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Development of demonstration system for fault diagnosis of rotating equipments using RK4 test rig

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ABSTRACT

Rotating machinery is an essential equipment in the manufacturing industry, of which the fault can lead to the interruption of whole production line. To prevent such fault, there have been a large number of studies for Prognostics and Health Management (PHM) technology. However, most studies have been focused on a specific algorithm or component, making it difficult to apply them in the field. In this study, a demonstration system for integrated fault diagnosis is developed for critical fault modes in the rotating equipment such as the mass Unbalance, shaft misalignment, and the bearing fault using the vibration signals. To this end, Bently Nevada's RK4 rotor kit is revised to impose the fault modes easily. The solution is developed to detect anomalies, identify fault modes, and diagnose them in real time. Coupling ISO-based anomaly detection, rotating shaft fault diagnosis and bearing fault diagnosis, the system is configured to enable comprehensive condition monitoring. The results are demonstrated by real-time simulation of each fault on the test-rig.

1. INTRODUCTION

Rotating equipment is an important machine used in production sites, and their faults have a significant impact against the efficient operations. To prevent this, research on Prognostics and Health Management (PHM) is actively being conducted. However, most existing studies have focused on the academic research on specific fault diagnosis algorithms, which makes it hard to apply to actual industrial sites. Motivated by this, this study aims to develop a demonstration system capable of performing anomaly detection and fault diagnosis for important fault modes of rotating machinery.

To this end, experimental environment by revising Bently Nevada's RK4 rotor kit is provided to induce major fault modes of rotating equipment easily and quickly in real-time. Then ISO-based anomaly detection, fault diagnosis of rotating shaft and bearing are performed, which provide a comprehensive understanding of the PHM process.

In ISO-based anomaly detection, the abnormal state of rotating machinery is evaluated by applying the algorithms and criteria specified in ISO 20816-3. Additionally, following the PHM algorithm developed by the author, the collected vibration data is subjected to signal processing, and characteristic frequencies are extracted. This enables the identification of fault types such as mass Unbalance, misalignment, and bearing issues, thus facilitating the diagnosis of faults in the rotating equipment.

The system can demonstrate the diagnosis of several fault modes in the test rig in real-time and in an integrated way. As a result, it helps the field equipment engineers as well as the managers to easily understand the concept of PHM technology and its benefits with respect to the rotating machinery.

2. METHODOLOGY

The demo system for the rotating machinery proposed in this study consists of three main models as follows:

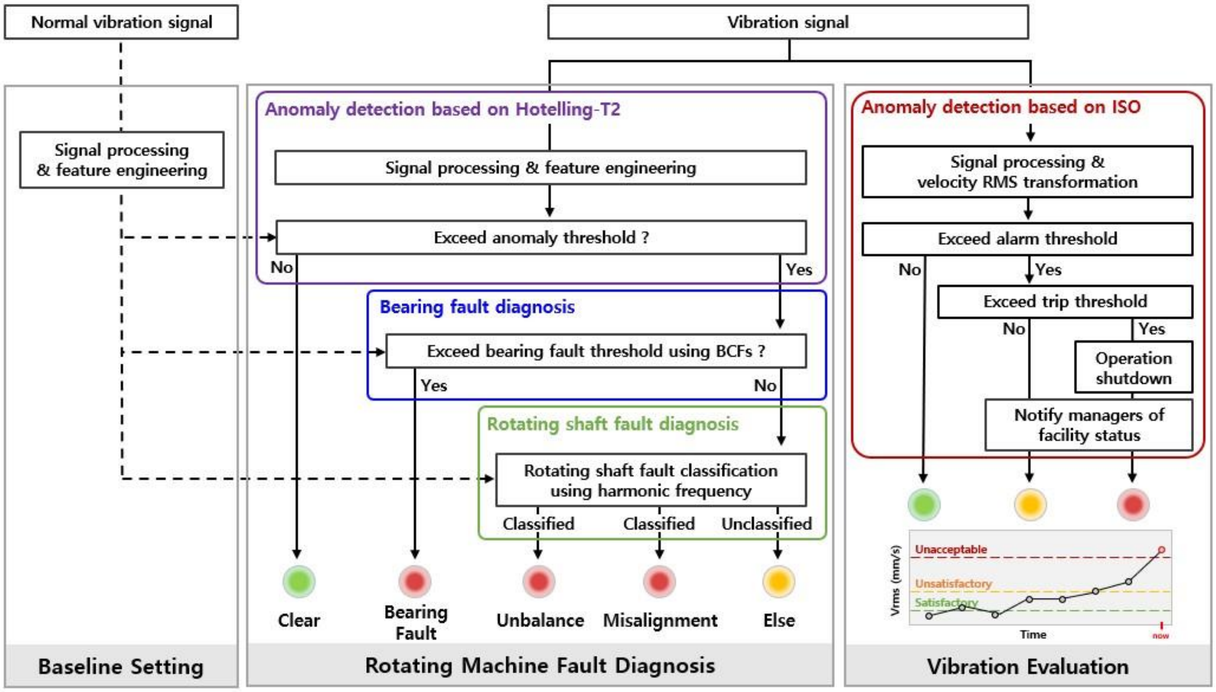


Figure 1. Demonstration system flow chart

1. Abnormal vibration detection of rotating machinery based on ISO 20816 standards.

2. Anomaly detection based on Hotelling-T2.

3. Bearing and rotating shaft fault diagnosis using bearing characteristic frequencies features.

These three models work complementary with each other to detect anomaly as well as to diagnose the faults of shaft and bearing: Since the model 1, the vibration criteria by ISO 20816, diagnoses only the overall condition in terms of the severity from the normal, more elaborate approaches are desired by the model 2 and 3. Furthermore, the decision by model 1 may sometimes be incorrect, that is, it may indicate normal, while the faults exist in the shaft or bearing which are identified by model 2 and 3. Despite the mentioned concerns, ISO 20816 based anomaly model was included in the study due to its high prevalence in the industrial and research domains, with over 4,000 papers published on this keyword since 2010. Overall flow chart of the demo system is described in Fig. 1

2.1. Anomaly Detection by ISO 20816

2.1.1. Signal Pre-processing

The signal pre-processing consists of two parts. First is to remove unnecessary frequency bands: at operating speeds below 600 RPM, it must be band-pass filtered in the frequency range of 2 to 1000 Hz, while it should be 10 to 1000 Hz above 600 RPM. Next is to transform the acceleration signal into the velocity since the vibration signal is collected from the accelerometer. It is done by the trapezoidal integration.

$$\int_a^b f(x)dx \approx \sum_{k=1}^{N} \frac{f(x_{k-1}) + f(x_k)}{2} \triangle x_k \tag{1}$$

2.1.2. Vibration Evaluation Criteria of ISO 20816

Once the velocity signal is obtained, the RMS is calculated to evaluate the vibration state by the criteria given by ISO. For this purpose, it is necessary to determine the class of driving motor in the rotating machine as shown in Table 1.

Table 1. Classification of the driving motor class of the rotor specified by ISO

Type	Details
Class1	Electric motors below 15 kW
Class2	Electric motors from 15KW to 75kW
Class3	Large machine with rigid foundation
Class4	Large machine with soft foundation

Then the severity is classified according to Fig. 2, which classifies each state by colors: good, satisfactory, unsatisfactory, and unacceptable. In this study, they are reduced into three states: ‘satisfactory’, ‘unsatisfactory’, and ‘unacceptable’, in which the first state includes the good & satisfactory in the figure.

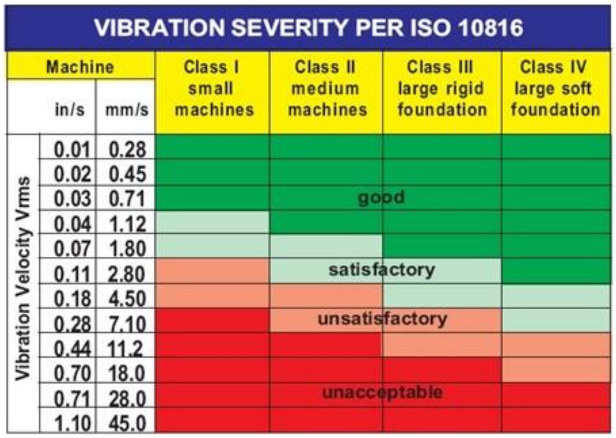


Figure 2. Vibration severity per ISO 10816-3(20816)

2.2. Anomaly Detection by PHM algorithm

To detect faults in shafts and bearings, a signal processing procedure is applied to the collected vibration signals, followed by an extraction of features from the processed signals. These extracted features are utilized for Hotelling-T2 calculation to classify normal and abnormal signals.

2.2.1. Signal Pre-processing

To extract the relevant features (frequencies) for the shaft and bearing, appropriate signal processing procedures are required for each.

For shaft fault detection, signal preprocessing begins with removing unnecessary frequency bands and emphasizing the running frequency(X) through bandpass filtering. The range of the bandpass filter is from 1/4X to 3X of the running frequency. Next, envelope analysis (amplitude demodulation) is performed to remove potential resonance signals with high frequencies. Finally, fast Fourier transform (FFT) is conducted to convert the signals from the time domain to the frequency domain. In the case of bearing, signal preprocessing consists of signal separation, signal enhancement, envelope analysis, and feature extraction. Firstly, the raw vibration signal undergoes signal separation using an autoregressive (AR) model, from which a residual signal is extracted. To preserve signals related to bearing defects, the optimal model order is selected to maximize the kurtosis of the residual. Next, a signal enhancement step is performed to amplify the impact signal, especially when the defect signal is still small. For this purpose, the Minimum Entropy Deconvolution (MED) technique is utilized. Additionally, envelope analysis (amplitude demodulation) is carried out to remove potential resonance signals with high frequencies. Finally, FFT is applied to convert the time-domain signals to the frequency domain.

2.2.2. Feature extraction

The extracted features are computed for the processed data after signal processing. For preprocessing data, harmonics(1~3X) of running frequencies are extracted, while for the bearing preprocessing data, harmonics(1~3X) of BCFs (Bearing Characteristic Frequencies) are extracted. Additionally, time-domain features such as RMS (Root Mean Square) and Kurtosis are extracted for each processed signal. The detailed list of extracted features is presented in Table.2.

Table 2. Extracted features list.

Harmonics of running frequencies (1~3X)
Harmonics of BCFs (1~3X)
Kurtosis in rotational preprocessing data
RMS in rotational preprocessing data
Kurtosis in bearing preprocessing data
RMS in bearing preprocessing data

2.2.3. Hotelling-T2

In the process of performing bearing and shaft anomaly detection, the previously extracted features are utilized as input values. Additionally, for T2 calculation, it is essential to have collected data in a normal operating state, which is then used as a reference to detect anomalies when monitored data deviates from the established normal state. The detailed formula for T2 is as follows:

$$\boldsymbol{T^2 = n[y - \bar{x}]^T S^{-1}[y - \bar{x}]} \tag{2}$$

where y is the vector of features in normal operating condition, $\bar{x}$ is the mean of the y , S is the covariance matrix of y, and n is the number of cycles up to current point. Given that the T^2distribution is given by:

$$\boldsymbol{T^2 \sim \frac{p(n-1)}{n-p} F_{\alpha,(p,n-p)}} \tag{3}$$

where α is a significance level, and p is the size of the vector y. The threshold that separates anomaly is given as follows:

$$\boldsymbol{UCL = \frac{p(n+1)(n-1)}{n^2 - np} F_{\alpha,(p,n-p)}} \tag{4}$$

In this study, the UCL (Upper Control Limit) is set at $\alpha = 0.01$.

2.3. Fault Diagnosis

After anomaly detection, a faulty signal is conducted to determine the type of fault that occurred. In this stage, the classification is based on the BCF. Specifically, when an anomaly is detected with significant variations in the BCF, it is classified as a bearing fault. Conversely, if an anomaly is detected in the rotor, but there is no obvious change in the

BCF, a shaft fault diagnosis is performed. The following section provides a detailed explanation of this methodology.

2.3.1. Bearing fault diagnosis

In bearings, BCF (Bearing Characteristic Frequency) is used for diagnosing faults. Bearing faults can occur in the inner race, outer race, and rolling element. BCF is a theoretical frequency value calculated based on the operating speed and bearing geometry information, and it allows us to determine the presence of bearing faults. The sum of BCF harmonics is utilized as a single metric to assess bearing faults, as it specifically represents fault signals related to bearing faults. This metric serves as an indicator for identifying bearing faults in cases where anomalies do not show significant changes in BCF values.

Fig. 3 represents the frequency spectra analyzed for normal and each faulty signal using the bearing signal preprocessing method. Looking at the figure, it can be observed that there are distinct changes in BCF when comparing the bearing fault condition with the normal and shaft fault conditions.

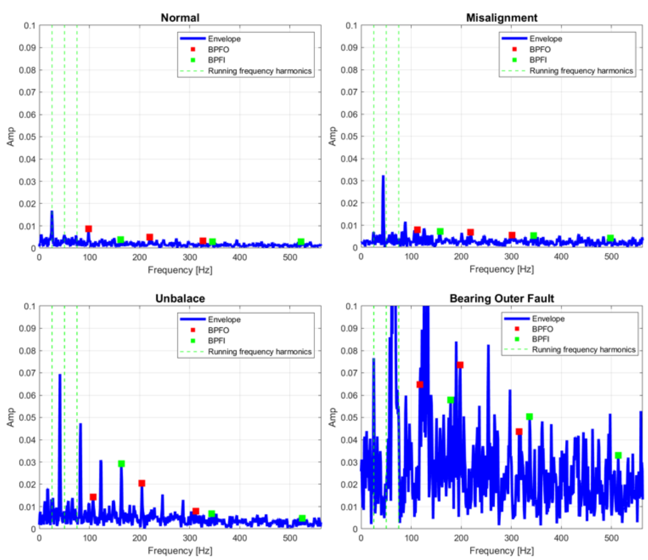


Figure 3. The frequency spectra analyzed for normal and each faulty signals

2.3.2. Shaft fault diagnosis

In the case of unbalance, as the eccentricity of the mass increases, there is a tendency for the amplitude of the 1X component to increase, and the fault is diagnosed based on the running frequency. Shaft misalignment occurs due to over angle, parallelism error, and bending of the shaft, and compared to the 1X component, there is a tendency for the amplitudes of the 2X and sometimes higher harmonics to be larger. Therefore, shaft fault diagnosis is performed based on the amplitudes of the 1X and 2X components in the frequency spectrum. The harmonic tendencies of mass Unbalance and shaft misalignment with respect to harmonics of the running frequency can be observed in Fig. 4.

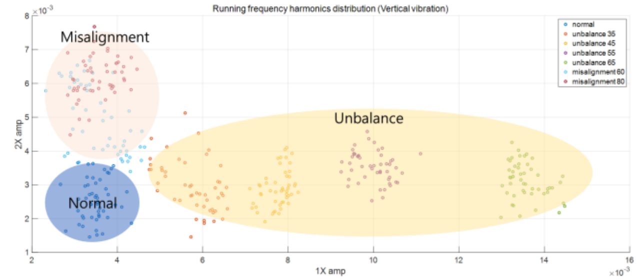


Figure 4. Characteristic frequency trends with shaft fault severity

3. Application

The RK4 test bed is an experimental equipment for analyzing the characteristics of a rotating body manufactured by Bently Nevada. The author modified the device as shown in Fig. 5 to implement mass Unbalance and shaft misalignment, which are the fault modes of the rotating shaft. It was also revised to switch easily between the normal and defective bearing. To realize bearing fault, bearings with artificial and natural defects are used at the inner and outer races of the bearing.

The RK4 test bed consists of a 75kW motor, shaft, housing, and mass disk. A motor speed regulator is connected to supply power to the test bed and control the rotation speed. It acquires data from the vertical vibration sensor attached to the bearing housing and the NI-9232 DAQ module. Data were acquired at 1500 rpm and a sampling rate of 12.8 kHz.

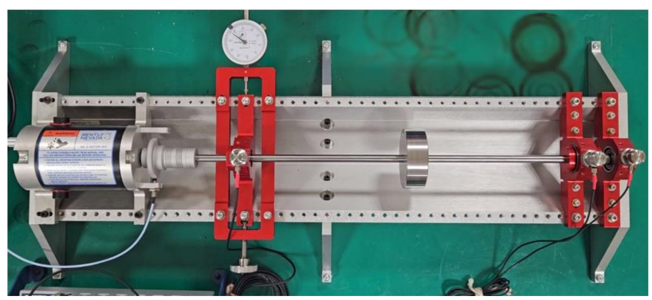


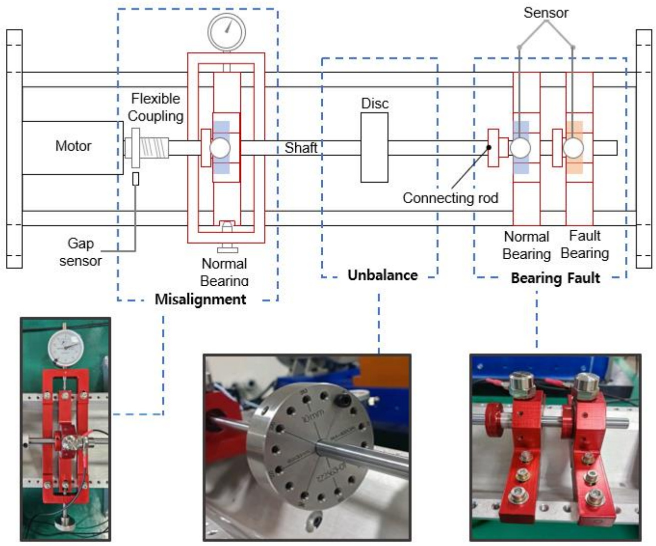
Figure 5. Bentley Nevada's RK4 test bed

For shaft misalignment, a device capable of implementing angular misalignment was constructed adjacent to the motor. The level of angular misalignment can be adjusted by moving the end of the shaft horizontally using a handle. This can be seen in Fig. 6(a).

For unbalance, an eccentric mass condition was created by attaching bolts to the centrally located disc. The level can be adjusted according to the weight of the bolts. This can be observed in Fig. 6(b).

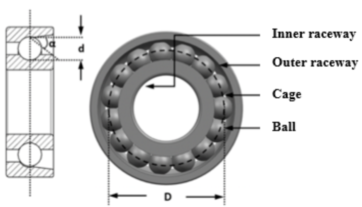
NSK 7202BW ball bearings were used, and the specifications for the bearings can be found in Fig. 7(a). Additionally, artificial defects (b) were created on the inner race and outer race through Electrical Discharge Machining (EDM).

To facilitate the easy transition from a normal bearing to a defective bearing, the normal and defective bearings were installed adjacent to each other as shown in Fig. 6(c). The device was configured to have one of them fixed and the other attached to the shaft through disassembly and assembly of connecting links.



(a) (b) (c)

Figure 6. Schematic diagram of RK4 test bed implementing fault modes of rotating machine
a) Misalignment part b) Unbalance part c) Bearing fault part



Inner race diameter (mm)	15
Outer race diameter (mm)	35
Ball diameter (mm)	6
Num of balls	11

(a)

(b)

Figure 7. Outer and inner race fault information of bearing
a) NSK 7202 BW Specification b) Artificial fault

3.1. Result Discussion

3.1.1. Anomaly Detection by ISO 20816

The results of detecting abnormal states in the rotating body based on the vibration severity criteria specified in ISO 20816-3 are presented in Fig. 8.

For shaft faults, the data obtained by setting the fault level to the highest during the experiment were taken as a reference in the results. According to the anomaly detection based on ISO criteria, both unbalance and misalignment exhibit higher vibration levels than the normal state but are classified as normal. However, bearing faults are classified into the caution range due to significantly higher vibration levels with substantial deviations.

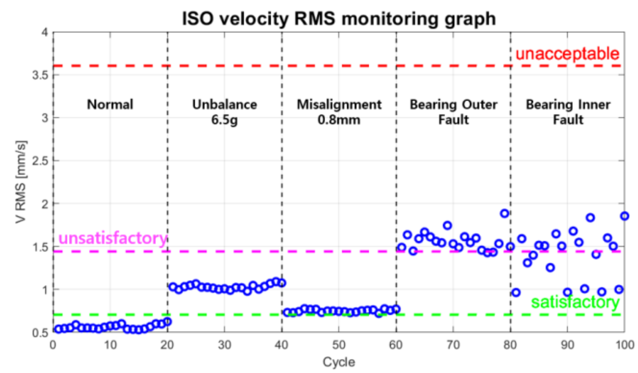


Figure 8. Anomaly detection results base on ISO

3.1.2. Anomaly Detection by Hotelling-T2

The results of anomaly detection in the rotating body using Hotelling-T2 are shown in Fig. 9.

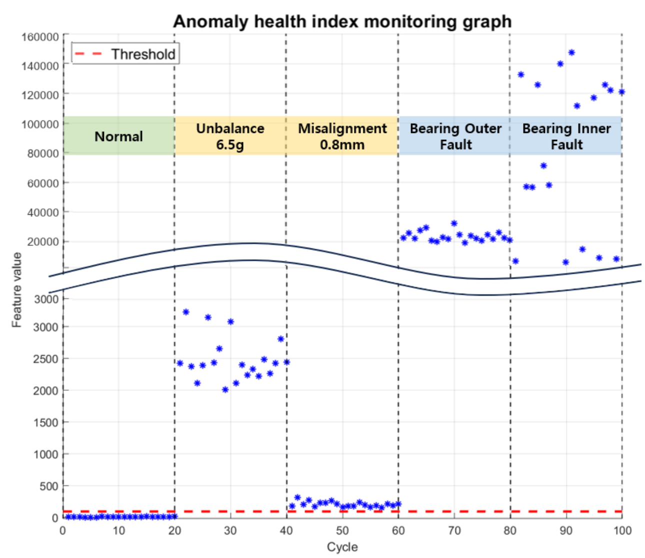


Figure 9. Anomaly detection results using Hotelling-T2

The threshold for anomaly detection, represented by the red dotted horizontal line, separates the normal state from faults (shaft and bearing) at a significance level of 5%. If the data points exceed this threshold, it is considered that there is an anomaly in the rotating body, and the next step is to determine whether there is a bearing fault.

3.1.3. Fault Diagnosis

The results of fault diagnosis for the rotating body are presented in Fig. 10.

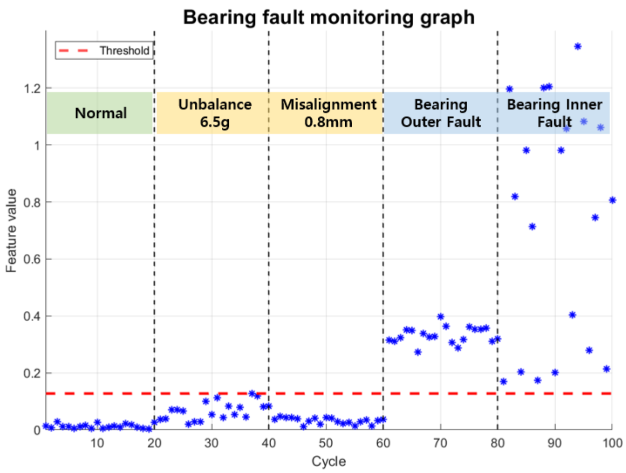


Figure 10. The classification of shaft faults and bearing faults

The classification of shaft faults and bearing faults is based on the magnitude of the BCFs, which represents the characteristic frequencies of the bearing. If the data points exceed the threshold, they are considered as bearing faults. otherwise, they are classified as shaft faults. The threshold used in the fault diagnosis is set at 10 times the level generated from the distribution of the normal state. This threshold setting criterion may require adjustment by field engineers based on empirical data and experience.

If classified as a shaft fault, further diagnosis is conducted to determine whether it is caused by unbalance or shaft misalignment, using the magnitudes of the running frequency (1X) and its harmonics (2X). Similarly, the threshold is generated using the distribution of the normal state to diagnose the fault condition.

3.2. User Platform for Demo System

Fig. 11 and Fig. 12 are the user interface (UI) of the demo system using the three models: anomaly detection-based ISO 20816, rotating shaft fault diagnosis, and the bearing fault diagnosis.

The UI is largely composed of 3 steps: initial value setting, anomaly detection, and diagnosis. In the initial value setting, user can set the initial input variables required for each anomaly detection and diagnosis. In the ISO anomaly detection, the class can be set according to the motor power of the target to be monitored, and the vibration severity can be identified. In the shaft fault diagnosis, the rotation speed and the collection period for frequency component analysis and the data collection time per cycle are input to obtain the required result. The bearing fault diagnosis uses the geometrical properties of the bearing as the input to calculate the bearing characteristic frequency. After the successful completion of normal signal collection, information regarding the normal signals is stored in a data file. Subsequently, upon clicking the 'start' button, monitoring begins, and T2 calculations and threshold determination are performed using the collected normal data. The system then monitors the state of the collected data based on these criteria. The result-displaying UI consists of four main sections: ISO standard anomaly detection results area, bearing fault diagnosis area, rotating machinery fault diagnosis area, and T2 anomaly detection and bearing fault monitoring status area.

In the ISO standard anomaly detection results area, the velocity RMS values are presented according to the ISO standards, and the system determines the condition based on the ISO baseline, indicating the status through lamps.

The bearing fault diagnosis area shows the analyzed BCF in spectrum domain. If a bearing fault is detected, the corresponding lamp illuminates.

In the rotating machinery fault diagnosis area, two-dimensional graphs are displayed for the 1X and 2X components of the running frequency. By monitoring the trends of the 1X and 2X amplitude, the system diagnoses faults such as Unbalance and misalignment and indicates them through lamps.

Lastly, the T2 anomaly detection and bearing fault monitoring status area serves as a cumulative display of parameters used as the basis for lamp activation. These parameters act as integrity factors and allow users to assess the machinery's condition over time.

Overall, this design enables users to make judgments about the machinery's status in real-time, providing a comprehensive monitoring system.

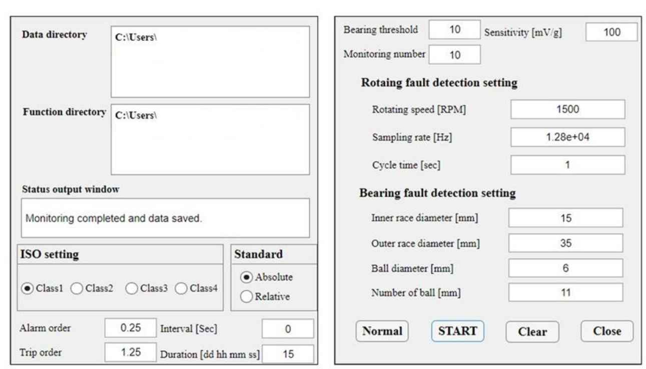


Figure 11. Initial setting window in the user interface (UI)

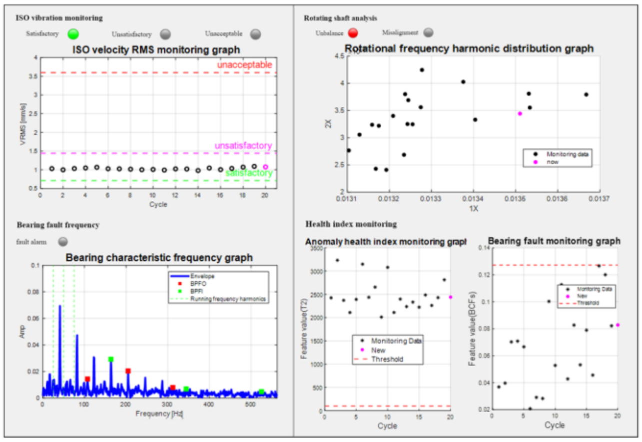


Figure 12. Vibration monitoring and detailed fault diagnosis window in the user interface (UI)

4. Conclusion

In this study, a demonstration system was developed using the RK4 rotor kit to detect abnormalities in the rotating body based on vibration signals and fault diagnosis algorithms to identify the shaft and bearing faults. An experimental environment that can apply fault modes easily, which are the mass Unbalance, shaft misalignment, and bearing defect, was established. It was confirmed that the demo system detects anomaly and diagnoses each fault mode successfully. In addition, it was confirmed that the three anomaly detection and diagnosis models are applied complementing each other to reach an appropriate conclusion. By means of the system, the maintenance engineer in the field can understand the concept of PHM easily by their own hand, and succeed to apply the PHM for their equipment.

Acknowledgement

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