

Article

Fault Simulating Test Bed for Developing Diagnostic Algorithm of the Geared Rotating Machinery of Ships

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Abstract: To prevent critical failure of the functional machinery of a ship, condition monitoring technologies have been much studied in recent times. In this respect, securing a fault database is a top priority in technology development. In this paper, we developed a test bed that simulates the LNG (liquefied natural gas) re-liquefaction system installed on LNG carriers to obtain data in various types of faults of ship machinery. To maintain rotor-dynamics characteristics, the structure was scaled based on the critical speed margin of the dynamic system. The developed test bed includes a gearbox and multiple shafts. It can simulate mass imbalance, misalignment, bearing fault, gear fault and impeller fault. To verify the validity of the vibration data obtained from the developed test bed, experiments were conducted on three fault modes: main shaft imbalance, pinion shaft imbalance, and gear fault. The time series data and FFT results were analyzed, and time domain features were extracted and statistically validated. Additionally, a simple diagnosis model was developed using the acquired data to evaluate its performance. The test data show distinct data with respect to fault conditions, and we can expect that the diagnosis algorithm can be developed using the test data. The developed test bed can provide not only for the fault data of a single component of the rotating machine but also for the combined fault data of the total system. In addition, we expect that it will solve the problem of securing fault data in the development of condition diagnosis technology if reliability is verified by identifying correlations by comparing data from the real system and data from the scaled test bed.

Keywords: rotating machinery; fault diagnosis; fault-simulating test bed; LNG liquefaction system; geared shaft



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1. Introduction

Rotating machinery such as compressors, steam turbines, industrial fans, and aircraft engines is essential in industrial, civil, and military fields [1–3]. There has been an increasing interest in the lifespan of specific components such as bearings in rotating machinery and electric power equipment [4–6]. As performance requirements increase, rotating machinery is exposed to various and harsh operating conditions, and faults can occur due to high load and fatigue [7,8]. In this respect, research is moving apace to detect faults and diagnose conditions in order to reduce the enormous economic/fatal costs that happen when rotating machines break down.

Specially, there are many rotating machines that perform special functions to maintain operation of a ship [9]. Generators and pumps used for the operation and continued functioning of a ship and ships requiring specialized functions like LNG (liquefied natural gas) carriers require a variety of rotating machinery. Unlike other transportation, such as land vehicles, airplanes, and small ships, large ships operate for a long period of time, so sudden faults in rotating machines can lead to inoperability and are difficult to repair immediately. These problems lead to large economic losses, about USD 900,000, which is

more than 10% of the operating costs of a 4000 TEU (twenty-foot equivalent unit) container ship, including the cost of replacing materials for ship maintenance and the cost of support staff [10].

Early condition diagnosis technology for rotating machines was conducted by predicting potential failure modes and assessing risks using the FMEA (failure mode and effect analysis) standard of MIL-STD-1692A [11]. After that, fault diagnosis technology was developed based on condition monitoring that determines the presence of faults through acquisition of vibrational data. Various signal processing techniques are used to secure features from vibration signals, and further research to determine and analyze faults using machine learning is in progress [12–14]. Furthermore, recent research has been conducted on high-concentration time frequency analysis (TFA) techniques based on chirplet transform for the condition monitoring of wind turbine bearings. This reflects the ongoing development of diagnostic technologies in various fields [15].

Recently, there has been research into PHM (prognostics and health management) technology, which goes beyond determining the presence of faults and diagnosing the condition. It involves fault analysis, fault isolation, and prognostics, enabling planned maintenance. In the steps for PHM, techniques for discovering and classifying faults include statistically based, data-based, and model-based methods. A statistically based method that detects faults through statistical processing using obtained data requires a large amount of data. A model-based method has high accuracy and is effective when there are difficulties in obtaining data [16,17]. In addition, research has been conducted to secure degradation data for a system using model-based methods and developing a regression model to predict RUL (remaining useful life) [18–20]. Model-based methods essentially require data used to verify the model, even if the amount is small [21,22]. Data-based methods do not require physical models and proceed through machine learning, but require large amounts of data. In this way, securing normal operation data and fault data is essential in developing status diagnosis and fault prediction technology for rotating machinery. However, most rotating machinery that diagnoses conditions and predicts fault are large and expensive, so there are limitations in obtaining fault data. To challenge these problems, research has been conducted to secure fault data by the implementation of test beds that simulate real rotating mechanical systems, and this is considered an important technological field [23–28].

A test bed that simulates a real rotating machine system is often able to obtain fault data of specific single components of a rotating machine. PRONOSTIA, developed by FEMTO-ST, can obtain fault data on bearings, a representative component of rotating machinery. PRONOSTIA provides fault data for rolling bearings used in the IEEE PHM challenge held in 2012 [29]. Additionally, Zaza developed a machinery fault simulator (MFS) to verify the vibration simulation model. The MFS can simulate shaft misalignment and rotates at 2000 rpm, making it possible to collect vibration data [30]. CWRU (Case Western Reserve University) in the United States provides fault data on rolling bearings according to load and rotation speed [31]. The IMS dataset of the University of Cincinnati provides fault data on single bearings from experiments using a test bed [32]. In previous research, equipment targeting specific components of rotating machines has been developed, and the equipment specifications are summarized in Table A2. However, since the above studies provide fault data for specific single components of rotating machinery, they cannot provide data on various faults and combined faults of the total system. Therefore, there are limitations in diagnosing the status and predicting fault for the total system.

In this study, we developed a test bed that can simulate fault data of the total system by implementing faults that can occur in geared rotating machinery. The target rotating machine is a re-liquefaction system that liquefies bog (boil-off gas) on an LNG carrier. The developed test bed can implement various fault modes, including main shaft mass imbalance, pinion shaft mass imbalance, and gear faults that can occur in gearboxes and rotating machines with multiple shafts.

This research has the strength of being able to comprehensively simulate faults that may occur in rotating machinery, including gearboxes. Using the developed test bed, experiments can be conducted on various fault modes and fault levels, thus providing the necessary fault data for the development of PHM technologies.

The paper is structured as follows. In Section 2, the structure of the LNG re-liquefaction system is described. In Section 3, scaling down of a real rotating machinery system is conducted, and the design of the test bed is described. Additionally, possible implementation fault modes are presented. In Section 4, the data acquisition system will be described. In Section 5, a case study for validating the effectiveness of the developed test bed will be provided through development of a simple diagnosis method based on the shallow machine learning algorithm. The nomenclature and parameters used in this study are listed in Table A1.

2. Layout of the Re-Liquefaction System

The re-liquefaction system compresses the nitrogen refrigerant through a three-stage compressor, adiabatically expands it through a first-stage expansion turbine, and delivers it to the heat exchanger. BOG is re-liquefied through heat exchange in a heat exchanger using the delivered nitrogen refrigerant. Figure 1 shows the heat exchange cycle of the re-liquefaction system, and Figure 2 shows physical layout of the re-liquefaction system [33].

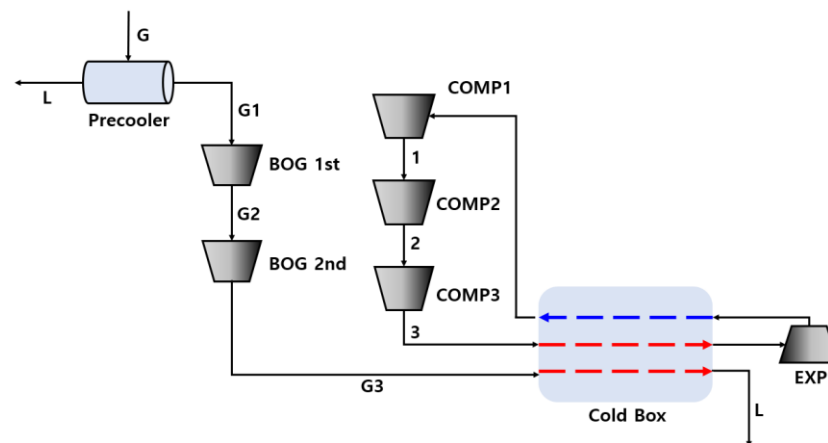


Figure 1. Cycle model of re-liquefaction system.

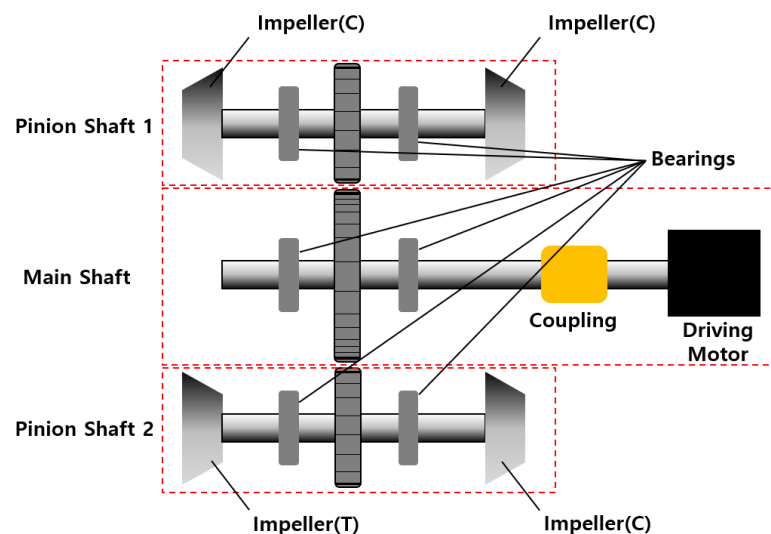


Figure 2. Physical layout of the re-liquefaction system.

The re-liquefaction system consists of one main shaft and two pinion shafts, and a total of three shafts are connected by a gearbox. In addition, an aerodynamic force is applied to ends of the pinion shaft due to the rotation of the impeller. The re-liquefaction system has a motor for rotation, six bearings to support shafts, three compressors, one expansion turbine, and a gearbox. In this study, the re-liquefaction system was simplified and scaled down to enhance accessibility and operability in terms of obtaining fault data. One pinion shaft was excluded in the test bed, and the gears were replaced with a spur gear to simplify the rotor system.

Since the rotor shafts are connected through gear meshes, not only the lateral motion of the rotor but also the torsional motion must be considered in dynamic response. Therefore, the test bed was developed to simulate mass imbalance and shaft misalignment faults in terms of lateral motion, and three fault modes were implemented—gear fault, bearing fault, and impeller fault—in terms of torsional motion. Figure 3 shows the structure of the developed test bed.

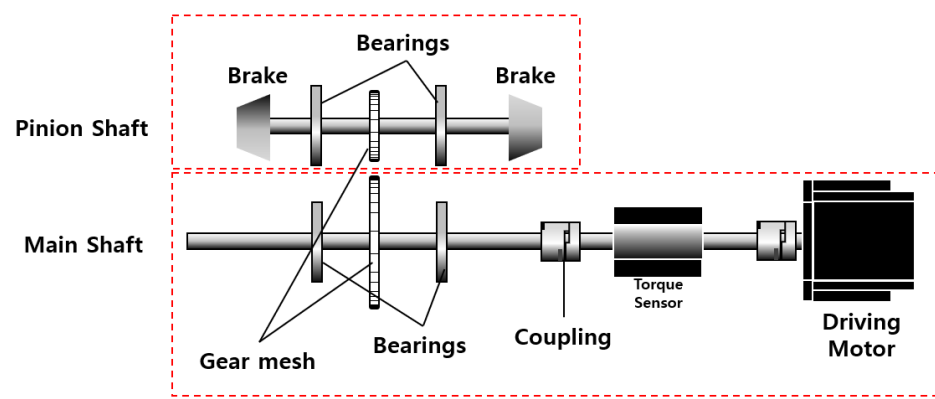


Figure 3. Physical layout of the test bed with two rotating shafts and gear mesh.

3. Test Bed Design

3.1. Test Bed Scaling

The target re-liquefaction system has a 3 m-long main shaft rotating at 2000 rpm and gears with a 1/10 gear ratio. Considering the operating speed of the real system, the pinion shaft speed is too high to simulate in the laboratory. Therefore, downscaling was performed while maintaining the characteristics of the real system in terms of rotordynamics. When scaling is performed while maintaining rotordynamics characteristics, the margin is equalized by adjusting the ratio of critical speed and rotational speed [34]. In rotating machinery, critical speed means natural frequency. If the rotation shaft is assumed to be a cylindrical beam, the critical speed (ω_{cr}) can be expressed as a function of shaft length (l), shaft diameter (d), Young's modulus (E) and density (ρ):

$$\omega_{cr} = \sqrt{\frac{k}{m}} = \sqrt{\frac{3Ed^2}{16\rho l^4}} \quad (1)$$

In this study, since the material of the shaft is assumed to be the same and the ratio of Young's modulus and density is constant, the critical speed is as follows:

$$\omega_{cr} = \bar{C} \frac{d}{l^2} \quad (2)$$

where $\bar{C}$ is a constant value, such as $\sqrt{3E/16\rho}$. Therefore, the ratio of critical speed and rotational speed for scaling rotating machines is as follows:

$$R_{cr} = \frac{\omega}{\omega_{cr}} \approx \frac{\omega l^2}{\bar{C} d} \quad (3)$$

In this study, scaling was performed by maintaining a critical speed margin identical to that of the real system. Thus, if the scaled system has the same (R_{cr}) value as one of the reference system, it has similar resonance characteristics. However, if it is kept at the same value, the rotation speed of the pinion shaft becomes too high to operate in a laboratory environment. The pinion shaft is relatively smaller than the main shaft and bull gear and is considered to have a small effect on rotordynamics, so the speed of the pinion shaft was reduced by adjusting the gear ratio due to the limitations of the test bed operating environment. R_{cr} of each component is described in Table 1. The test bed is driven by a BLDC motor (brushless DC motor) and is connected through a coupling at the end of the main shaft. Considering the maximum operating speed of the main shaft, a motor with a maximum speed of 3000 RPM and 2 kW was selected. The specifications of the test bed designed by scaling down using critical speed margin (R_{cr}) are shown in Table 2.

Table 1. R_{cr} value of the test bed.

Components	Reference (R_{cr})	Test Bed (R_{cr})
Main shaft	74,468	74,468
Bull gear	12.7	12.7
Pinion shaft	384,027	38,206

Table 2. Specifications of the developed test bed.

	Value
Main shaft length (m)	0.8
Pinion shaft length (m)	0.39
Gear ratio	0.68
Main shaft max speed(rpm)	3000
Pinion shaft max speed(rpm)	4400

3.2. Design of Rotating Components

The gear diameter was designed at 0.22 m based on the critical speed margin in Table 1. Initially, the gears were designed with 100 teeth for the bull gear and 80 teeth for the pinion gear. However, considering the high gear-mesh frequency, this was adjusted to 50 teeth for the bull gear and 34 teeth for the pinion gear.

In the test bed, it must be easy to control the torque applied through the brake to simulate damage to the impeller. In this respect, hysteresis brakes were installed at both ends of the pinion shaft to simulate the aerodynamic force applied due to the rotation of the impeller on the test bed. Hysteresis brakes were controlled by the applied current. Figure 4 shows the hysteresis brakes mounted on both ends of the pinion shaft.

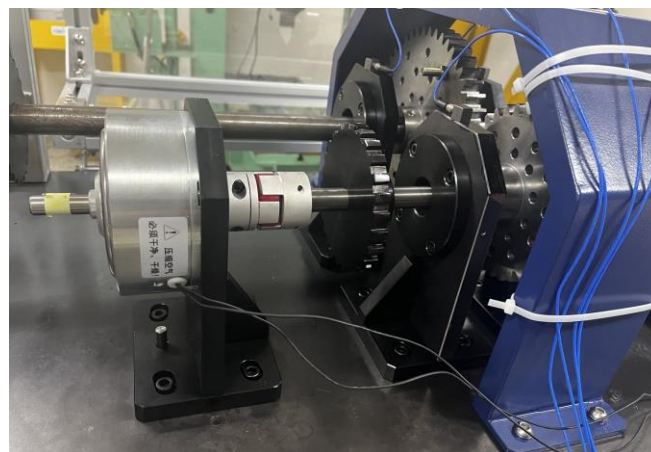


Figure 4. Hysteresis brake for applying the end load at the pinion shaft.

The specifications of the hysteresis brake were selected considering the acceleration time of the test bed according to the applied load. The equivalent rotational inertia for the rotor system of the test bed was calculated as follows.

Equivalent stiffness was obtained by calculating the rotational stiffness of each shaft and component of the test bed, and the loaded torque was calculated through equivalent rotational inertia. Using the torque calculated in this way, the velocity profile according to the maximum torque of the motor was calculated and the motor was selected. Using the calculated equivalent rotational inertia ($I_{eq} = 0.26 \text{ kgm}^2$), the velocity profile of the test bed can be obtained as follows:

$$I_{eq} = I_{main} + I_{bull} + \left(\frac{N_{bull}}{N_{pinion}} \right)^2 (I_{pinion} + I_{pinion \text{ gear}}) \quad (4)$$

$$\dot{\omega} = \left(T_{motor} - \left(\frac{N_{bull}}{N_{pinion}} \right) T_{load} \right) / I_{eq} \quad (5)$$

Assuming that brakes of the same specifications were installed on both ends of the pinion shaft, the acceleration time of the test bed according to the applied load is shown in Figure 5.

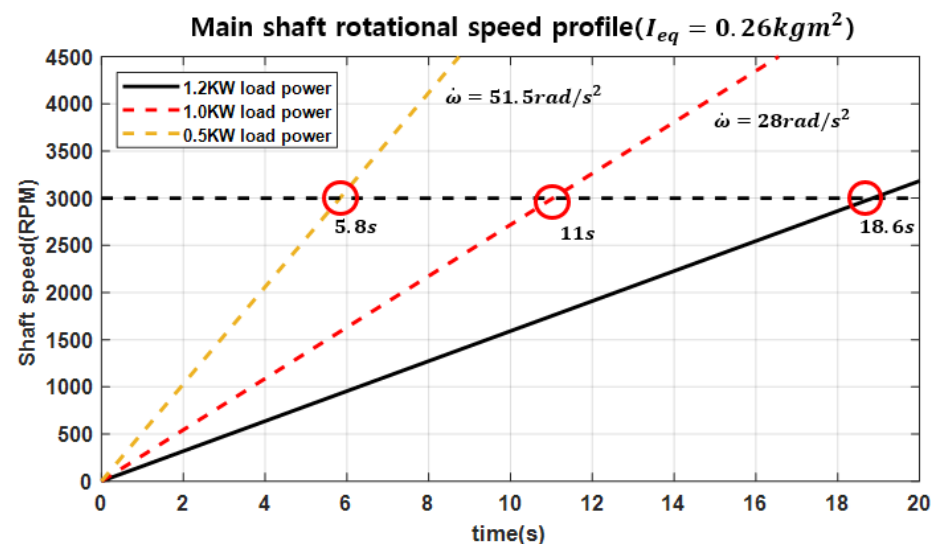


Figure 5. Rotational speed profile of the main shaft with respect to the hysteresis brake load power.

When evaluating the acceleration time according to the load applied by the hysteresis brake, a 1.0 kW-level brake was selected with a maximum speed reaching time of approximately 10 seconds, considering the convenience of the experiment. The main shaft is supported by two ball bearings and one roller bearing, while the pinion shaft is supported by one ball bearing and one roller bearing each. Detailed geometric specifications and components are summarized in Table 3 representing the rotating components of the test bed. The hardware configuration of the developed test bed is depicted in Figure 6.

Table 3. Specifications of rotating components for the developed test bed.

	Value
Number of bull gear teeth	50
Number of pinion gear teeth	34
16005 ball bearing (EA)	2
16003 ball bearing (EA)	1
NJ205 roller bearing (EA)	1
NJ203 roller bearing (EA)	1
Hysteresis brake (max torque, Nm)	2

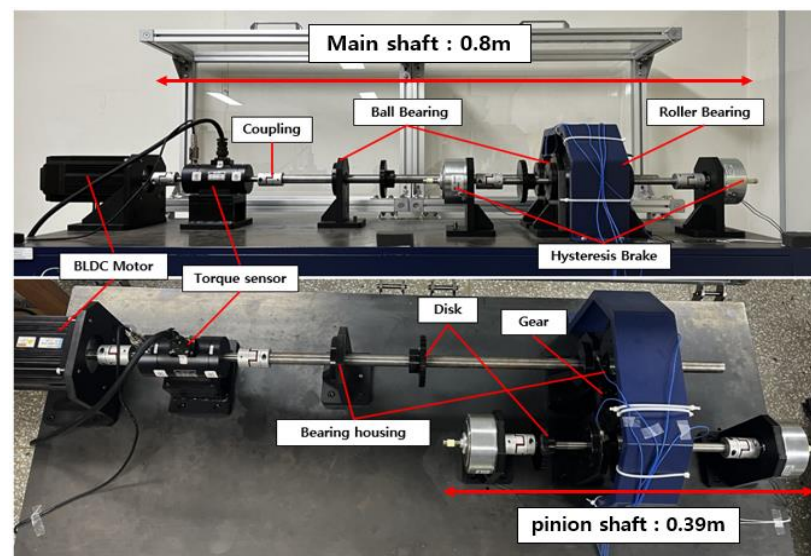


Figure 6. Hardware of the developed test bed.

3.3. Fault Mode Candidates

The test bed can implement shaft mass imbalance, shaft misalignment, bearing faults, gear faults and impeller faults. Figure 7 shows the fault modes that can be implemented in the test bed [35].

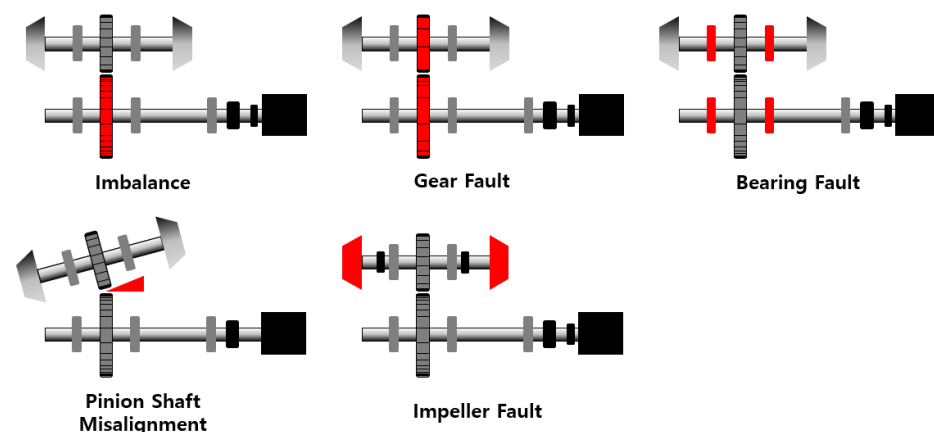


Figure 7. Possible fault modes of the multi-rotor system including gear mesh.

In the case of mass imbalance, it was designed based on balancing quality grade 16 (G16) in ISO 21940 [36]. Table 4 shows the results of calculating the allowable residual imbalance of each shaft based on the maximum rotation speed. As shown in Figure 8, it was designed to enable the creation of mass imbalance according to the amount of eccentricity by fastening bolts and nuts.

Table 4. Test bed of permissible residual Imbalance (G16).

	Permissible Residual Imbalance
Main shaft	0.004329 kg·cm
Pinion shaft	0.001156 kg·cm

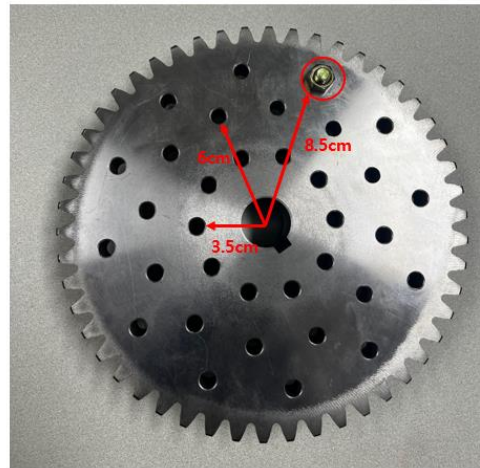


Figure 8. Imbalance condition gear.

The shaft misalignment of the test bed can be assigned by tilting up to 1 degree, as shown in Figure 9. In a rotating system with a gearbox, damage and wear of gear teeth may occur during operation. In the developed test bed, damage to gears occurred, as shown in Figure 10. In addition, the test bed can simulate an impeller fault by controlling the load applied by the hysteresis brake.

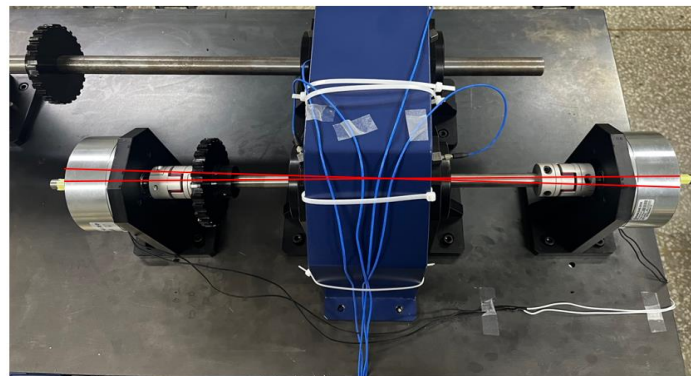


Figure 9. Pinion shaft misalignment condition.

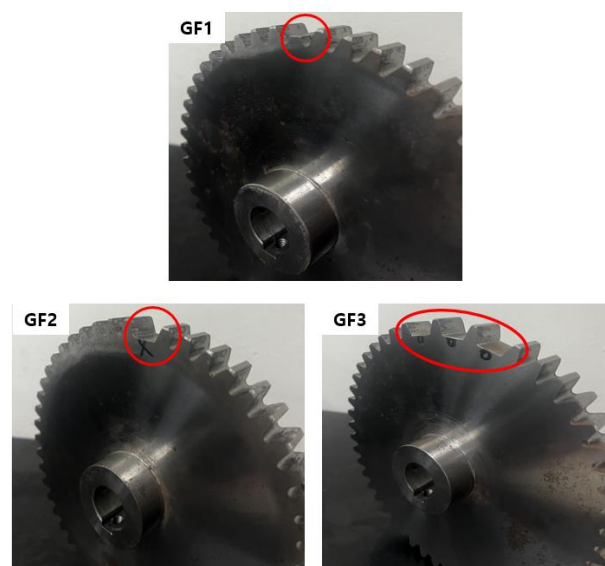


Figure 10. Gear fault modes.

4. Control and Data Acquisition System

The control and data acquisition system of the test bed is mainly configured with a BLDC motor, a hysteresis brake, a control system, and vibration signal measurement, as shown in Figure 11.

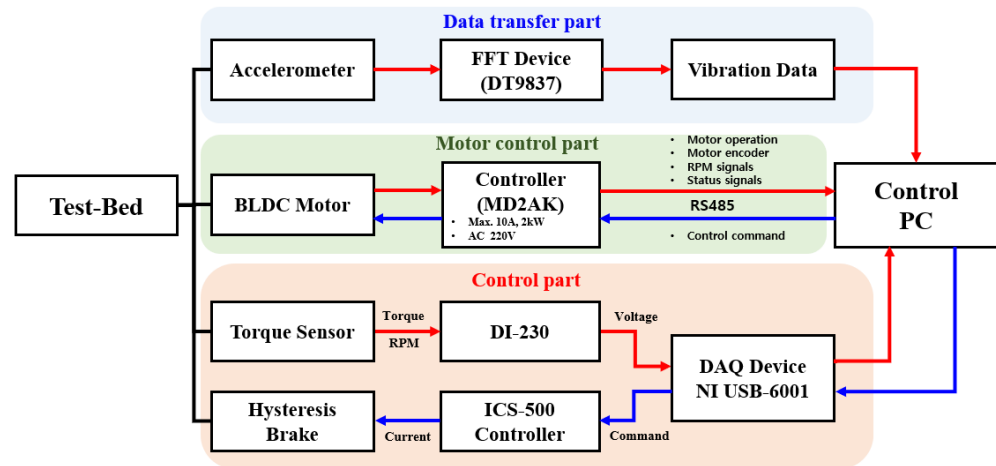


Figure 11. Measurement and control systems for the test bed.

The sub-components are controlled by one control PC. Hysteresis brakes can be controlled by applied current through a DAQ device connected to the control PC. The motor driver sends the motor's status and receives control demands from the control PC through RS485 communication. To measure the torque applied to the BLDC motor in the test bed, a torque sensor is positioned between the motor and the main shaft using a coupling. It can measure torque with a rated capacity of 5 kgf-m and can measure up to 10,000 RPM. The signal from the torque sensor can be transmitted to the control PC through a digital indicator and DAQ device.

To measure the fault vibration signal, accelerometers were installed in bearing housings. Assuming a maximum rotational speed of the main shaft of 3000 RPM, the maximum required frequency for the accelerometers was calculated. Detailed calculation results are shown in Table 5.

Table 5. Maximum frequencies and recommended frequencies for each signal.

Signals	Maximum Frequency (Hz)	Recommended Sampling Frequency (Hz)
Main shaft rotor $1 \times$	50	300
Pinion rotor $1 \times$	74	440
Gear-mesh frequency	2500	7500
Main shaft bearing BPFI	400	1200
Pinion shaft bearing BPFI	516	1548

Considering the gear-mesh frequency, which is the maximum frequency of the equipment, a PCB Piezotronics 333B30 model accelerometer was mounted on the bearing housing. Figure 12 shows the mounting position of the accelerometer on the bearing housing. Two accelerometers were installed in the bearing housing on the gear side of the main shaft and two were installed in the bearing housing of the pinion shaft. The sensors installed in the main shaft ball bearing housing, in the main shaft roller bearing housing, in the pinion shaft ball bearing housing, and in the pinion shaft roller bearing housing are labeled channels 1, 3, 2, and 4, respectively.

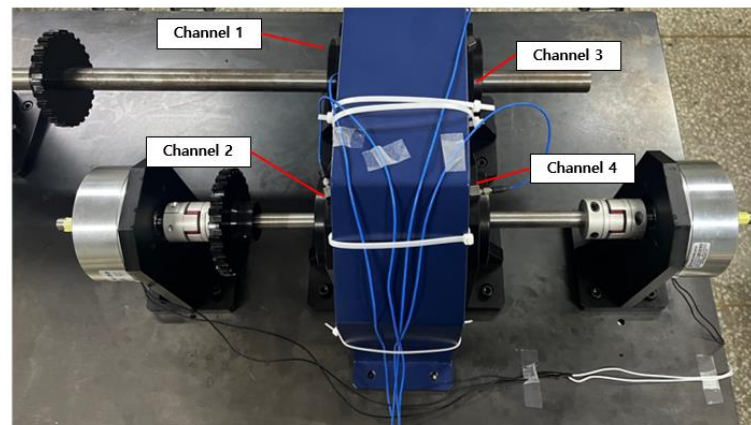


Figure 12. Measurement points of accelerometer.

The Data Translation DT9837 model was used as dynamic signal DAQ equipment for signal processing of accelerometers. It is connected to the control PC through USB connection of the DT9837, and it can monitor the acceleration signal in real time and perform fast Fourier transform. Time series data from the test bed were acquired at a sampling rate of 6000 Hz for about 1 min for individual test cases. Hanning window with excellent frequency resolution performance was applied to the data and fast Fourier transform was conducted.

5. Case Study Using the Developed Test Bed

Section 5 confirms the validity of vibration data acquired from the test bed developed in this study. In Section 5.1, vibration data are acquired for three representative fault modes, and in Section 5.2, the validity of the obtained fault data is confirmed. Data validation is initially conducted based on time series data and FFT results, and is additionally conducted on time domain features, which enables rapid diagnosis without the need for transformation of the vibration signal. In Section 5.3, a stepwise diagnosis model that is expected to perform the best using time domain features is developed and the results are analyzed.

5.1. Collecting the Fault Data

A case study was conducted on several fault modes to confirm the validity of the data acquired from the developed test bed. Fault data include five imbalance cases and three gear fault cases. Table 6 shows the degree of imbalance of the main shaft and pinion shaft, and the gear fault was implemented as shown in Figure 10.

Table 6. Imbalance conditions.

	Type	Degree of Imbalance
Main shaft imbalance 1	MS_IM1	0.204 kg·cm
Main shaft imbalance 2	MS_IM2	0.408 kg·cm
Main shaft imbalance 3	MS_IM3	0.54 kg·cm
Pinion shaft imbalance 1	PS_IM1	0.132 kg·cm
Pinion shaft imbalance 2	PS_IM2	0.264 kg·cm

Figures 13–15 show time series data and FFT results of each fault mode. The conducted experiments on shaft imbalance and gear faults suggest that overall mass imbalance occurred, and thus FFT was visualized up to 100 Hz, which is related to the rotational frequency. In the high-frequency range associated with gear faults, noise is mixed in, indicating that additional data processing is necessary to utilize the high-frequency data ef-

fectively. In the case of shaft imbalance, it is difficult to find faults using time series data. However, in the FFT results, it can be seen that there is a difference in the $1\times$ component in terms of frequency because the imbalance acts as an external force according to the rotation period.

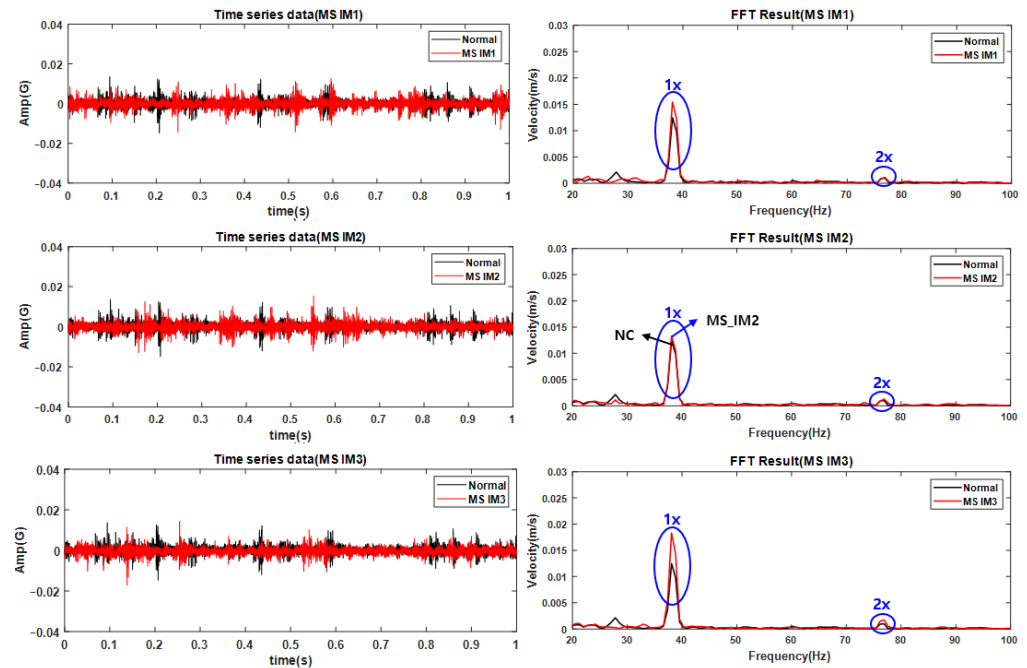


Figure 13. Comparison of normal condition and main shaft imbalance data measured form channel 1 at 2300 rpm (MS_IM 1: 0.204 kg·cm imbalance, MS_IM 2: 0.408 kg·cm imbalance, MS_IM 3: 0.54 kg·cm imbalance).

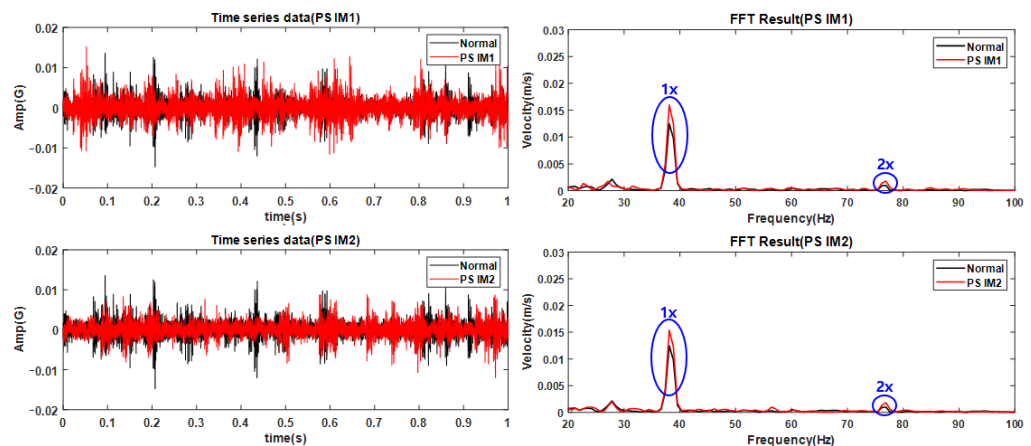


Figure 14. Comparison of normal condition and pinion shaft imbalance data measured from channel 1 at 2300 rpm (PS_IM 1: 0.132 kg·cm imbalance, PS_IM 2: 0.264 kg·cm imbalance).

Figure 15 shows the results of gear fault comparisons. The experiment was conducted on three gear faults, as shown in Figure 10. Gear faults change in peak amplitude depending on the level of the fault in time series data, and since the loss of gear teeth is also an imbalance condition, it also shows a difference in amplitude in $1\times$ frequency (38 Hz).

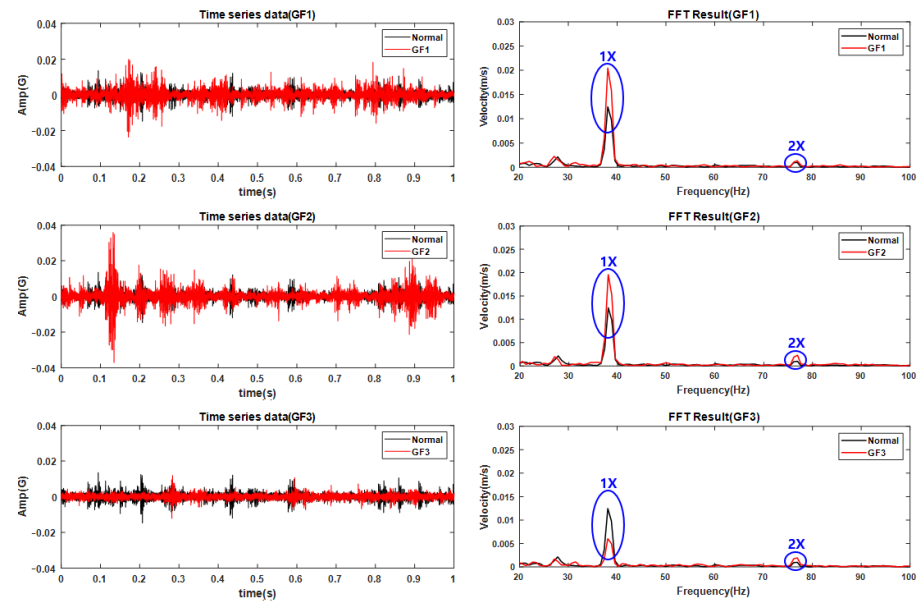


Figure 15. Comparison of normal condition and gear fault data measured from channel 1 at 2300 rpm (NC, GF1, GF2 and GF3).

Comparing the eight cases of fault data and normal data results, there are limitations in detecting faults using time series data. Additionally, if FFT is used, faults can be detected through the difference between normal data and fault data, but there are limitations in diagnosing the type of fault. In this study, the validity of test bed data was confirmed using time series features.

5.2. Fault Data Validation

To validate the effectiveness of faulty conditions, representative features were extracted from the time series that did not require a data transformation process. A total of 12 representative time domain features were defined: four statistical features (mean absolute, variance, kurtosis, skewness) and eight physical features (RMS, peak, peak to peak, standard deviation, shape factor, impulse factor, crest factor, clearance factor).

To verify the distribution of the extracted 12 time domain features, they were randomly grouped into sets of three and visualized without using any specific algorithm. The first group is formed by shape factor–RMS–mean abs, and the second group is variance–impulse factor–standard deviation. The third group consists of peak to peak–kurtosis–skewness, and the remainder forms the fourth group. Figure 16 shows the results in a 3D plot using the extracted time domain features.

It can be observed that the main shaft imbalance condition is difficult to classify from the normal condition. However, it can be seen that the pinion shaft imbalance and gear fault are distinguished from the normal condition.

It is difficult to confirm the distribution of features for each fault mode of the test bed from the previous 3D plot results. Therefore, the distribution of time series features according to condition was confirmed using an error bar chart. The error bar chart displays the maximum, minimum, and median values using solid lines. The top of the box corresponds to the top 0.75 quartile and the bottom of the box corresponds to the top 0.25 quartile. The smaller the box, the more likely it is that the data are concentrated around the median value. Figure 17 shows peak-to-peak data distribution.

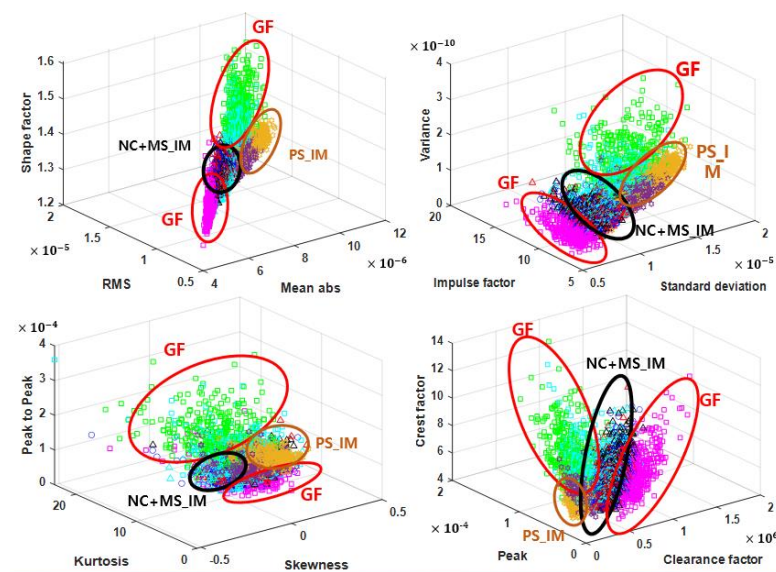


Figure 16. 3D plot of data distribution (case 1: shape factor–RMS–mean abs, case 2: variance–impulse factor–standard deviation, case 3: peak to peak–kurtosis–skewness, case 4: crest factor–peak–clearance factor).

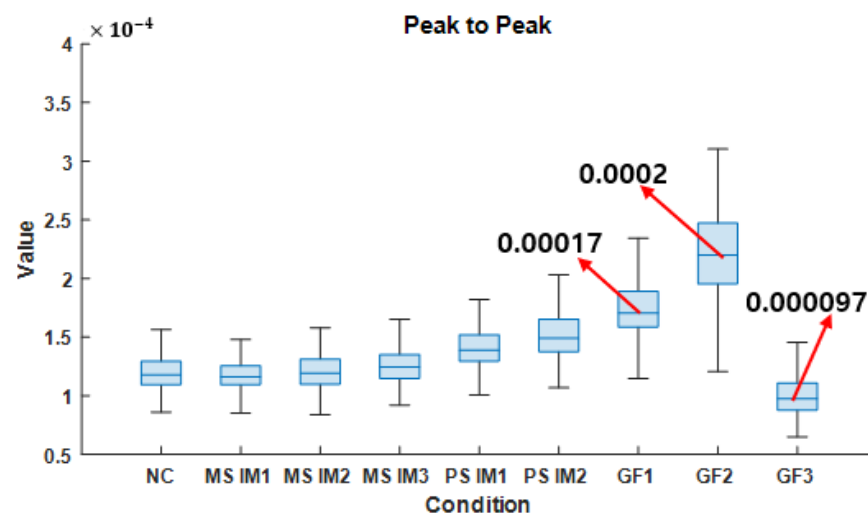


Figure 17. Peak-to-peak distribution according to condition.

Peak-to-peak values, which means the amplitude of vibration, show certain differences depending on the fault mode. This phenomenon also appears in Peak, which has a similar meaning. Peak to peak shows a clear difference in the distribution of gear defect data. The difference between the median values of GF2 and GF3 is 0.002 and 0.000097, which is a large difference. If additional data preprocessing is performed, it is believed that pinion shaft imbalance and gear faults can be effectively classified.

Shape factor, impulse factor, crest factor and clearance factor are signals generated in relation to machine collisions in rotating mechanical systems. Even in the test bed where two rotation shafts were connected by gears, the four features showed similar data trends. There was a significant change in gear fault, and there was also a change in pinion shaft imbalance. Figures 18 and 19 show the shape factor and clearance factor as representatives of the four features. When comparing the maximum and minimum values of the clearance factor quartile under the pinion shaft imbalance condition in Figure 19, there is a clear distribution difference of 4.5×10^5 and 4.4×10^5 . Using the clearance factor to classify pinion shaft imbalance is expected to yield good results.

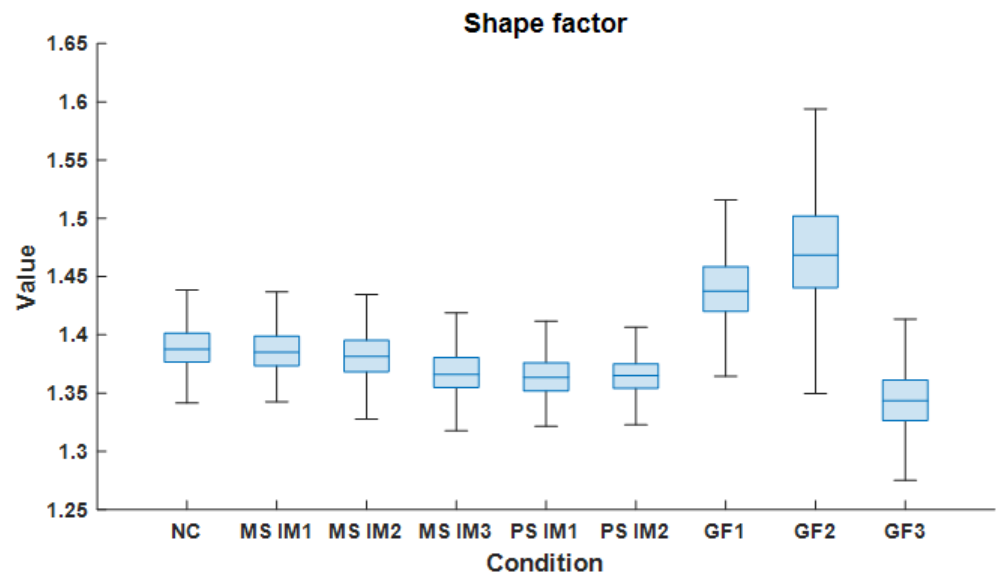


Figure 18. Shape factor distribution according to condition.

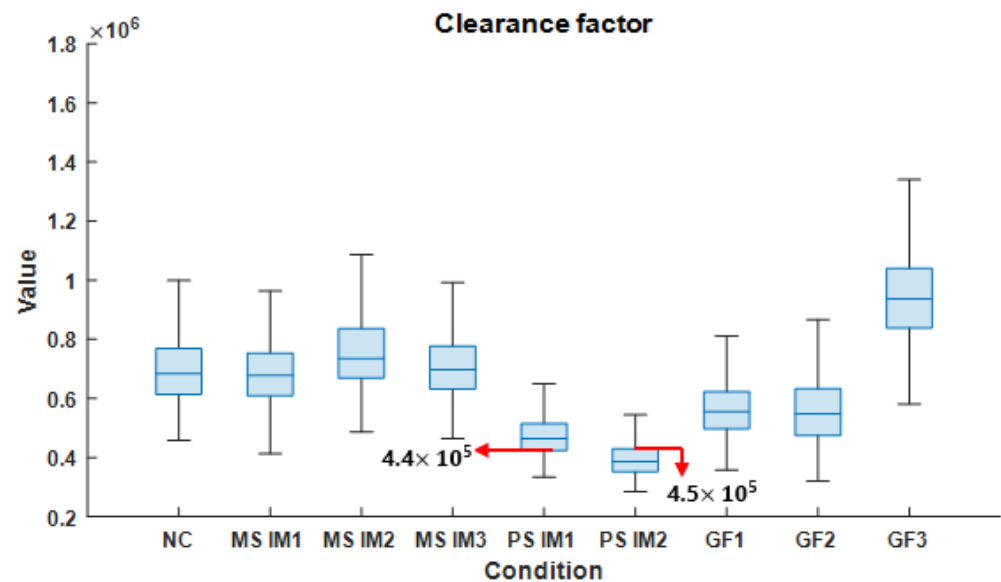


Figure 19. Clearance factor distribution according to condition.

Figure 20 shows the data distribution for the skewness feature for each fault mode. Skewness shows differences in data distribution in main shaft imbalance, but the data are almost similar to pinion shaft imbalance. When using skewness, it is believed that effective diagnosis will be possible by using another feature that shows clear differences in main shaft imbalance and pinion shaft imbalance at the same time.

The trends of normal condition data and fault data obtained through the test bed were confirmed through the error bar chart of the time domain feature. Differences in data could be confirmed in a number of features for pinion shaft imbalance and gear fault, but main shaft imbalance showed relatively small differences.

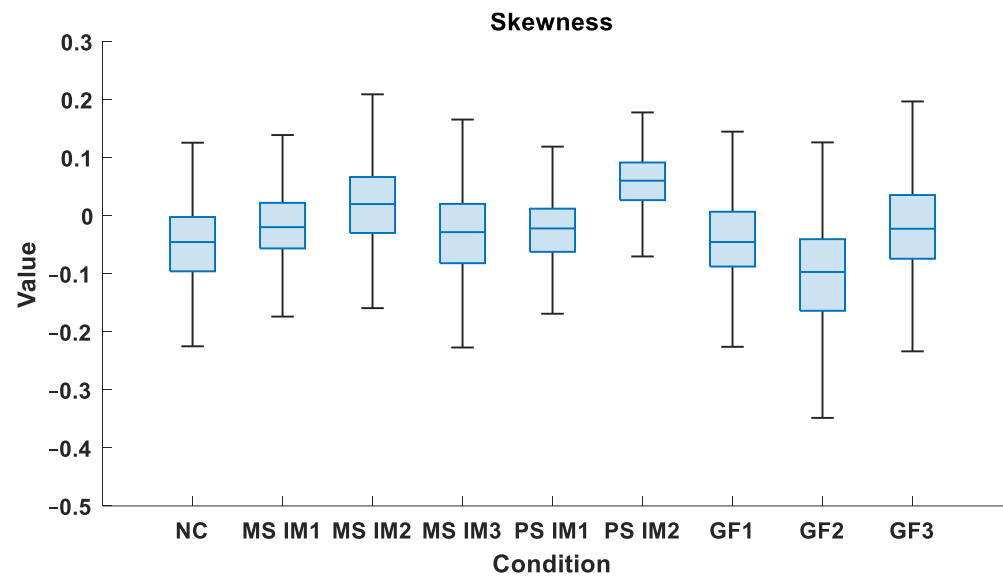


Figure 20. Skewness distribution according to condition.

5.3. Data Using Case

In this study, a simple fault diagnosis model was developed using the test bed to show the usefulness of the data. When developing a fault diagnosis model using machine learning, the amount of data affects the performance of the model, so techniques to increase the amount of data have been studied [37–39]. When diagnosing rotating machinery using vibration signals, there is often a lack of sufficient data. Therefore, various studies have been conducted on segmenting the data or using algorithms to generate data. The performance of the model varies depending on the segmentation size, with higher performance observed when the data is segmented in sizes related to the rotation period [40]. In this paper, the data sample acquired at 2300 rpm was segmented into 0.52 seconds, 1.04 seconds, 2.08 seconds, and 3.12 seconds, which are the sizes corresponding to the reciprocal of the rotation period, and considering the limitations of model performance and data amount, data of 1.04 seconds were used. We generated 9000 data samples of that size and used them for machine learning. One data sample contains 40 cycles.

The fault diagnosis model was developed using all 12 time domain features presented previously and used the KNN (k-nearest neighbor) algorithm. The KNN algorithm classifies based on the distances to neighboring data points [41]. The fault diagnosis model was trained using MATLAB classification toolbox. Out of the 9000 data samples obtained through data augmentation, 8100 were used as training data and 900 were used as validation data.

Figure 21 shows the structure of the developed fault diagnosis model. The developed fault diagnosis model operates with the initial step of inputting test data into the model, where the first classification model determines the presence of faults. In the second step, the data classified as faulty are entered into a model that classifies the type of fault. Subsequently, the data classified by the type of fault are entered into models that classify the level of each fault. This process ultimately leads to the final diagnosis of faults. Table 7 summarizes the performance evaluation metrics of the step-wise classification models.

Table 7. Results of fault diagnosis model (%).

Model	Accuracy	Precision	Recall	F1 Score
Fault Detection	97.80	92.01	98.81	95.28
Case Classification	99.87	99.83	99.88	99.86

Table 7. Cont.

Model	Accuracy	Precision	Recall	F1 Score
MS_IM	88.42	88.95	88.07	88.50
PS_IM	98.50	98.54	98.50	98.51
GF	94.91	95.08	94.91	95.00

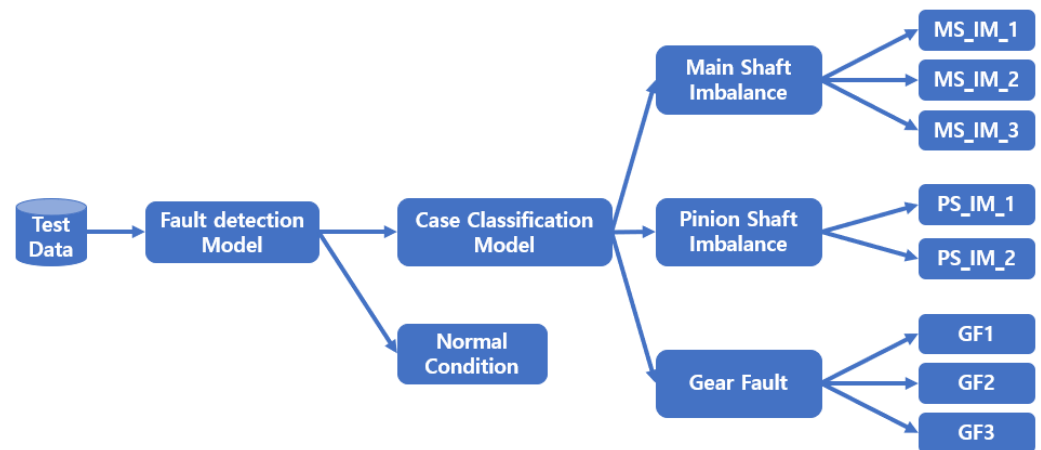


Figure 21. Fault diagnosis model structure.

The performance of the developed model is calculated using a confusion matrix: TP (true positive), TN (true negative), FP (false positive), and FN (false negative). The calculation formula is as follows:

$$\text{Accuracy}(\%) = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (6)$$

$$\text{Precision}(\%) = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (7)$$

$$\text{Recall}(\%) = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (8)$$

$$\text{F1 - score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

As shown in Table 7, we observe that the performance of the first-step model, which determines the presence of faults in the system, exhibits an accuracy of over 98%. The model for classifying the type of fault in the second step exhibits higher accuracy—99%. Even though classification for the MS_IM1 is still lower than 80%, classification for MS_IM1 and MS_IM3 was successfully conducted. Moreover, the pinion shaft imbalance and gear fault classification models exhibit high accuracy.

The diagnostic model developed in this study was created using the most basic machine learning algorithm to validate the vibration data obtained through the test bed. It is believed that developing the model using the latest technology, which provides various theoretical innovations, and undergoing additional data preprocessing will result in improved performance.

6. Discussion

The developed test bed can implement not only single-component faults but also various types of faults that occur in rotating machines. Therefore, combined fault data can be obtained, such as combinations of gear fault and bearing faults, combinations of imbalance and impeller faults, etc. Additionally, the developed test bed differs from the widely used CWRU dataset, which focuses on providing vibration data specifically for bearing faults.

The CWRU dataset basically provides bearing fault data acquired at 1700 rpm. Data are in MATLAB format. Data are acquired at 12,000 and 48,000 sampling rates and provided at different levels of faults in the bearing inner race, outer race and elements. The CWRU dataset differs from the test bed developed in this study in that 16 accelerometers were used to analyze the fault location and level for bearing fault diagnosis.

During scaling of the test bed, we simplified the rotor system by eliminating one pinion gear shaft. Due to this limitation, we cannot simulate composite gear-mesh conditions on both sides of the main shaft. However, even with a single gear mesh, we believe that the test bed can reflect the coupling effect of lateral vibration and torsional vibrations.

By analyzing the fault data from the test bed, we found that it is difficult to classify faults using only time series raw data or FFT of vibration signals due to insignificant signal levels in each fault condition. However, in terms of data validation, there are clear differences in features in different fault conditions, except the main shaft imbalance case. Differences between normal condition, pinion shaft imbalance, and gear fault could be confirmed in four time domain features related to collision of rotating machines. Additionally, skewness showed differences between normal condition and main shaft imbalance data, but these data showed a similar trend to pinion shaft imbalance. This implies that the faults in the target system can be detected and classified using the simple classification method, but to detect the main shaft imbalance condition, a more sophisticated algorithm is needed. This was found in the results from the classification example. In this study, we applied stepwise diagnosis to enhance classification performance. In further research, more enhanced diagnosis algorithms should be investigated to solve the limitations of the current classification method.

In this study, we provided only vibration signals for fault detection and diagnosis. However, additional motor information (torque, current), temperature, and orbit on the test bed can be obtained from the test bed. Thus, we can use additional data for fault diagnosis and not only vibration data in the future. Moreover, if quantities of data increase through repeating tests, a fault database can be used not only for fault diagnosis but also for useful life prediction considering combinations of faults. And, Some of the fault data collected has been provided in the Supplementary Materials.

7. Conclusions

In this paper, to address the challenge of obtaining fault data for condition monitoring of rotating machinery, a test bed simulating real rotating machinery was developed to acquire fault data. Previous test beds have limitations in providing fault data only for single components of rotating machinery. To overcome this shortcoming, a test bed that can simulate various fault modes occurring in rotating machinery was designed for simulating LNG re-liquefaction systems installed on ships.

When we designed the test bed, scaling work was performed while maintaining the dynamic characteristics of the rotor in order to simulate the vibration signal of the real system. In addition, the developed test bed can simulate various fault modes that can occur in rotating machines with gearboxes and multiple shafts, such as mass imbalance, shaft misalignment, bearing fault, gear fault, and impeller fault.

To validate the obtained vibration data, data were obtained by conducting experiments on main shaft imbalance, pinion shaft imbalance, and gear faults, including normal conditions. The obtained vibration data were for grouping and validation based on the representative features of the vibrational signals. When the distribution of the 12 features was examined using an error bar chart, distinct differences were observed for each fault mode. However, it appears insufficient to classify the levels of main shaft imbalance. Therefore, a simple diagnostic model suitable for using the data obtained from the test bed was developed and its performance was evaluated. The developed diagnostic model was supplemented with a stepwise model to improve the classification of main shaft imbalance. The model achieved accuracy of 97.8% for fault detection and 99.8% for fault classification. Ad-

ditionally, for the main shaft imbalance, which was expected to perform poorly, the model demonstrated performance of 88%.

The test bed developed in this paper is considered one solution to address the limitations of existing fault simulation equipment, which often target specific components of rotating machinery. It is expected to simulate faults with various levels, enabling not only condition monitoring but also remaining useful life (RUL) prediction techniques. If the correlation between acquired fault data and measured data from real systems is established in the future, the fault database obtained through the test bed can be utilized for developing condition monitoring techniques for real systems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse12060917/s1>, Data for the 9 conditions mentioned in the main text is provided. The data samples are raw data collected over 1 minute, and the file format is CSV. The file names include the type of fault and the level.

Author Contributions: D.M.K.: conceptualization, methodology, validation, investigation, writing; S.H.K.: validation, investigation, writing; H.M.S.: methodology, investigation; S.J.K.: methodology, validation, investigation, writing, supervision, project administration. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Table A1. Nomenclature in the manuscript.

Symbol	Description	Symbol	Description
BLDC	brushless DC motor	TEU	twenty-foot equivalent unit
BOG	boil-off gas	$\bar{C}$	constant number
BPFI	ball pass frequency inner race	D_1	rotor shaft diameter
COMP	compressor	D_2	rotor disk diameter
E	young's modulus	I_{Bull}	bull gear rotational inertia
EXP	expander	I_{eq}	equivalent rotational inertia
FFT	fast Fourier transform	I_{main}	main shaft rotational inertia
FMEA	failure mode and effect analysis	I_{Pinion}	pinion shaft rotational inertia
GAN	generative adversarial network	$I_{Pinion\ gear}$	pinion gear rotational inertia
GF	gear fault	l	shaft length
ISO	International Organization for Standardization	N_{Bull}	number of bull gear teeth
KNN	k-nearest neighbor	N_{Pinion}	number of pinion gear teeth
NC	normal condition	ρ	density
LNG	liquified natural gas	R_{cr}	critical speed margin
MS_IM	main shaft imbalance	ω	rotational speed
RPM	revolutions per minute	ω_{cr}	critical speed

Table A2. Summary of fault simulation equipment in previous research.

Name	Target	Provided Data Type	Shaft Speed (rpm)
Qiang's [27]	High-speed ceramic ball bearing	Vibration/temperature	10,000–50,000
RS3M1 [28]	Centrifugal compressor rotor	Vibration	6500
PRONOSTIA [29]	Rolling bearing	Vibration	2830
MFS [30]	Parallel misalignment	Vibration	2000
CWRU [31]	Rolling bearing	Vibration	1700
IMS [32]	Rolling bearing	Vibration/temperature	2000

Appendix A.1. Dataset Description

This dataset was collected at an advanced powertrain laboratory at Chungnam National University. The purpose of the test bed is to collect vibration data on fault modes that may occur in a rotating machine where two shafts are connected by gears.

Appendix A.1.1. General Information

- Main shaft: length 0.8 m, diameter 0.025 m
- Pinion shaft: length 0.39 m, diameter 0.017 m
- Bull gear: diameter 0.22 m, number of teeth: 50
- Pinion gear: diameter 0.15 m, number of teeth: 34
- BLDC motor: TM13-A2033-S-4P-Z (max speed 3000 rpm, max torque 6.34 Nm)
- 2 roller bearing (SKF NJ203, NJ205), 2 ball bearing (SKF 16005, 16003)
- Four accelerometers are mounted in the bearing housing, PCB piezotronics 333B30 IEPE-type
- AHB-203A (max torque 2 Nm, max speed 20,000 rpm)—hysteresis brakes load the aerodynamic force at both ends of the pinion shaft
- Data acquisition system: NI-USB 6001
- Fault modes: main shaft imbalance, pinion shaft imbalance, shaft misalignment, gear fault, bearing fault, impeller fault

Appendix A.1.2. Data Description

The data were acquired at a constant speed of 2300 RPM with a sampling rate of 6000 Hz. A summarized dataset is presented in Table A3.

Table A3. Dataset description.

	Number of Files	Duration of Recording	Channel	Fault Mode	Brake Torque (Nm)
Dataset 1	10	1 min	1	Normal	-
Dataset 2	6	1 min	1	MS_IM (0.204 kg·cm)	-
Dataset 3	6	1 min	1	MS_IM (0.408 kg·cm)	-
Dataset 4	6	1 min	1	MS_IM (0.41 kg·cm)	-
Dataset 5	6	1 min	1	PS_IM (0.132 kg·cm)	-
Dataset 6	6	1 min	1	PS_IM (0.264 kg·cm)	-
Dataset 7	6	1 min	1	GF (half tooth damaged)	-
Dataset 8	6	1 min	1	GF (1 tooth damaged)	-
Dataset 9	6	1 min	1	GF (3 teeth damaged)	-
Dataset 10	10	1 min	2	Normal	-

Table A3. Cont.

	Number of Files	Duration of Recording	Channel	Fault Mode	Brake Torque (Nm)
Dataset 11	6	1 min	1	MS_IM (0.204 kg·cm)	-
Dataset 12	6	1 min	1	MS_IM (0.408 kg·cm)	-
Dataset 13	6	1 min	1	MS_IM (0.41 kg·cm)	-
Dataset 14	6	1 min	1	PS_IM (0.132 kg·cm)	-
Dataset 15	6	1 min	1	PS_IM (0.264 kg·cm)	-
Dataset 16	6	1 min	1	GF (half tooth damaged)	-
Dataset 17	6	1 min	1	GF (1 tooth damaged)	-
Dataset 18	6	1 min	1	GF (3 teeth damaged)	-

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