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STUDY OF THE CAPABILITY OF DETECTION OF STRUCTURAL ABNORMALITY IN ROTATING MACHINES WITH SSA

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Abstract

The detection of the presence of a structural abnormality in rotating machines with parts without gap, such as rigid couplings, by using the conventional method of vibration RMS, is difficult. This work investigates the application of Singular Spectral Analysis (SSA) to change detection in rotating machines. The performance of this technique is quantitatively evaluated in the scenario of misalignment in a turbopump assembly with rigid coupling. It is shown that a statistically significant change appears when using the Change Score calculated using the SSA method. Comparison with special indicators of a structural abnormality is also performed. Since the SSA detects changes in the shape of the signal, it is much more sensitive to changes related to abnormality than conventional methods or the use of special indicators.

Key words : Change Detection, Structural Abnormalities, Singular Spectral Analysis (SSA), Signal Processing, Condition Monitoring, Rotating Machine

1. Introduction

Abnormalities in rotating machines can be classified into two categories. Mechanical damage, such as failure of bearings or gears, and structural abnormality such as unbalance or misalignment. Measuring changes in the level of vibration is a conventional method for detecting mechanical damage. However, structural abnormalities are difficult to detect with conventional methods (Komura, et al., 2002). However, this method depends on the type of the rotating machine and is not always successful. For such cases, a new method is investigated.

In this study, the Singular Spectral Analysis (SSA) is applied to vibration signals and its performance is evaluated in terms of sensitivity to changes associated with structural abnormalities. SSA is a technique that applies principal component analysis to time series, and can be used in various ways such as filtering, forecasting, and change detection (Golyandina, N. et al., 2001). SSA has been successfully applied to the detection of changes in weather patterns (Okayasu, et al., 2012, Itoh and Kurths, 2011, Itoh and Marwan, 2013), and to the movement of a human body (Nishida, 2014).

This paper is organized as follows. The second section describes the experimental setup and the details of the change detection method with SSA including its principles, parameters and computation of scores. Before the conclusions, the third section presents and discusses the results of the method that is compared to conventional methods, as well as to the method that makes use of special spectral indicators.

2. Methodology

2.1 Experimental setup

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For each experiment, offset misalignment is introduced on the shaft between the motor part and the pump part of a horizontal turbo-pump. The technical specifications of the pump are given in Table 1.

Because there is no gap in rigid couplings, introducing misalignment when assembling the pump is not possible. For this reason, after a normal assembling, a shim is inserted between the motor and its foundation in order to introduce the abnormality. The offset is quantified by the thickness of the shim. The amount of offset for each experiment is given in Table 2.

Table 1 Pump technical specifications

Pump Type	Horizontal volute pump
Power	1.5 kW
Rotation Speed	≒3000 rpm
Coupling Type	Flanged rigid coupling

Table 2 Amount of offset for each experiment

State	Amount of offset
Normal	0.0 mm
Misalignment 1	0.5 mm
Misalignment 2	1.0 mm
Misalignment 3	1.5 mm
Misalignment 4	2.5 mm
Misalignment 5	3.0 mm

Measurements are performed simultaneously with 6 channels (two 3-axis vibration acceleration sensors), that are located on the motor and pump bearings respectively (see Figure 1). Data are acquired at the sampling rate of 20 kHz and each acquisition has a duration of 10 seconds. For each experiment, data are acquired intermittently 10 times.

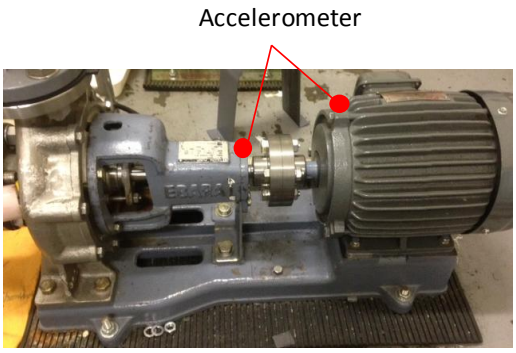


Fig 1 Location of the accelerometers

2.2 Change detection method with SSA

2.2.1 Principles

SSA is a technique that applies principal component analysis to time series. The essence of SSA is to build a history matrix from time series and extract temporal features by calculating the principal components of this matrix. Various analyses can then be performed by using the extracted principal components. In this study, a method is applied that evaluates the degree of change by comparing the principal components extracted from reference data to the principal components extracted from target data. While the method of computation of the degree of change is based on (Ide and Inoue, 2004), Ide performs a time shift on reference data in order to obtain a method that detects change points in continuous data. In this study, to conform to the scenario where an operator performs intermittent measurements of vibration data, the method uses a fixed interval as reference data.

Let $\{x_t : t = 1,2,\dots\}$ be a time series. $\boldsymbol{x}_1 = \{x_i, x_{i+1}, \dots, x_{i+n}\}^t$ is a part of x_t that is fixed and represents the

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normal state. $\boldsymbol{x}_2 = \{x_j, x_{j+1} \ldots, x_{j+n}\}^t$ is another part of x_t that is compared to $\boldsymbol{x}_1$ to evaluate whether a change occurred or not. H_1 and H_2 are history matrices that are created from $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$:

$$H_1 = \begin{pmatrix} x_i & x_{i+1} & \cdots & x_{n-m+i} \\ x_{i+1} & x_{i+2} & \cdots & x_{n-m+i+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i+m-1} & x_{i+m} & \cdots & x_{n+i-1} \end{pmatrix}$$
$$H_2 = \begin{pmatrix} x_j & x_{j+1} & \cdots & x_{n-m+j} \\ x_{j+1} & x_{j+2} & \cdots & x_{n-m+j+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{j+m-1} & x_{j+m} & \cdots & x_{n+j-1} \end{pmatrix} \quad (1)$$

where m and n are empirical parameters. The eigenvalue decomposition is applied to H_1 and H_2:

$$H_1 H_1^t = U \Lambda_1 U^t, \qquad H_2 H_2^t = V \Lambda_2 V^t \quad (2)$$

where U and V are matrices which columns are the eigenvectors of H_1 and H_2. These eigenvectors are arranged in descending order of the corresponding eigenvalues:

$$U = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots \boldsymbol{u}_m\}, \qquad V = \{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots \boldsymbol{v}_m\} \quad (3)$$

The degree of change of $\boldsymbol{x}_2$ compared to $\boldsymbol{x}_1$ is quantified by the "change score" z, defined as:

$$z \equiv 1 - \sum_{i=1}^{r} (\boldsymbol{u}_i^t \cdot \boldsymbol{v}_1)^2 \quad (4)$$

where r is an empirical parameter that determines the number of largest principal components that are used for comparison.

2.2.2 Parameters

In order to perform the calculations described above, it is necessary to set the parameters m and n in equation (1) as well as the parameter r in equation (4). m is the dimension of the principal components vectors and n is the number of data points used for computing the principal components. Because the method detects changes of state in the time series from the change of the principal components, it is necessary to choose a sufficiently large dimension for the principal components so that the characteristics of the time series are captured appropriately. If the dimension of the principal components vector m is relatively small, the high frequency components will dominate. If m is relatively large, the low frequency components will appear. Therefore the frequency domain should be determined from the characteristics of the acquired signals in order to choose an appropriate value of m.

For this determination, a simple spectral analysis is first performed. Examples of the spectrum of vibration signals acquired for some of the experiments are shown in Fig 2. Each of these spectrums is the average of the spectrums obtained from 10 measurements.

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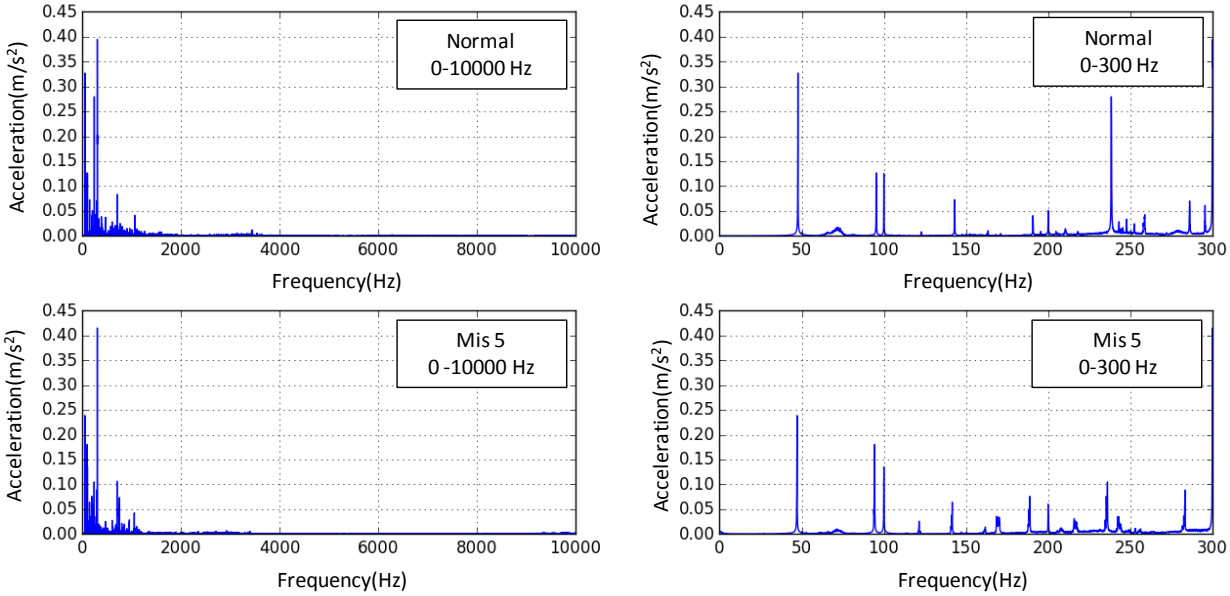


Fig 2 Average spectrum of the acceleration in the horizontal direction of the motor bearing.

Fig 2 shows that the main spectral components are under 1kHz in all cases. Moreover, the lowest main spectral component is 50Hz, which is the rotation frequency of the axis. As the same remarks can be done for the cases not shown in Fig 2 (other directions and location), the frequency domain can be set to 50～1000Hz.

Since the frequency domain is limited to up to 1kHz and the sampling rate is 20kHz, the data can be downsampled to avoid that the size of the matrix during the computation becomes unnecessary large. The number of samples is divided by 10 so that the Nyquist frequency becomes equal to 1kHz. The value of m should be chosen so that the information down to 50Hz is included. The lower value of 33.3Hz is chosen to ensure that no information is lost. The sampling rate after downsampling is 2kHz and the frequency of 33.3Hz corresponds to a duration of 0.03 seconds, which implies that the value of m is 60 samples $(2000 \times 0.03 = 60)$.

n is the data length to be used once for the calculation of the principal components and $n - m + 1$ corresponds to the number of samples used by the principal component analysis. A balance must be found as more general principal components are obtained with a larger number of samples, but the computational cost of the matrices is increased. In order to verify the influence of the value of n on the results, several values of n are used: 2, 3, and 4 times the value of m.

r in equation (4) determines the number of principal components that are used when computing the change score. The magnitude of the eigenvalues obtained by equation (2) represents the amount of information of the corresponding principal components. It is thus suitable to set a threshold on the magnitude of the eignevalues to determine the number of principal components to be used for the score calculation.

The ratio p_i of the sum of a number of the largest eigenvalues over the sum of all the eigenvalues is defined as

$$p_i = \frac{\sum_{k=1}^{i} \lambda_k}{\sum_{k=1}^{m} \lambda_k} \qquad (i = 1,2,3 \ldots m) \tag{5}$$

with λ_k the eigenvalue corresponding to the k-th principal component obtained from equation (2). r is determined as the smallest value of i such as p_i is larger than the threshold p =0.2, 0.4, or 0.6.

2.2.3 Change score computation

As described in 2.2.1, the method calculates the degree of change of the principal components between the base interval and the target interval. Considering that even in stable conditions, acquired signals show significant variation, it is not sufficient to use a single interval in the normal state as the base interval. Therefore, the change score of a target interval is computed from the average of the scores calculated for several base intervals in normal state. Moreover, the same computation is performed for all six channels, that are measured simultaneously, and the average of these scores is the final change score of a given target interval. The base intervals are extracted from all acquisitions in normal state

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with an interval equals to $10n$ in order to limit the computational cost. A diagram of the calculation process is shown in Fig 3. The notations used in this figure are defined as follows.

T_i: i-th target interval (i=1,2,3...N_T)

B_j: j-th base interval (j=1,2,3....N_B)

S_{ij}^c: Change score computed from T_i and B_j for channel c (c=1,2,…,6)

Z_i^c: Change score for channel c for the i-th target interval

Z_i: average Change score for i-th target interval (average of scores Z_i^1 to Z_i^6)

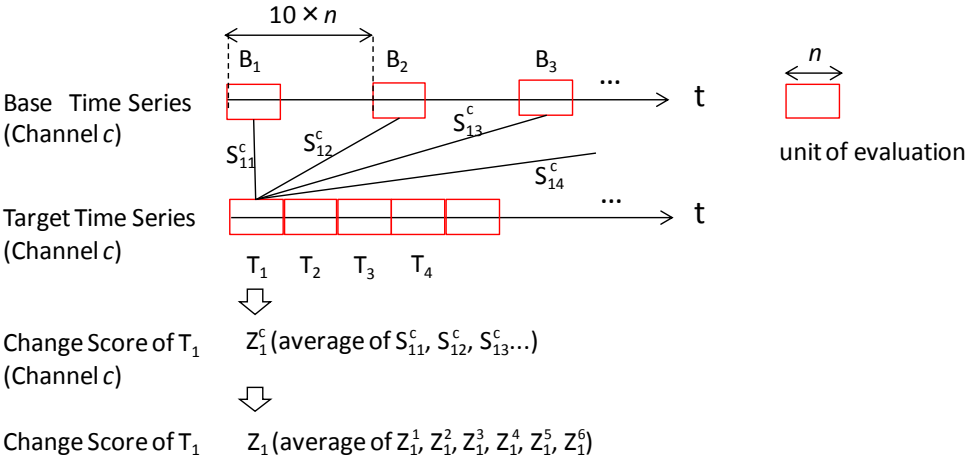


Fig 3 Computation of the change score

2.3 Other features

For comparison to the change score of the SSA method, other features are calculated.

2.3.1 RMS

RMS is an indicator of the level of vibrations and is a widely used indicator. Both the RMS of the vibration acceleration and of the integral of the acceleration, the vibration velocity, are computed. For the reference data x of size N, the RMS is defined by

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2} \tag{6}$$

Computation is done on each target interval and for each channel before averaging on all channels. Unlike in the case of the change score, the data used for computing these features are not downsampled.

2.3.2 Spectrum feature

Generally, in presence of a structural abnormality, the vibration components corresponding to the rotation frequency and its harmonics tend to increase. In this study, the components of the frequency power spectrum corresponding to the rotation frequency and its harmonics, used as features by (Komura, et al., 2002) are calculated.

The power spectrum of the vibration acceleration signal $p(f)$ is normalized by the sum of the values of the power spectrum over the whole frequency range, a_{ps}. The normalized spectrum is $s(f) = \frac{p(f)}{a_{ps}}$. In addition, the feature indicating the presence of a structural abnormality is defined as follows, with f_0 the rotation frequency of the machine, and if_0 the $n-1$ first harmonics $(2 \le i \le n)$,

$$f_{sd} = s(f) + s(2f) + \cdots + s(nf) \tag{7}$$

From a preliminary analysis of the power spectrum, a value of $n = 10$ is chosen to include the main components. The value of f_{sd} is computed on the vibration velocity spectrum of each acquisition of 10s and is averaged for the six channels.

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3. Experimental results

3.1 Comparison of change score to other features

The results of the calculation of the change score, the RMS of the acceleration and velocity and the spectrum feature are shown in Fig 4. The data points in the graphs represent the average value of each feature, for each experiment and for all N_T evaluations, and the error bars represent the standard deviation ($\pm \sigma$).

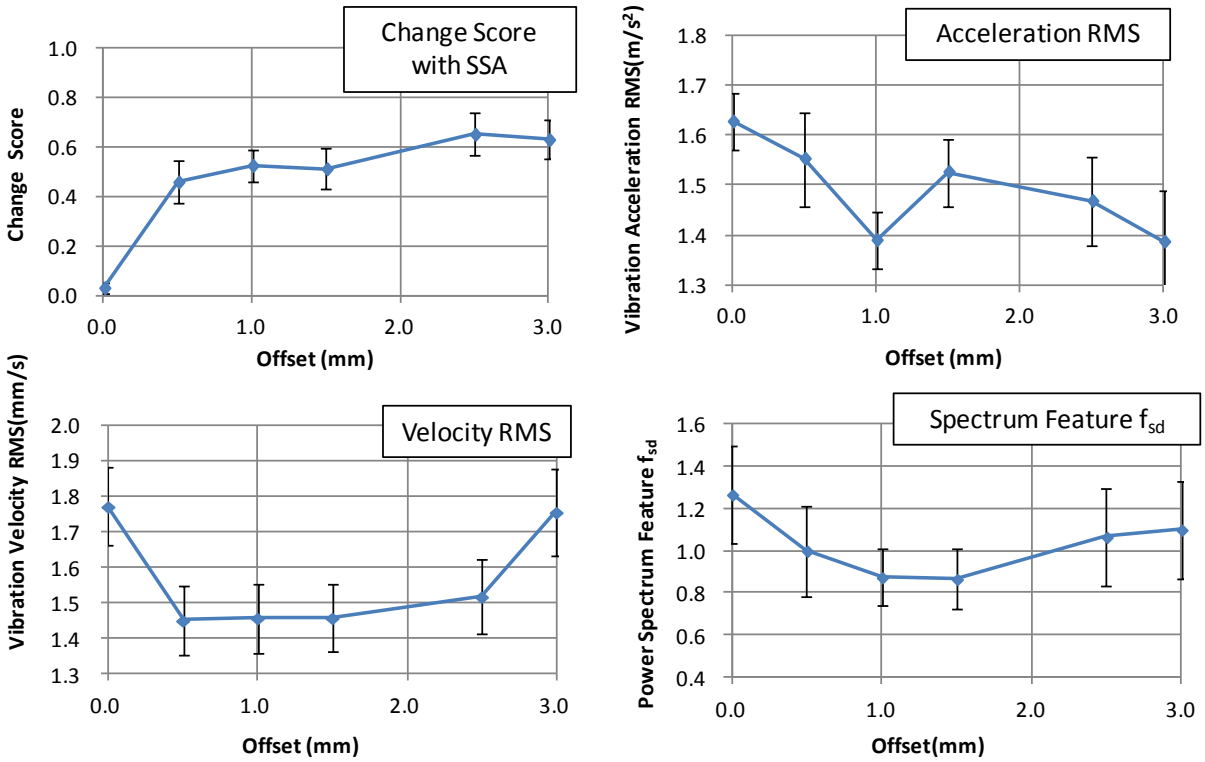


Fig 4 Comparison of the change score to the other features (SSA parameters: m=60, n=180, p=0.4)

Although the most commonly used features in vibration diagnosis are the RMS of the acceleration and velocity, that correspond to the magnitude of the vibrations, the expected tendency of an increase of the RMS along with the amount of misalignment was not observed in this study (see Fig 4). It was not possible to detect the abnormality with RMS. The stress exerted on the shaft and bearing should have increased along with the amount of misalignment, but as the structure doesn't have gaps, and the coupling is of rigid type, there is not much influence on the vibration level.

Similarly, no increase of the spectrum feature is observed. It is difficult to detect a structural abnormality through conventional methods.

On the contrary, the change score of the SSA method is always higher when misalignment is present than in the normal state. The change due to an abnormality is large when the standard deviation in normal operation is considered.

3.2 Evaluation of the influence of the parameters

The value of m, which is the dimension of the principal components of the SSA , can be set according to the frequency range. However, there is no standard criterion for setting n, the length of the data used to compute the principal components, as well as r, the amount of principal components used to compute the change score. Therefore, in order to evaluate the effect of these parameters, several values are evaluated. The results for several values of n and r are shown in Fig 5. The value of r is determined according to the value of p as described in section 2.2.2, and the larger the value of p is, the more principal components of lower rank are included in the calculation of the score.

As can be seen from Fig. 5, the score is higher when misalignment is present than when conditions are normal,

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regardless of the value of the parameters or the amount of offset. When considering the standard deviation in normal operation, it is clear that detection of abnormalities is possible. Moreover, the results are not affected significantly by the value of n that can be set as twice the value of m.

On the contrary the value of p has a significant influence on the results, and the score is lower for larger values of p as equation (4) shows. However, the most important aspect is not the height of the score, but whether the score changes significantly in the abnormal state compared to its value and variation in normal state. In this case, it is possible to detect an abnormality for all three values of p.

While the score tends to saturate for an amount of offset larger than 1.0 mm, it can be seen that the score has a tendency to increase with the offset in the range 0～1.0 mm. This score is an effective sensitive indicator for the very small levels of misalignment.

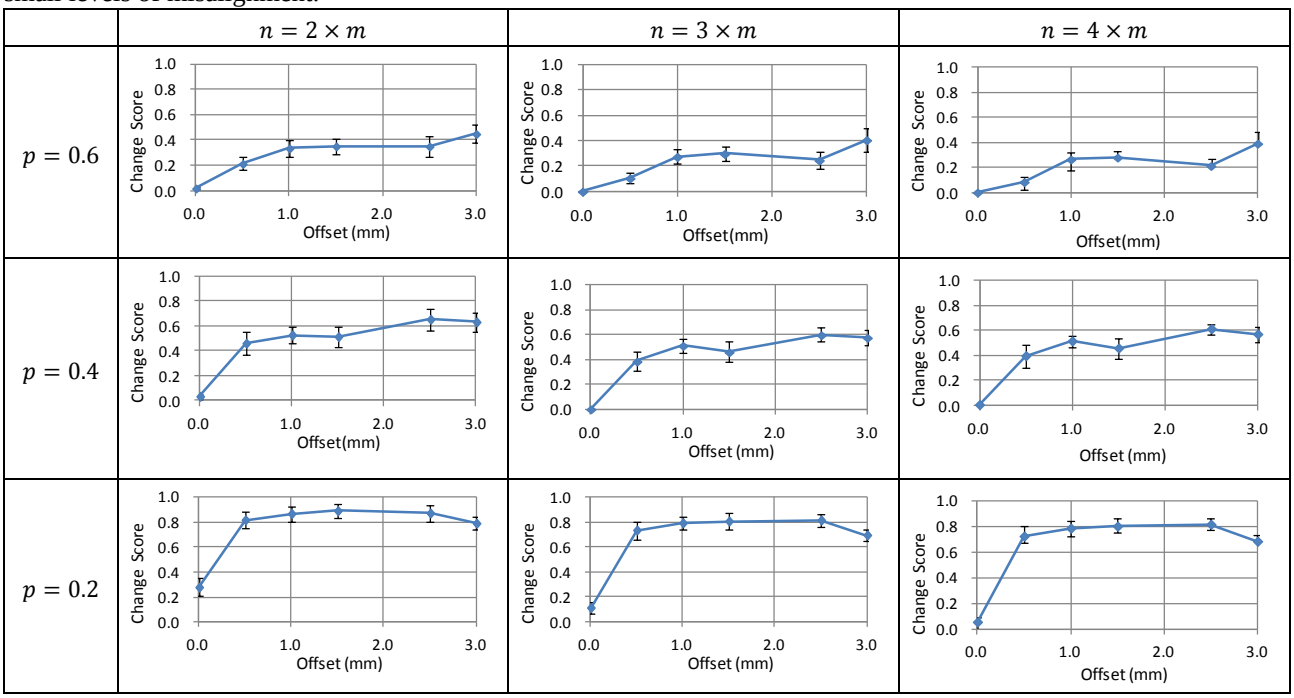


Fig 5 Comparison of the results depending on the parameters of the change score ($m = 60$)

4. Conclusion

Structural abnormalities in rotating machines are generally difficult to detect using the magnitude of vibration alone. Furthermore, depending on the structure, it is not always possible to clearly detect the abnormality using the magnitude of the rotation frequency and its harmonics. In order to solve this problem, the SSA method was used on experimental data from a misaligned pump, and it's effectiveness was demonstrated.

The conventional indicators in vibration diagnosis (vibration acceleration RMS, vibration velocity RMS) and the spectrum feature were not effective for detecting abnormalities. It was demonstrated that these same abnormalities can be detected with the change score of the SSA method. As for the parameters used in the calculation of the change score, by appropriately determining the value of m, depending on the frequency range, the influence on the results of the other parameters is small. The detection capability was not adversely affected even when changing the value of these parameters.

The change score that was derived from the SSA method, can be considered as a sensitive indicator for the detection of structural abnormalities. In addition to microscopic misalignment, we hope to expand the application of this method to more data sets from other experimental systems that include different types of structural abnormalities.

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