Hindawi
Structural Control and Health Monitoring
Volume 2024, Article ID 6150717, 14 pages
https://doi.org/10.1155/2024/6150717

Research Article

Development of Rotor Balancing Algorithm for a High-Precision Rotor System considering Dynamic Reliability through Automatic-Adaptive DBSCAN

Joon Ha Jung,[1] **Byungock Kim**,[2] **Woong Jae Na**,[3] **and Yun-ho Shin**[4]

[1]*Department of Industrial Engineering, Ajou University, Yeongtong-gu, Suwon 16499, Republic of Korea*
[2]*Department of System Dynamics, Korea Institute of Machinery & Materials, Yuseong-gu, Daejeon 34103, Republic of Korea*
[3]*Global Core Research Center for Ships and Offshore Plants, Pusan National University, Busan 46241, Republic of Korea*
[4]*Department of Naval Architecture & Ocean Engineering, Pusan National University, Geumjeong-gu, Busan 46241, Republic of Korea*

Correspondence should be addressed to Yun-ho Shin; shinyh77@pusan.ac.kr

Received 20 February 2023; Revised 26 November 2023; Accepted 27 December 2023; Published 16 January 2024

Academic Editor: Suparno Mukhopadhyay

Recently, the demand for high-precision balancing of rotors has increased in the automobile industry, as more rotors are designed to rotate at ever-higher speeds to maximize energy efficiency. The accumulation of measurement uncertainty in the balancing process decreases the accuracy of the unbalanced mass estimation, which is the ultimate goal of balancing. Here, the problem of uncertainty is shown through a Monte Carlo simulation of signals acquired from an actual production line. To reduce the effect of measurement uncertainty in the balancing procedures, a signal-processing technique that increases the dynamic reliability of the signal is proposed. The suggested method is based on density-based spatial clustering of applications with noise (DBSCAN) with the use of the orthogonality-based averaging method. Specifically, by adjusting radius values while clustering samples through the use of the DBSCAN method, the outliers that arise due to uncertainty are successfully removed. In this work, our proposed automatic-adaptive DBSCAN (AA-DBSCAN) method is validated by applying it to a balancing machine used for blower rotors in fuel cell electric vehicles. The results show that the deviation of the extracted influence coefficients is up to 0.0050, whereas the proposed method reduced it to less than 0.0037. In addition, the suggested procedure reduced the deviations of the unbalanced mass phase estimation by 35.2% as compared to the results found by the conventional method. Consequently, through the validation test, the suggested method was found to have the largest vibration decrease of any method considered in the study.

1. Introduction

Recently, the requirements for a high-precision balancing approach have become more urgent due to the paradigm shift of transportation methods that use electricity or hydrogen. In addition, advances of the semiconductor industry have enabled the realization of high-precision integrated circuits. In general, balancing is carried out in a way that measures the amount of balancing while rotating the rotating body to be balanced using a driving unit and by performing the balancing through the application of a counter mass or by cutting [1, 2]. Because uncertainties, such as driving unit control, power transmission, and sensor uncertainties, are inherently included in this process, a deviation in the balancing results is inevitable, even in tests under the same conditions. Attempts to reduce these uncertainties have been consistently explored in the signal processing field [3]; however, most of them have used the method of removing the uncertainty by using the concept of the average through continuous repeated tests to satisfy the criteria. As an alternative, signal processing methodologies have also frequently sought to estimate and remove uncertainty by adding a measuring point or balancing conditions.

The most frequently used method for balancing a rotor system is to rotate the master specimen at a constant speed, derive the influence coefficient from it, and then estimate the amount and position of unbalanced mass of the target specimens based on this information [4, 5]. In addition, a method of balancing using a waterfall chart, which extracts vibrations from a variable-speed system, is also widely used [6, 7]. Similar to the influence coefficient method, a technique for on-site field balancing has been developed, as well, and has been used for a system in its assembled state [8, 9]. Still, researchers seek a balancing method in two primary areas: improvement in balancing accuracy and reduction in balancing time. However, the common pursuit of all of these existing balancing methods is to develop and apply a method that maximizes the accuracy of balancing because balancing is directly related to the life cycle of the rotor system. In addition, developers of balancing machines have traditionally applied their own knowledge to satisfy their customer's requirements, with no incentive to disclose methodologies more broadly. That said, various signal processing methodologies have been studied to improve the estimation accuracy of the balancing. Studies on balancing that consider the measurement uncertainty [10], the amplitude and phase uncertainty of the vibration signal based on the fuzzy theory [11–13], and the uncertainty of the weight and position of the balancing weight have been conducted in prior work [14]. In addition, research has been accomplished to develop active balancing technology according to the rotating speed, examining the influence coefficients by using the driving unit and feedback control; however, the focus has been on the design of the mechanical parts rather than on the dynamic-reliability-related content explored through the signal processing [15].

In this study, to extend the work of these previous studies, we apply the density-based spatial clustering of applications with noise (DBSCAN) method to remove the uncertainty accumulated in the unbalanced mass estimation process. Further, we propose to use an adaptive DBSCAN method and confirm its effectiveness through the entire process of actual balancing. The adaptive DBSCAN approach is modified to automatically define the two hyperparameters: the minimum number of data to form a core group and the density radius value. For the conventional DBSCAN method, the two hyperparameters should have been defined manually, which requires several trials. In contrast, the proposed automatic-adaptive DBSCAN (AA-DBSCAN) determines the two hyperparameters automatically to remove outliers. While studies related to adaptive DBSCAN have been ongoing recently with other researchers [16–18], few studies have been conducted with the goal of eliminating measurement uncertainty in rotating systems or balancing machines; important issues remain to be solved.

In this study, for the purpose of high-precision balancing, the design of the accelerometer-based measuring unit in a balancing machine is proposed, and the vibration characteristics and equipment operation range are analyzed. In addition, in the balancing process, the measurement uncertainty accumulation is analyzed/explained using Monte Carlo simulations. Although the orthogonality-based average method [19], which is one of the previously proposed uncertainty removal methods, is applied, it is confirmed that the reproducibility was very low by examining the repeated measurement results of the test specimens when the balancing amount was computed. This low reproducibility is due to the accumulation of uncertainty from the measurements of the master specimen in the work of determining the influence coefficients. To resolve this phenomenon, a signal processing procedure that can increase the dynamic reliability of signals is proposed to mitigate measurement uncertainty, as suggested for adaptive DBSCAN when orthogonality-based average methods are applied. In addition, a case study is explored to verify that the dynamic reliability of the measured signal can be improved while the measurement uncertainty is decreased using the proposed technique, and it was confirmed that uncertainty can be alleviated when the suggested procedure in this study is applied.

The remainder of this paper is structured as follows. In Section 2, the measuring unit for a balancing machine is designed, and its performance and uncertainty are discussed. In Section 3, the dynamic reliability enhancement methodology, including the automatic-adaptive DBSCAN approach is proposed. In Section 4, the proposed method's effectiveness is verified through the examination of a case study of a standard specimen. In Section 5, conclusions are offered.

2. Design and Uncertainty Analysis of the Measuring Part in a Balancing Machine

2.1. Design of the Measuring Part in a Balancing Machine. Briefly, the measuring part of a balancing machine is composed of a belt-driving part, a sensing part, and an isolating part. The belt-driving part is in charge of the rotational excitation to generate centrifugal force due to unbalance; the sensing part is the part that measures the vibration signal generated by the centrifugal force. Lastly, the isolating part is an element that is designed to block unintended vibration that may be measured in the sensing part. The detailed configuration of the measuring part of the balancing machine used in the study was designed and manufactured as shown in Figure 1(a), with consideration of manufacturing convenience, compact configuration, and improved isolation performance. The designed balancing machine integrates a steel frame and stone plate with one isolating part to maximize the isolation performance. The sensing part in the balancing machine was designed in the form of a thin beam to minimize the disturbance and other directional modes, except for the measured axis. Table 1 describes the detailed design specifications of the driving part, sensor part, and isolation part.

In a design process of a balancing machine, the natural frequencies of a balancing machine should be considered. If the two frequencies are located closely, the accuracy of an unbalance estimation of a rotor may decrease due to resonance. Thus, to test if natural frequencies of the balancing machine do not overlap with the operation frequency, an impact hammer test was performed. Figure 2 presents the location of the sensors for the impact hammer test. A frequency response function (FRF) of each signal from each

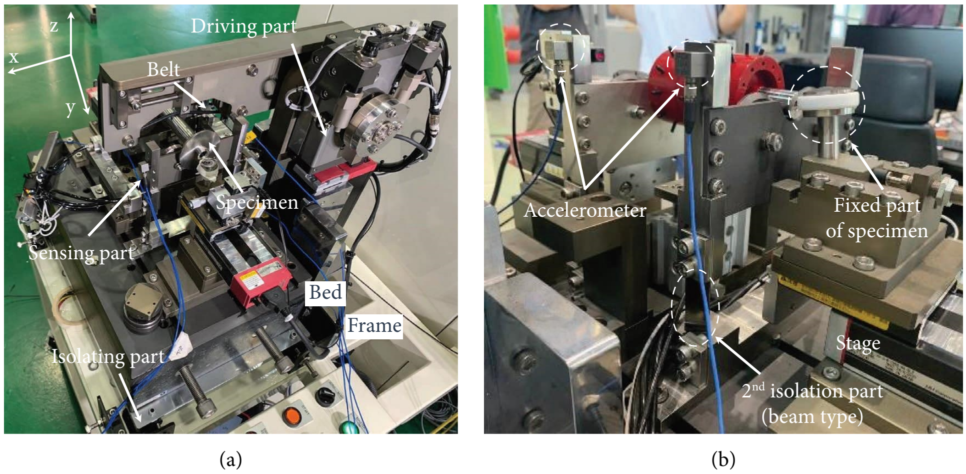

Figure 1: Measuring part of the balancing machine: (a) belt-driving, sensing, and isolation parts and (b) sensing part.

sensor is shown in Figure 3. The result shows that the natural frequencies of all sensors are not close to the target rotation frequency, which is 55 Hz in this study.

Acceleration was chosen as the quantity for deriving the amount of vibration induced by the unbalanced mass. Measurement of acceleration has advantages, such as convenience of sensor installation and lightweight sensors; here, an accelerometer with a sensitivity of 500 mV/g was selected as the sensor for the sensing part. The sampling frequency was determined as 50 kHz, considering the reliability of the measured data and the aliasing effect. Two measurement locations were chosen; they are indicated as planes 1 and 2 as shown in Figure 4. The overall process for estimating the amount of unbalance through appropriate signal processing from the rotation of the belt-driving part with the specimen is shown in Figure 5.

For such a balancing problem, which has two correction planes with two vibration sensors at a single rotation speed, at least four measurements are required, including the extraction of the influence coefficient using a master specimen. During the measurements, uncertainty at each test could accumulate. In Section 2.2, the accumulation of measurement uncertainty that happens when estimating the unbalance using the manufactured measuring part is explained, and the detailed signal processing procedures proposed to improve it are outlined in Section 3.

2.2. Measurement Uncertainty Analysis of the Balancing Machine

2.2.1. Influence Coefficient Method (ICM). The influence coefficient method is widely used to measure the unbalance of a rotor. The influence coefficient method is based on the assumption of linearity between the influence coefficient and the vibration response. The influence coefficient is defined as the effect of a unit's unbalanced mass on the magnitude and phase of the vibration signal. The coefficients can be a single value or a matrix of multiple values, according to the number of balancing (correction) planes (N), the number of vibration measurement points (M), and the number of rotation speeds (O). Balancing (correction) plane indicates an axial position of a rotor where a correction mass can be placed, and the measurement point denotes a number of sensors attached to a balancing machine. To obtain the influence coefficient, the magnitude and phase of the rotational speed component (1X) are extracted from the measured vibration response. The

Table 1: Specifications of the measuring part of the balancing machine.

Items	Specifications	Quantities
Actuator (rotor)	1,000 rpm~5,000 rpm	1 EA
Accelerometer	PCB 333B40 500 mV/g	2 EA
Correction plane	Front and rear	2 EA
Measurement plane	Front and rear beams	2 EA

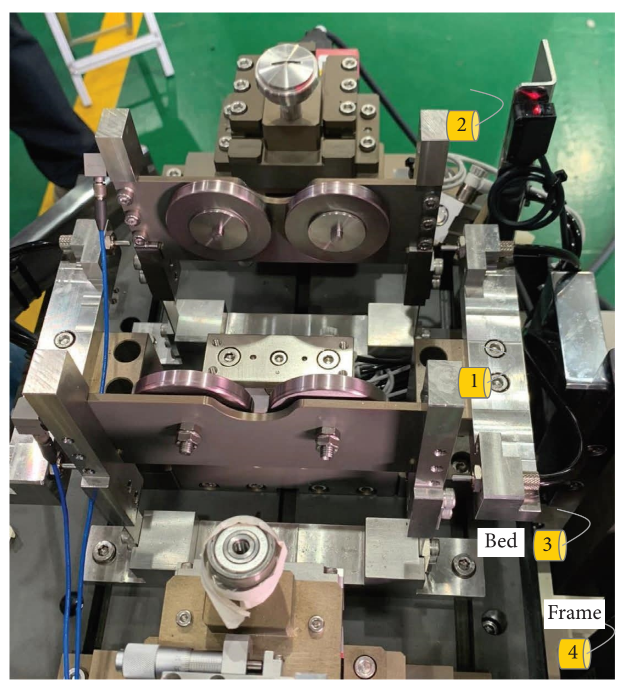

Figure 2: Experimental setup for impact hammer test of the balancing machine.

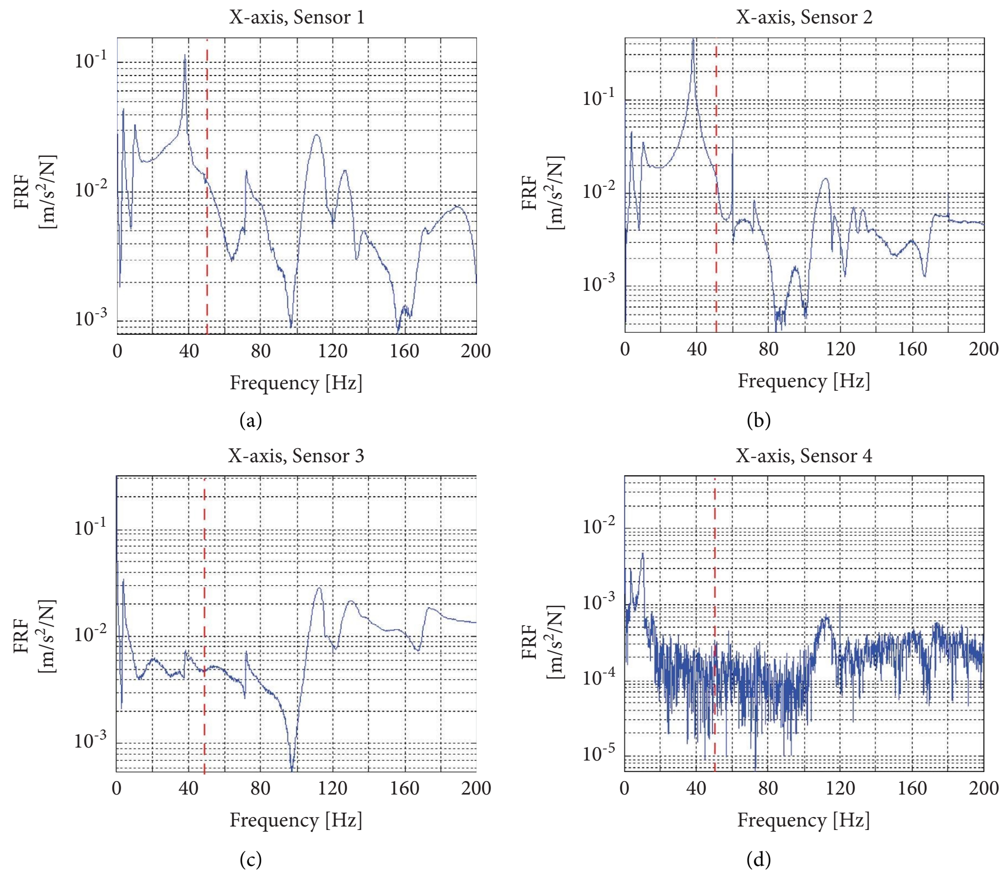

Figure 3: Frequency response of impact hammer test: (a) sensor 1, (b) sensor 2, (c) sensor 3, and (d) sensor 4.

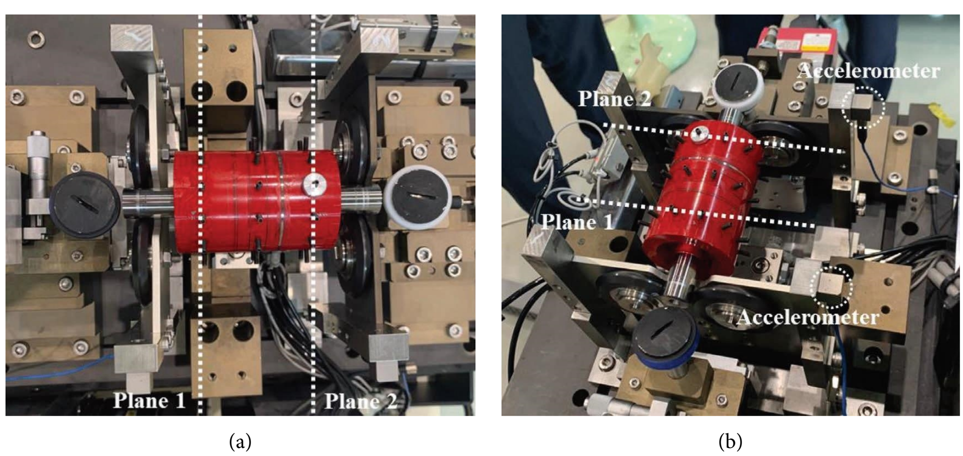

Figure 4: Sensing part of the balancing machine, including correction planes 1 and 2.

unbalanced mass (m_u) of the rotating body generates an excitation force with the rotational speed (ω) of the vibration signal by $F = m_u e\omega^2$. The equation shows the linear relationship between the unbalanced mass and the excitation force (vibration), which indicates a linear relationship between the vibration response and the unbalanced mass as well. Note that any vibration signals including displacement, velocity, and acceleration can be used because the ICM uses the relative effect of signal vectors.

The balancing method that uses the influence coefficient has been widely used for large turbomachinery, such as turbines and compressors. Similarly, the method is also used in small-scale rotors with faster rotational speeds, where short production time is required. For example, turbochargers of automobiles, which are produced in a significantly large quantity, use the influence coefficient method to reduce the production time. Regardless of the application, the principle of the influence coefficient method is identical.

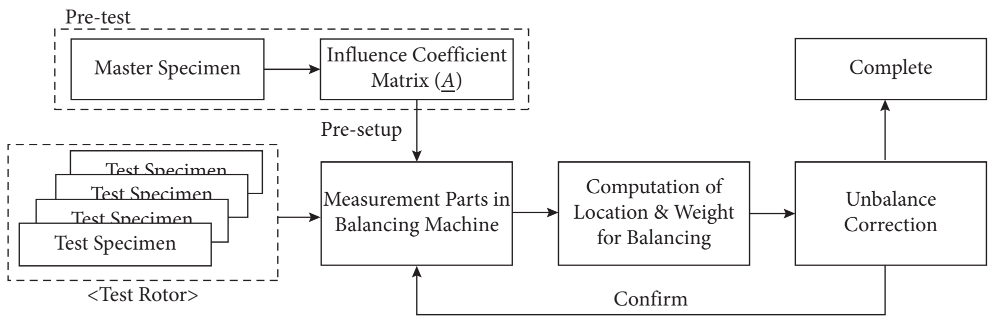

Figure 5: Procedure for estimation of the unbalanced mass of the rotor.

For example, the balancing procedure of 2 correction planes (N) and 2 measuring points (M), at a single rpm (O), by the influence coefficient can be described as follows. First, the vibration response at the initial state is obtained and presented as follows:

$$\vec{\mathbf{V}}_O = \left(\vec{V}_{1O}, \vec{V}_{2O}\right), \tag{1}$$

where $\vec{\mathbf{V}}_{iO}$ denotes vibration response in complex form at the i^{th} measuring point. The magnitude of a vibration response vector is defined by the magnitude of 1X frequency, and the phase of a vibration response vector is defined by the absolute phase of 1X frequency with respect to a key phasor signal. Then, a trial mass (m) is placed at correction planes a and b, sequentially. The vibration response at each trial is defined as $\vec{\mathbf{V}}_a$ and $\vec{\mathbf{V}}_b$, respectively, and the response can be described as shown in the following equations:

$$\vec{\mathbf{V}}_a = \left(\vec{V}_{1a}, \vec{V}_{2a}\right), \tag{2}$$

$$\vec{\mathbf{V}}_b = \left(\vec{V}_{1b}, \vec{V}_{2b}\right). \tag{3}$$

Next, the influence coefficient matrix (ICM) is derived by the following equation:

$$\mathbf{A} = \begin{bmatrix} \vec{\alpha}_{1a} & \vec{\alpha}_{1b} \\ \vec{\alpha}_{2a} & \vec{\alpha}_{2b} \end{bmatrix} = \begin{bmatrix} \dfrac{\left(\vec{V}_{1a} - \vec{V}_{1o}\right)}{m}, & \dfrac{\left(\vec{V}_{1b} - \vec{V}_{1o}\right)}{m}, \\ \dfrac{\left(\vec{V}_{2a} - \vec{V}_{2o}\right)}{m}, & \dfrac{\left(\vec{V}_{2b} - \vec{V}_{2o}\right)}{m}, \end{bmatrix}, \tag{4}$$

where $\vec{\alpha}_{ix}$ is the influence coefficient of a unit weight on the x correction plane at the i^{th} measuring point. As the ICM is derived from three trials, the magnitude and angle of unbalanced mass and of an identical rotor can be estimated through the inverse ICM, which is stated in the following equation:

$$\mathbf{A}^{-1} \times \vec{\mathbf{V}}_t = \begin{bmatrix} \vec{\alpha}_{1a}, & \vec{\alpha}_{1b}, \\ \vec{\alpha}_{2a}, & \vec{\alpha}_{2b}. \end{bmatrix}^{-1} \left[\vec{V}_{1t} \quad \vec{V}_{2t}\right]^T, \quad \text{where } \vec{\mathbf{V}}_t = \left(\vec{V}_{1t}, \vec{V}_{2t}\right). \tag{5}$$

In equation (5), $\vec{\mathbf{V}}_t$ is the vibration response of the test specimen.

2.2.2. Effect of Measurement Uncertainties in ICM. The ICM method is widely used in many industries to estimate the unbalanced mass of a rotor. To calculate ICM, magnitude and phase at a rotational speed frequency (1X magnitude and phase) from the vibration signals are required by fast Fourier transform (FFT). However, measurement of vibration signals always includes uncertainty. As measurement uncertainty exists in every vibration measurement, inaccurate results can be obtained if the uncertainty is not considered. For example, a turbocharger production line performs two-plane balancing of every specimen as shown in Figure 6, which is identical to the problem described in Section 2.2.1. To construct the ICM, three independent tests are required, each containing uncertainties. By randomly selecting the 1X magnitude and phase from the measured vibration signals, the unbalanced mass of a test specimen is calculated differently for each selected signal. Specifically, a considerate amount of a second long vibration signal can be extracted from a ten-second-long signal. Thus, different results are obtained for each selected vibration signal as shown in Figure 7. The result indicates that the phase of an unbalanced mass cannot be estimated precisely, as the distributions have significantly large deviations. The red dots are the three results estimated on-site.

The most common method used to reduce such large deviations is to average out a few samples. However, averaging can still lead to a biased estimated result if the test condition is not steady. For turbochargers, only a short period of time is allowed in mass production lines, which are capable of extracting only a few samples of 1X magnitude and phase. Estimation of the unbalanced mass by a small number of samples may lead to biased results.

Obviously, not all rotors are affected by the measurement uncertainty. However, as the size of the rotor gets smaller and the speed faster, even a small amount of uncertainty can

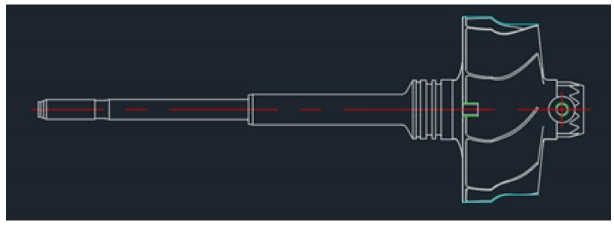

Figure 6: Drawing of a turbocharger test specimen.

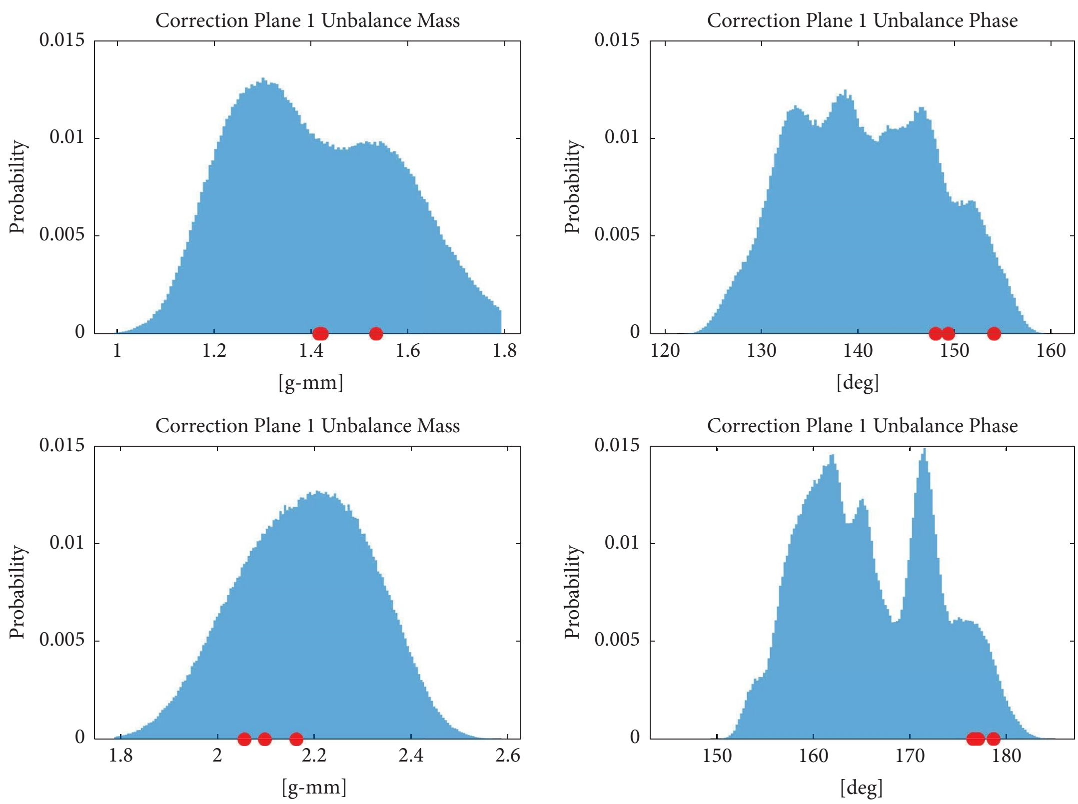

Figure 7: Unbalanced mass calculation by random selection for a turbocharger.

decrease the accuracy of the unbalanced mass estimation. Thus, the next section suggests a novel method to reduce the uncertainty of vibration signals.

3. Suggestion of a Dynamic Reliability Enhancement Methodology for a Balancing Machine

3.1. Overall Scheme. As a signal-processing method to eliminate the measurement uncertainty (as described in Section 2.2), this study proposes a signal-processing method that consists of the following three steps. First, by using the orthogonality between the sine function of the fundamental frequency and measured acceleration signal, the amplitude and phase of the fundamental frequency component at planes 1 and 2, corresponding to the rotational speed, are computed. Secondly, the amplitudes and phases at planes 1 and 2 are regarded as features and performed principal component analysis (PCA) to distinguish them more clearly. Each feature was normalized using the standard deviation and mean value of the four features, and then a principal axis transformation was performed. Thirdly, by using the adaptive-clustering method, we estimate the amplitudes and phases in the representative group with relatively high density for four features composed of the vibration amplitude and phase information calculated from two planes. This makes it possible to eliminate the uncertainty of the measured signals where a relatively high noise level exists but where high precision is still required. The overall procedure for signal processing is summarized in Figure 8.

3.2. Orthogonality-Based Average (OBA) Method. The orthogonality of the sine function is the basis of the Fourier transform. The orthogonality-based filtering can extract a specific frequency component of a signal by multiplying the original signal with two reference signals: a sine signal and a cosine signal of a specific frequency. Other frequency components will sum up to zero value when a signal is

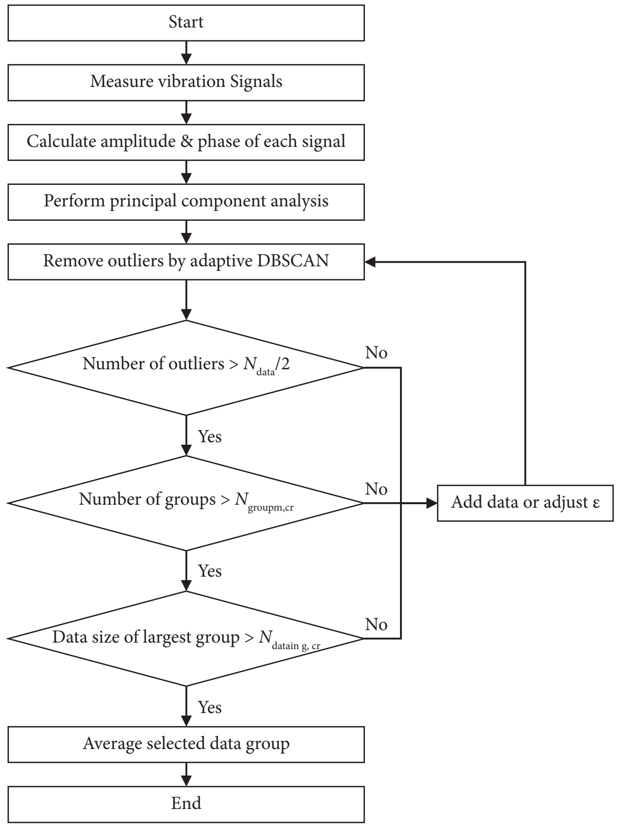

Figure 8: Overall procedure for signal processing with the proposed adaptive-clustering method.

multiplied with the reference sine and cosine signals. Thus, the "orthogonality-based filtering" will remove all frequency components except the frequency component of a reference signal. Using this characteristic, the rotational frequency component of the rotor can be extracted from the vibration signal. First, the signal is decomposed into the cosine and sine components as described in equations (6) and (7). y_m denotes the m^{th} sample of the vibration signal, f denotes the rotational frequency, and t_m denotes the time step of the m^{th} sample. U_{cosine} and U_{sine} indicate the magnitude of the f frequency cosine and sine components of the signal y_m, respectively. Then, the squared sum of cosine and sine magnitudes can be derived as in equation (8), which is equivalent to the magnitude of the f frequency component of the signal. Also, the phase of the signal can also be derived using equation (9).

$$U_{\text{cosine}} = \frac{\sum_{m=1}^{M} \left[\cos\left(2\pi f t_m\right) \bullet y_m\right]}{\sum_{m=1}^{M} \left[\cos\left(2\pi f t_m\right)\right]^2}, \tag{6}$$

$$U_{\text{sine}} = \frac{\sum_{m=1}^{M} \left[\sin\left(2\pi f t_m\right) \bullet y_m\right]}{\sum_{m=1}^{M} \left[\sin\left(2\pi f t_m\right)\right]^2}, \tag{7}$$

$$U = \sqrt{U_c^{\,2} + U_s^{\,2}}, \tag{8}$$

$$\varphi = \arctan\left(\frac{U_s}{U_c}\right). \tag{9}$$

The orthogonality-based filtering is a very useful method when the fluctuation of the rotational speed is not significant; it computes the representative magnitude and phase by using the average value over several predefined cycles. However, when the data for a relatively long time is used, the computed value may not reflect the fluctuation characteristics. In addition, it may be difficult to estimate the exact amplitude according to the variation of the rotational force. Thus, the magnitude and phase were calculated from a vibration signal of 20 rotations of the rotor through an empirical study. Specifically, a balancing machine user inquired to reduce the balancing time, in which the maximum number of rotations included was 20.

3.3. Automatic-Adaptive DBSCAN (AA-DBSCAN). The measurement uncertainty in the results of the orthogonality-based average method still exists. This is manifested by the signal-to-noise ratio of the sensor, the speed control instability of the driving part, the bearing and belt vibration, and the floor vibration. In order to achieve high-precision balancing, which is gradually becoming more required in industrial fields, it is necessary to remove this uncertainty as much as possible and to increase the dynamic reliability of the measurement part. In this study, based on DBSCAN [20, 21], which is a widely used clustering method, a method for classifying representative values based on data in dense locations is suggested. The basic concept of DBSCAN is shown in Figure 9; it classifies the data without prior learning based on the predesigned error radius (ε) and the minimum number of data within the radius (min. pts.) based on the data at high density. Core points are defined as the center point when there are more than min pts within the error radius, and when a core point becomes part of a cluster of different core points, it becomes one cluster connected to each other. Points that belong to a cluster but cannot themselves become core points are called border points, and they mainly form the outskirts of the cluster. Points that do not belong to any cluster are defined as noise points or outliers.

Conventional DBSCAN does not input the number of groups; instead, it gradually forms groups using the design parameters, the radius, and the minimum number of data within the radius. However, in the case of balancing, it is necessary to find the hyper-parameters, the specific values of design parameters, through trial and error, according to the target specimen and the test conditions. Because the process is a very long and tedious, we propose a method of adapting the radius value so that sufficient groups are divided in the condition where the minimum number of data is fixed. The detailed procedure is described as following. First, it is checked whether the number of valid data (N_{valid}) is larger than the outlier data, as described in equation (10), and we confirmed whether the number of derived groups (N_{group}) satisfies equation (11), except for outliers. Then, as in equation (12), the radius is gradually adapted or another measured dataset is added until the condition for the number of valid data ($N_{\text{data in core group}}$) to be equal to or greater than a certain level of criteria is satisfied. That is, the loop is repeated until all conditions are satisfied, and the average of the data in the group satisfying equations (10)–(12) is calculated as a representative value.

$$N_{\text{valid}} \geq N_{\text{outlier}}, \tag{10}$$

$$N_{\text{group}} \geq N_{\text{group,cr}}, \tag{11}$$

$$N_{\text{data in core group}} \geq N_{\text{data in group,cr}}. \tag{12}$$

$N_{\text{group,cr}}$ is designed to be two or more, as the minimum number of groups, and $N_{\text{data in core group,cr}}$ is empirically selected to be 20 or more, as the minimum number of valid data. Here, an important part is the adaptation method of the ε value, which applies the concept of the Bolzano method to find the existence of a valid group. The ε value is adapted by repeating the process using half of the value of the previous ones so that it converges to a certain value where all conditions are satisfied. If equations (10)–(12) are not satisfied, while the ε value decreases to a size that is no longer meaningful (here, it is empirically selected as 0.001), the above process is repeated by adding the number of datasets. ε_{i+1} is calculated as described in equation (13) when there is a group between ε_i and ε_{i-1} as shown in Figure 10.

$$\varepsilon_{i+1} = \frac{(\varepsilon_i + \varepsilon_{i-1})}{2}. \tag{13}$$

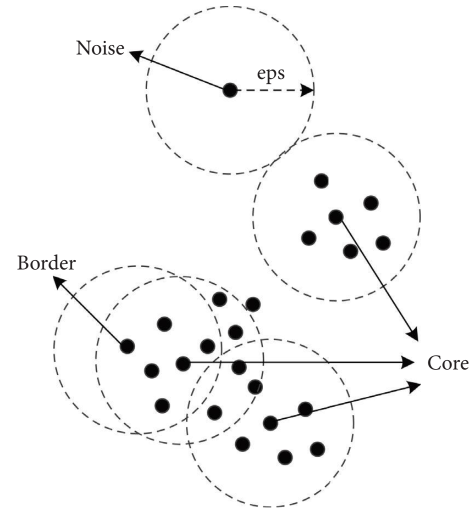

Figure 9: Basic concept of DBSCAN.

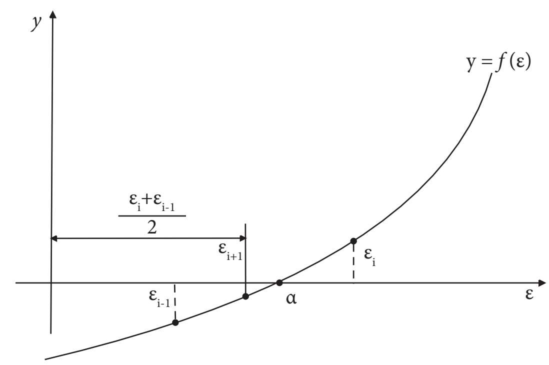

Figure 10: Description of the Bolzano method.

In the case of $i = 1$ and $i = 2$, $\varepsilon_0, \varepsilon_1$ were set to 0 and 1, respectively, and convergence was observed. Figure 11 shows the detailed description of the automatic-adaptive DBSCAN (AA-DBSCAN) methodology using a flowchart. Here, other parameters are described above except $d\varepsilon_{\text{cr}}$ and it is selected as 0.01 through trial and error method.

4. Case Study: Results and Discussion

The proposed AA-DBSCAN approach described in Section 3.3 is validated by applying it to a dataset acquired from the balancing machine. A detailed description of the balancing machine is described in Section 4.1 and results are provided in Section 4.2.

4.1. Description of the Validation Experiment. To validate the proposed method, a balancing case study was conducted, as stated in Section 2.2. The case study aims to derive the unbalanced mass of two-correction planes with the two channels of vibration signals at a fixed 3300 rpm, which makes the solution deterministic. The vibration signals were acquired using a rotor, which is shown in Figure 12. The signals were measured for five seconds only after the

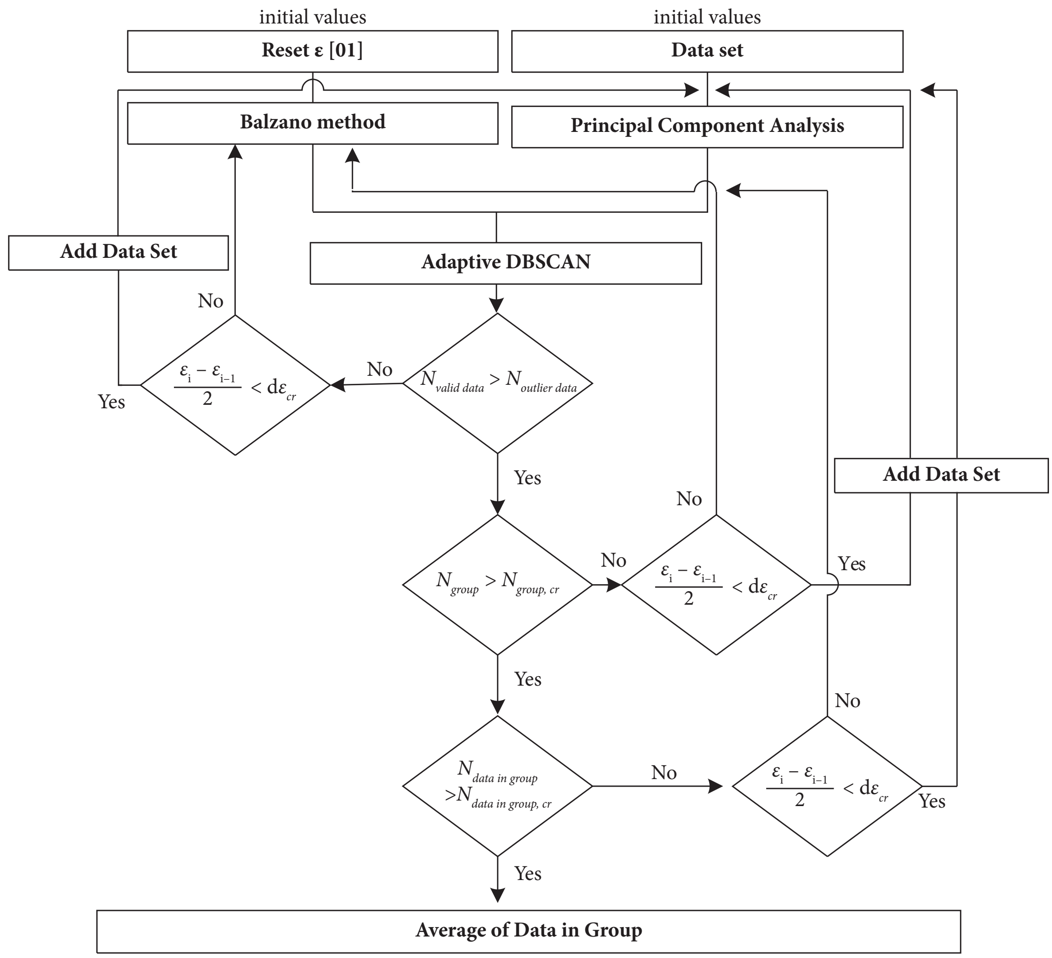

Figure 11: Detailed procedure of automatic-adaptive DBSCAN.

rotational speed of the rotor became stable using the testbed shown in Figure 2. The sampling rate of the vibration signals was set to 50 kHz, and each test was performed three times to assure the reliability of the experiment. A power spectrum density (PSD) function of vibration signals at 3300 rpm is presented in Figure 13. The PSD function presents a clear isolation frequency component at 55 Hz.

The experiment can be divided into two phases: an influence coefficient phase and a rotor unbalance estimation phase. In the first phase, three tests were performed to derive the influence coefficients of the proving rotor: an initial state, a trial mass at plane 1, and a trial mass at plane 2. All three tests were conducted three times. Using the acquired signals, AA-DBSCAN was used to extract the magnitude and the phase of the rotating frequency (1X), which is described in Section 3. Through the calculated magnitude and phase of the 1X rotational frequency, the influence coefficient of the rotor was derived. Then, in the rotor unbalance estimation phase, a different rotor, which presents a different unbalanced state, was tested. Using the influence coefficient derived from the previous phase, the unbalanced mass of the rotor was estimated. To validate the estimated unbalance mass, the calculated amount of mass is attached at the opposite direction to the estimated unbalance mass

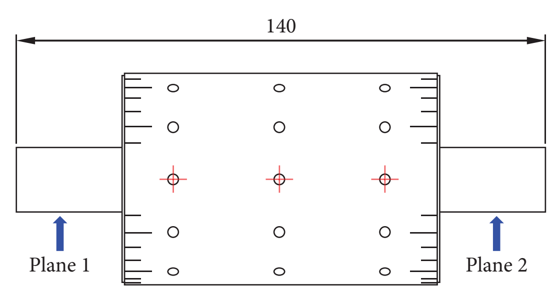

Figure 12: A drawing of the proving rotor used for the validation experiment.

direction, which will offset the unbalanced mass. If the estimated mass is accurate, the magnitude of vibration will decrease greatly as the unbalanced mass effect is compensated. Estimated unbalanced mass by each method was performed on the same test specimen, and vibration magnitudes were compared to validate the effectiveness of the proposed AA-DBSCAN method.

First, outliers of 1X magnitudes and phases of measured vibration signals were analyzed. As vibration signals encounter noises and shocks unregularly, outliers may be included in the measured signals. Most of the time, the outliers decrease the

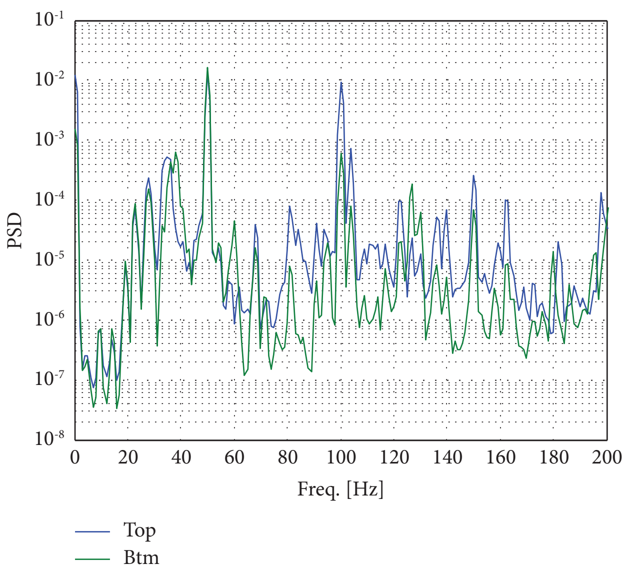

Figure 13: Power spectrum density of vibration signals at 3300 rpm.

accuracy of the unbalanced mass estimation. Thus, outliers removed by the AA-DBSCAN method were verified. Next, the deviations in the intermediate results were compared. Conventional methods do not consider the uncertainties, which cause deviations. Therefore, the scattered result of influence coefficients was compared to that of the proposed AA-DBSCAN method. Lastly, the decreased rate of vibration was compared quantitatively. Each estimated unbalanced mass was tested, and the decreased magnitude of vibration was compared. A more accurate estimate of unbalanced mass presents a larger decreased vibration magnitude.

4.2. Results and Discussion

4.2.1. Effect of Outlier Removal. Initially, three tests, summarized in Table 2, were performed to derive the influence coefficients. From the acquired five-second-long vibration signals, the amplitude and phase of 1X rotational speed were extracted every 20 cycles using the orthogonality-based averaging method. The number of possible 20 cycles within 5 seconds is 230,013, which is calculated by the following equation:

$$(50\,\text{kHz} \times 5\,\text{sec}) - 18,000 + 1 = 232{,}013. \quad (14)$$

As the number is too large to present in a figure, a few selected points of magnitude and phase of the initial state are presented. In Figures 14(a) and 14(b), two clusters are shown in green and blue colors, while red indicates outliers. By removing those outliers, the deviation can be reduced by over 30%. Among the two clusters, the one that has samples larger than 20 is selected. The results of AA-DBSCAN for the trial weight state at each correction plane are shown in Figures 15 and 16, respectively. For the trial weight states, the green cluster was selected to calculate the influence coefficient. Note that the amplitude increased significantly compared to that of the initial state as the trial weights were attached.

Table 2: Overview of test parameters for influence coefficient calculation.

Master rotor		Weight	Location	Radius
Initial	Correction plane 1	—	—	—
	Correction plane 2	—	—	—
Trial #1	Correction plane 1	0.073 gram	300 deg	28 mm
	Correction plane 2	—	—	—
Trial #2	Correction plane 1	—	—	—
	Correction plane 2	0.073 gram	180 deg	28 mm

4.2.2. Effect of Reduced Variance: Influence Coefficient Matrix (ICM). Influence coefficient matrix (ICM), **A**, is defined as the element that represents the influence of the weight of each correction plane. As the case study is defined by two correction planes with two channels of signals at a single target rotational speed, the ICM can be defined as follows:

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_{11} & \mathbf{a}_{12} \\ \mathbf{a}_{21} & \mathbf{a}_{22} \end{bmatrix}, \quad (15)$$

where $\mathbf{a}_{\mathbf{ij}}$ indicates the influence coefficient of the j^{th} correction plane on the j^{th} signal. To calculate the ICM, three tests are required: initial state and trial weight on correction plane 1 and 2 states, respectively. Uncertainty exists in each test, which leads to different ICMs, even under the same conditions. Specifically, a large deviation of ICMs may significantly decrease the accuracy of unbalanced mass estimation. Thus, the proposed AA-DBSCAN tries to estimate the unbalanced mass of the rotor by reducing uncertainties, while the conventional random selection approach estimates the unbalanced mass without reducing any uncertainties. The result of the influence coefficients is shown in Table 3. The proposed AA-DBSCAN method showed the least deviation of the influence coefficients among the methods compared in the table, which are shown in bold values. In addition, the random selection method, which used the conventional inverse notch filter to extract the magnitude and phase, showed the largest deviation of the influence coefficients.

4.2.3. Effect of Accurate Estimation of the Unbalanced Mass. The magnitude and phase of the unbalanced mass were estimated using the influence coefficient. Through a Monte Carlo (MC) simulation study, the unbalanced mass values were estimated, independently; the results are shown in Figure 17. The MC simulation selects a 0.36-second-long signal, which is equivalent to 20 cycles, randomly, from the 5-second-long signals. Since a 0.36-second-long signal corresponds to 18,000 samples, the number of selections for a unit signal from 5-second-long signal is 232,013 ($50\,\text{kHz} * 5\,\text{sec} - 18000 + 1$). Random selection of vibration signal was performed for the initial step, the trial #1 step, the trail #2 step, and the testing specimen step, which gives a significant large number of possible combinations, which is $232{,}013^4$. Thus, 10,000 were randomly selected, and the results were obtained for each method.

For both correction planes, the magnitudes of the unbalanced mass present minute differences among the three methods. However, the estimated phases raise a considerable amount of difference among the methods. Specifically, the

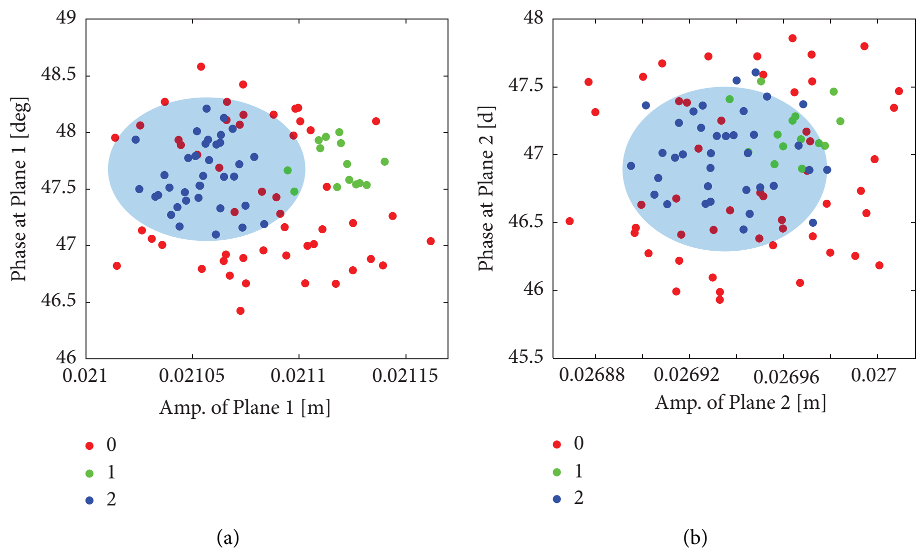

Figure 14: AA-DBSCAN results for 1X amplitude and phase at the initial state of the rotor.

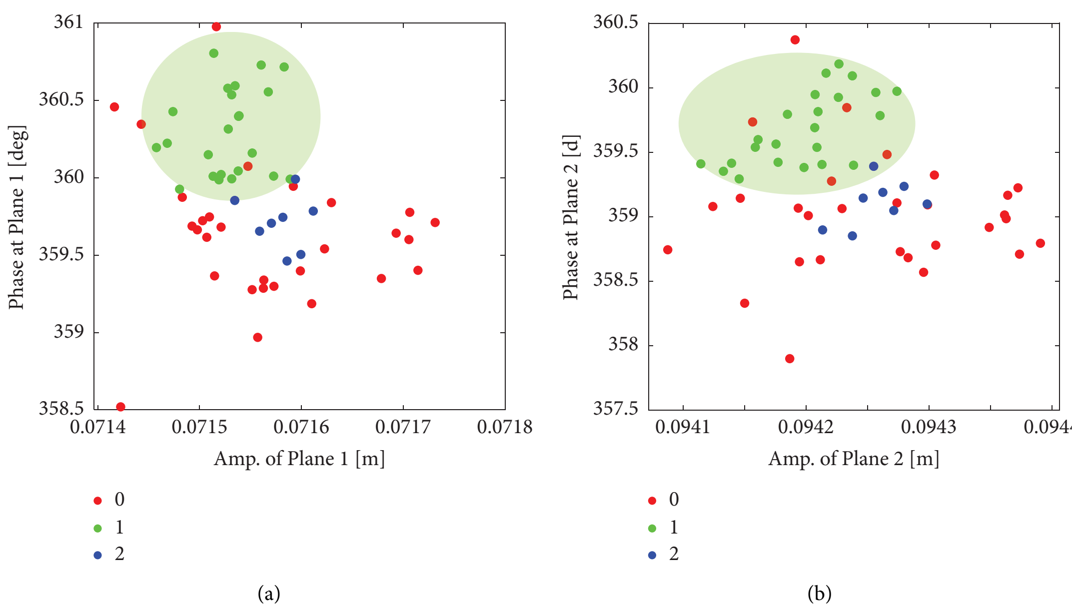

Figure 15: AA-DBSCAN results for 1X amplitude and phase at the trial weight on correction plane 1.

phase estimation found by AA-DBSCAN showed 35.2% and 33.7% decreased deviation, as compared to those of the random selection method at each correction plane in Table 4, which are shown in bold values. The reduced deviations are fairly predictable as outliers are removed when the influence coefficients are derived.

Still, the decreased deviation does not guarantee an accurate estimation. The biased estimate may lead to inaccurate results, which can lead to a limited decrease of vibration. Thus, to check which method has estimated the unbalanced mass most accurately, an extra test was performed by attaching the estimated unbalanced mass 180 degrees opposite from the estimated unbalanced mass location. If the unbalanced mass calculation is accurate, the attached counterweight will theoretically offset the unbalance of the rotor. The results of the final validation step are shown in Figure 18. The vibration amplitude of the 1X rotational frequency presented the lowest value when calculated by the suggested AA-DBSCAN method. In other words, the suggested AA-DBSCAN estimated the magnitude and the phase of unbalanced mass more accurately than other methods. Consequently, the proposed method not only reduced the deviation of the estimated results, it also increased the prediction accuracy, as compared to conventional methods.

In addition, the computation time was compared to validate the proposed AA-DBSCAN can be applied in fields. The result showed that the average of ten trials for the conventional method, the OBA method, and the proposed

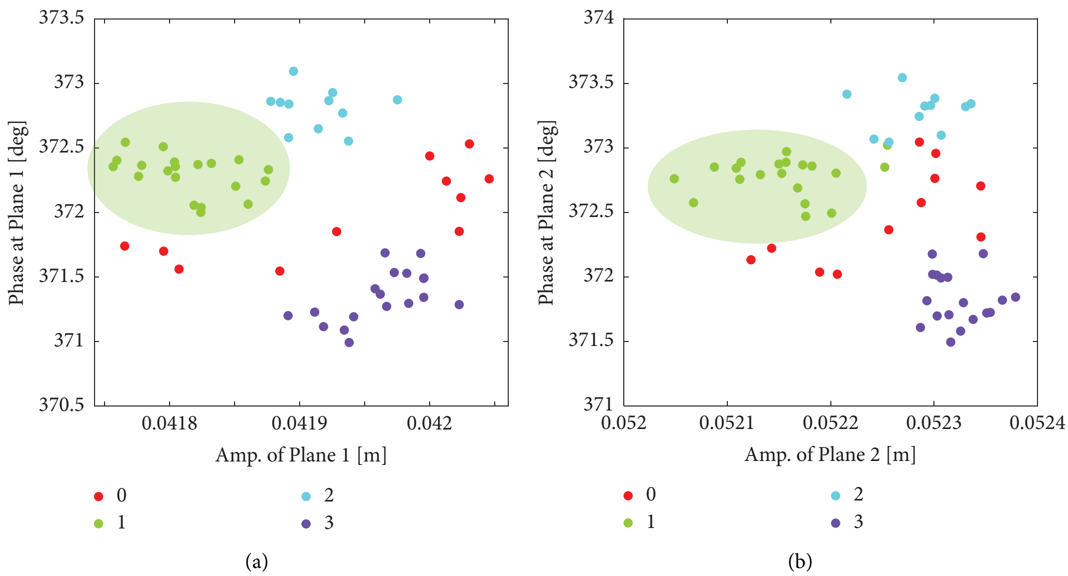

FIGURE 16: AA-DBSCAN results for 1X amplitude and phase at the trial weight on correction plane 2.

TABLE 3: Result of influence coefficient matrix for each method.

Methods	Influence coefficient matrix (A)							
	$\lvert a_{11}\rvert$		$\lvert a_{12}\rvert$		$\lvert a_{21}\rvert$		$\lvert a_{22}\rvert$	
	Average	Std	Average	Std	Average	Std	Average	Std
(Conventional) random selection	0.00919	0.0050	0.00070	0.00034	0.00071	0.00035	0.0087	0.00056
(Conventional) OBA	0.00923	0.0046	0.00075	0.00058	0.00088	0.00029	0.0087	0.00040
(Proposed) AA-DBSCAN	0.00914	**0.0037**	**0.00063**	**0.00026**	0.00051	**0.00027**	0.0088	**0.00037**

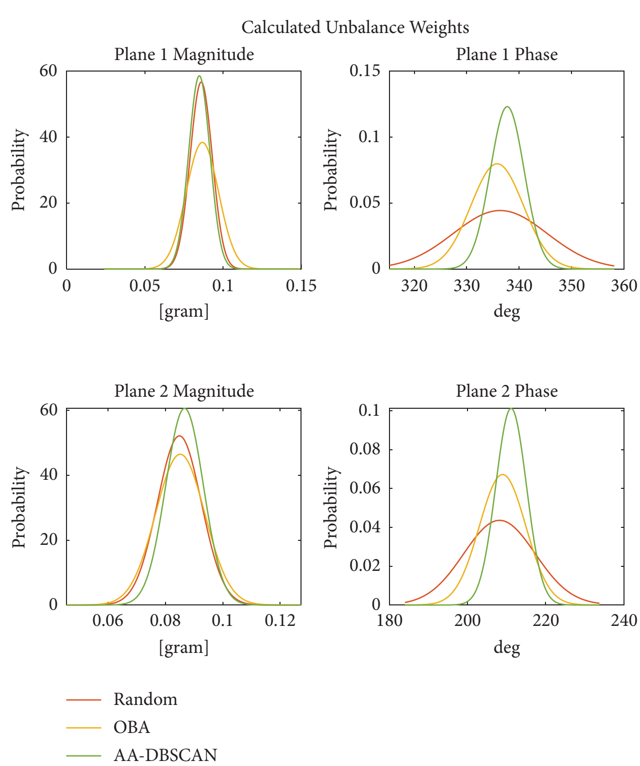

FIGURE 17: Estimated magnitude and phase of the unbalanced masses for each method.

Table 4: Average and deviation of the estimated unbalanced masses for each method.

Methods	Estimated unbalanced masses							
	Correction plane 1				Correction plane 2			
	Mass (gram)		Phase (deg)		Mass (gram)		Phase (deg)	
	Average	Std	Average	Std	Average	Std	Average	Std
(Conventional) random selection	0.0868	0.0104	335.81	5.00	0.0852	0.0086	208.97	5.94
(Conventional) OBA	0.0861	0.0070	336.39	8.99	0.0849	0.0077	208.18	9.15
(Proposed) AA-DBSCAN	0.0849	0.0068	337.74	**3.24**	0.0867	0.0066	211.15	**3.94**

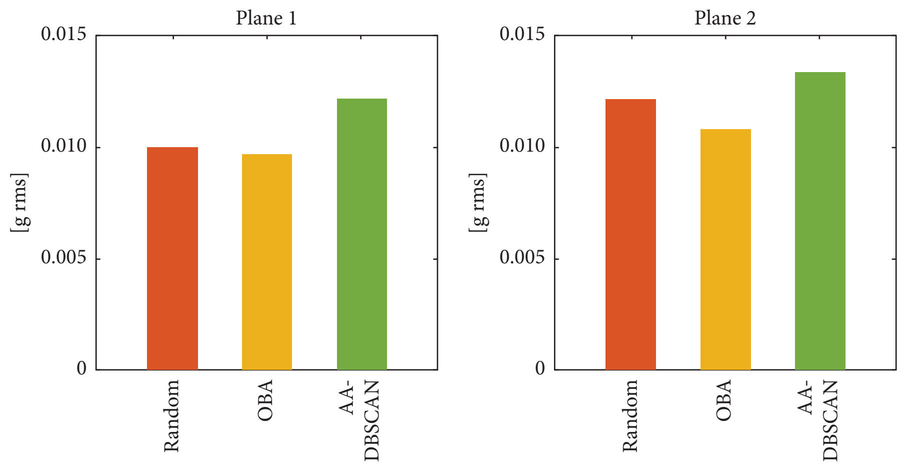

Figure 18: Decreased magnitude of 1X vibration calculated by each method.

AA-DBSCAN method showed 0.0073, 0.0516, and 0.3156 seconds. Although the AA-DBSCAN showed the longest processing time, the elapsed time of 0.3156 seconds has been accepted by users since it is a significantly short time when compared to the whole balancing time.

5. Conclusions

In this study, for the purpose of high-precision balancing, the design of an accelerometer-based measuring unit for a balancing machine was presented, and its possible operating range was analyzed through actual measurements of vibration. The accumulation of measurement uncertainty during the balancing process using the designed/manufactured measuring unit in the balancing machine was explained through Monte Carlo simulation. Although the orthogonality-based average method, which is one of the previously proposed methods for eliminating uncertainty, was used, it was confirmed from the repeated measurement results that uncertainty could still accumulate when determining the influence coefficients due to the accumulation of uncertainty from the measurement of the master specimen. A calculation procedure to mitigate measurement uncertainty was suggested by combining the proposed automatic-adaptive DBSCAN (AA-DBSCAN) method and the orthogonality-based average method. It was confirmed that the proposed method can improve the dynamic reliability of the measuring unit based on the fact that, when the existing method is used, the deviation of the extracted influence coefficients is up to 0.0050, whereas when the proposed method is used, the deviation is reduced to less than 0.0037. In addition, the estimated unbalance mass of the rotor calculated by the proposed AA-DBSCAN approach showed the most accurate results and the least deviation, as compared to those of the conventional method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

Joon Ha Jung and Byungock Kim are the co-first authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Joon Ha Jung investigated the study, proposed the methodology, contributed to data curation, and wrote the original draft. Byungock Kim proposed the methodology, contributed to algorithm development, and wrote, reviewed, and edited the manuscript. Woong Jae Na validated the study and reviewed the article. Yun-ho Shin conceptualized the study, performed supervision, contributed to organization, validated the data and study, and reviewed and edited the article.

Acknowledgments

This work was supported by the Technology Innovation Program (Project nos. 20010906 and 20023396) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea) and by the National Research Foundation of Korea under Project NRF-2022M1A2A2079987 and Project RS-2023-00240714.

References

[1] T. P. Goodman, "A least-squares method for computing balance corrections," *Journal of Engineering for Industry*, vol. 86, no. 3, pp. 273–277, 1964.
[2] X. Yu, "General influence coefficient algorithm in balancing of rotating machinery," *International Journal of Rotating Machinery*, vol. 10, no. 2, pp. 85–90, 2004.
[3] T. D. Popescu, "Detection and diagnosis of model parameter and noise variance changes with application in seismic signal processing," *Mechanical Systems and Signal Processing*, vol. 25, no. 5, pp. 1598–1616, 2011.
[4] W. C. Foiles, P. E. Allaire, and E. J. Gunter, "Review: rotor balancing," *Shock and Vibration*, vol. 5, no. 5-6, pp. 325–336, 1998.
[5] S. Zhou and J. Shi, "Active balancing and vibration control of rotating machinery: a survey," *The Shock and Vibration Digest*, vol. 33, no. 5, pp. 361–371, 2001.
[6] S. Jeong, E. Kim, K. Jeong, D. Jeon, and Y. B. Lee, "Effects of residual imbalance on the rotordynamic performance of variable-speed turbo blower," in *16th International Symposium on Transport Phenomena and Dynamics of Rotating Machinery*, HAL Open Science, Honolulu, HI, USA, 2016.
[7] S. Zhou and J. Shi, "The analytical imbalance response of Jeffcott rotor during acceleration," *Journal of Manufacturing Science and Engineering*, vol. 123, no. 2, pp. 299–302, 2001.
[8] F. Seve, A. Berlioz, R. Dufour, M. Charreyron, F. Peyaud, and L. Audouy, "Balancing of a variable speed rotary compressor: experimental and numerical investigations," 2000, https://core.ac.uk/download/pdf/4957171.pdf.
[9] Y. A. Khulief, M. A. Mohiuddin, and M. El-Gebeily, "A new method for field-balancing of high-speed flexible rotors without trial weights," *International Journal of Rotating Machinery*, vol. 2014, Article ID 603241, 11 pages, 2014.
[10] M. Tarabini and D. Scaccabarozzi, "Uncertainty-based combination of signal processing techniques for the identification of rotor imbalance," *Measurement*, vol. 114, pp. 409–416, 2018.
[11] M. Pota, M. Esposito, and G. de Pietro, "Transforming probability distributions into membership functions of fuzzy classes: a hypothesis test approach," *Fuzzy Sets and Systems*, vol. 233, pp. 52–73, 2013.
[12] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 15, no. 1, pp. 116–132, 1985.
[13] V. N. Carvalho, B. F. R. Rende, A. D. G. Silva, A. Ap Cavalini, and V. Steffen, "Robust balancing approach for rotating machines based on fuzzy logic," *Journal of Vibration and Acoustics*, vol. 140, no. 5, 2018.
[14] J. Datz, M. Karimi, and S. Marburg, "Effect of uncertainty in the balancing weights on the vibration response of a high-speed rotor," *Journal of Vibration and Acoustics*, vol. 143, no. 6, 2021.
[15] J.-D. Moon, B.-S. Kim, and S.-H. Lee, "Development of the active balancing device for high-speed spindle system using influence coefficients," *International Journal of Machine Tools and Manufacture*, vol. 46, no. 9, pp. 978–987, 2006.
[16] N. Xie, Z. Miao, J. Wang, and Q. Zhang, "Adaptive DBSCAN algorithm based on sample density gradient," in *Journal of Physics: Conference Series*, IOP Publishing, Guangzhou, China, 2019.
[17] W.-T. Wang, Y.-L. Wu, C.-Y. Tang, and M.-K. Hor, "Adaptive density-based spatial clustering of applications with noise (DBSCAN) according to data," in *Proceedings of the 2015 International Conference on Machine Learning and Cybernetics (ICMLC)*, pp. 445–451, IEEE, Dhaka, Bangladesh, September 2015.
[18] J.-H. Kim, J.-H. Choi, K.-H. Yoo, A. Nasridinov, and Aa-Dbscan, "AA-DBSCAN: an approximate adaptive DBSCAN for finding clusters with varying densities," *The Journal of Supercomputing*, vol. 75, no. 1, pp. 142–169, 2019.
[19] L. Svilainis and V. Dumbrava, "Amplitude and phase measurement in acquisition systems," *Matavimai*, vol. 2, pp. 21–25, 2006.
[20] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, pp. 226–231, Portland, Oregon, August 1996.
[21] J. Shen, X. Hao, Z. Liang, Y. Liu, W. Wang, and L. Shao, "Real-time superpixel segmentation by DBSCAN clustering algorithm," *IEEE Transactions on Image Processing*, vol. 25, no. 12, pp. 5933–5942, 2016.