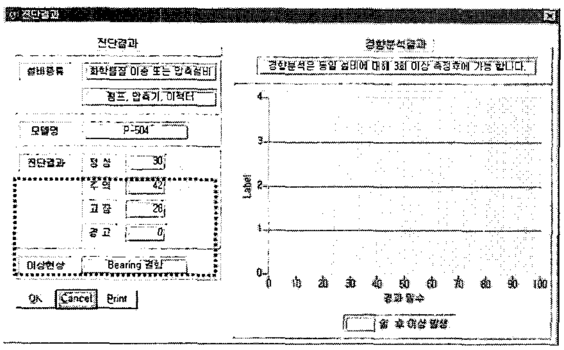
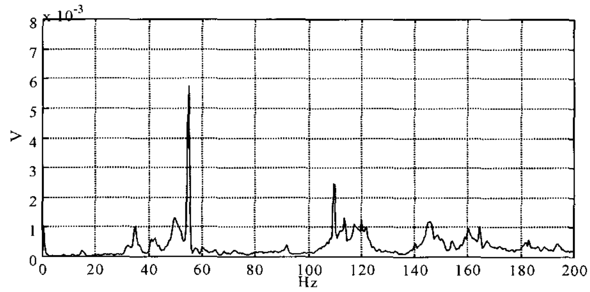


Fig. 13 Diagnostic results for a bearing fault

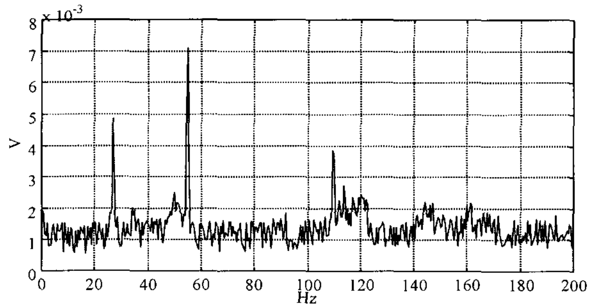
Fig. 12 shows the normal and abnormal acceleration signals used to diagnose a bearing fault. The first running frequency in the vertical direction and its corresponding harmonic frequency were modified to contain a side band and a RMS value with noise added such that it was 2.2 times its original value to represent an accelerometer signal that would occur with a bearing fault. Because of the high RMS value, a general diagnosis was able to verify that such a condition was "abnormal," but it was not able to determine that the cause was a "bearing fault." However, Fig. 13 illustrates that the developed diagnostic system indicated a "bearing fault" condition, and it judged the machinery to be in a "warning" condition.

4.4 Simulated diagnosis of an oil whip

The oil whip phenomenon occurs in the low-frequency region. Therefore, the accelerometer signal was measured until it reached 200 Hz to diagnose the phenomenon. Fig. 14 shows the normal and abnormal accelerometer signals associated with an oil whip; the oil whip was simulated by increasing the frequency near its peak value at 58 Hz, resulting in an amplitude that was three times greater than the normal signal. In addition, the overall RMS value was increased to 2.2 times its original value by adding random noise.



(a) Normal pump



(b) Pump with an oil whip

Fig. 14 Change in vibration signals caused by an oil whip

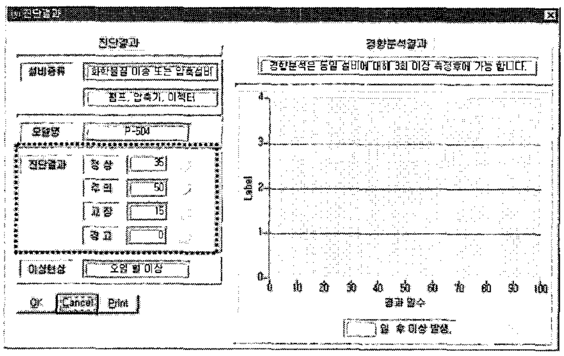
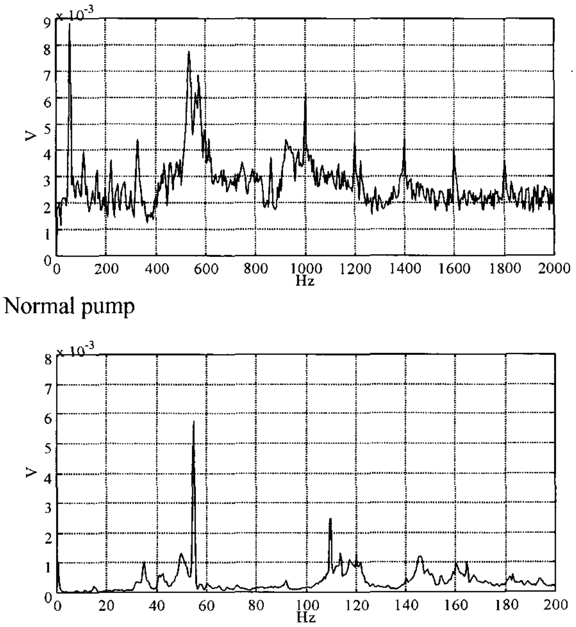


Fig. 15 Diagnostic results for an oil whip

As shown in Fig. 14(b), the general diagnostic method was able to identify the machinery as being in an abnormal condition due to the elevated RMS values. However, a general diagnosis would require continuous frequency analyses and monitoring in order to judge the abnormal condition as having resulted from an "oil whip." Fig. 15 shows that the developed diagnostic system indicated an "oil whip" phenomenon and it judged the machinery to be in a "warning" condition.

4.5 Simulated diagnosis of mechanical looseness

In order to generate an acceleration signal that would occur under mechanical looseness, a normal acceleration signal was added to the harmonic frequency component. The RMS value was also increased to three times its original value, as shown in Fig. 16.



(a) Normal pump

(b) Pump with mechanical looseness

Fig. 16 Change in vibration signals caused by mechanical looseness

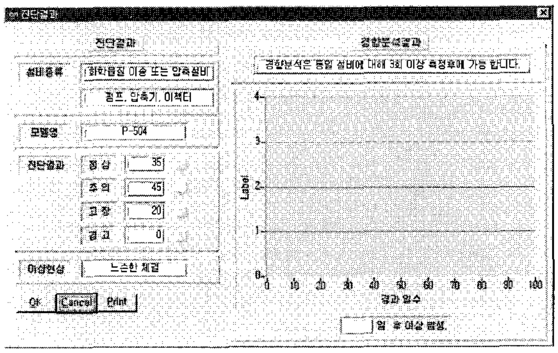


Fig. 17 Diagnostic results for mechanical looseness

The general diagnostic method was able to verify the occurrence of an abnormal condition due to the threefold increase in the RMS values. However, a more precise analysis was required to identify the root cause of the condition. Fig. 17 shows that the developed diagnostic system identified a "mechanical looseness" phenomenon, and the machinery was thus judged as being in a "warning" condition.

5. Conclusions

In this study, hardware and software were constructed to develop an expert diagnostic system. We performed diagnostic simulations using normal and modified accelerometer signals to identify abnormal conditions of a pump, which is a common form of rotating machinery in industry. The following conclusions were drawn from the simulations.

1. The constructed diagnostic monitoring system could both store vibration data and interface with a computer to analyze the vibration data.

2. By diagnosing five abnormal phenomena, the developed diagnostic system was verified to be more precise than a conventional diagnostic method, which only examined changes in the RMS values.

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