Modeling of Journal Bearings for Wear Diagnosis and Its Verification Using SVM

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ABSTRACT

In recent years, aging infrastructure facilities have become problems. Among infrastructure facilities, journal bearing is often used in pumps and other rotating machinery. Journal bearing may be worn in some rated condition, then, periodic inspection is required. However, inspecting these facilities sometimes involves disassembling the machinery, which require significant costs. To reduce such periodic inspection cost, wear diagnosis of journal bearings under operating conditions has been studied. In recent years, research related to wear diagnosis using machine learning has been increased. To build a machine learning model, a lot of training data is required. However, it is difficult for some machinery to obtain enough number of training data. In this paper, a mathematical model of a horizontal rotating shaft system supported by a journal bearing is used to generate training data for machine learning to diagnose the wear of the journal bearing. Wear of the journal bearing is represented as the increase of clearance. Next, the important feature for wear diagnosis is evaluated and selected, and a support vector machine (SVM) model is built. Using this SVM model, wear diagnosis of the journal bearing from the experimental data is conducted, and its validity is confirmed.

1. INTRODUCTION

Recently, the aging infrastructure facilities has become problems. These facilities include rotating machinery such as pumps. In rotating machinery, journal bearing is used to support the rotating shaft and reduce the vibration, and bearing may be worn in some rotating condition. So regular inspections on facilities are required. However, the inspections tend to involve disassembly of equipment, which incurs time and cost. To reduce such costs, wear diagnosis of journal bearing by condition monitoring is required.

Research on condition monitoring of journal bearings using machine learning has been investigated actively in recent years. Alves, Daniel, Castro, Machado, Cavalca, Gecgel, Dias, and Ekwaro-Osire (2020) built a mathematical model to simulate the failure conditions of journal bearings. A neural network algorithm was trained using the data generated by the simulation to diagnose the condition of the journal bearings. König, Sous, Chaib, and Jacobs (2021) measured the acoustic emission signals in experiment. The measured signals and a neural network were used to diagnose the wear of journal bearings.

The building of machine learning model generally requires training data. However, for some machines, it may be difficult to conduct tests many times and obtain enough number of training data because the tests take a very long time. Therefore, if reliable data can be generated using a mathematical model that represents the wear of journal bearing, it is possible to predict the approximate wear of journal bearing without collecting data by the tests, even when the design of other parts of the bearing or operating conditions are changed. These are significant advantages in reducing costs for condition monitoring and diagnosis of mechanical systems.

However, to our best knowledge, evaluation of the features for the wear diagnosis of journal bearing using both experiment and simulation has not been done. In this paper, a mathematical model for wear diagnosis of a journal bearing is constructed, and the features obtained from the simulation data and the experimental data are compared and evaluated. Then, an SVM model trained with the simulation data is used to diagnose wear of the journal bearing from the experimental data.

2. DATA ACQUISITION FOR EXPERIMENTS AND SIMULATIONS

2.1. Experimental apparatus and Methods

The experimental apparatus used in this paper is shown in Figure 1 and its schematic diagram is shown in Figure 2.

Figure 1. Experimental apparatus.

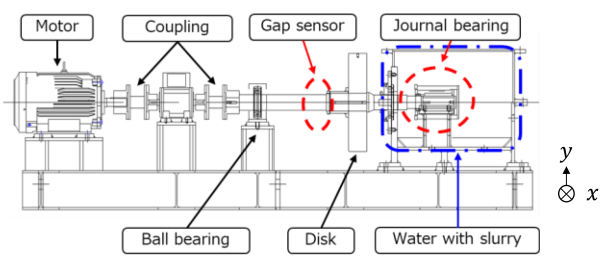

Figure 2. Schematic diagram of the experimental apparatus.

The journal bearing was set in water containing slurry with a concentration of 1000 ppm. This experimental apparatus was operated for 1600 hours at a rotational speed of 500 rpm to develop wear on the journal bearing. Then, the horizontal (x) and vertical (y) displacements of the shaft during operation were regularly measured at a sampling frequency of 1000 Hz for 30 seconds. Among the measured data, 12 measurement data up to the point before peeling occurred were used. To increase the number of data, each data was divided into three 10-second data sets for a total of 36 data sets.

The operation was stopped less frequently than the displacement measurements, and the wear of the journal bearing was measured. The wear was measured in the x and y directions at three axial locations.

2.2. Simulation assuming wear of journal bearing

A horizontal rotating shaft model with two disks is shown in Figure 3.

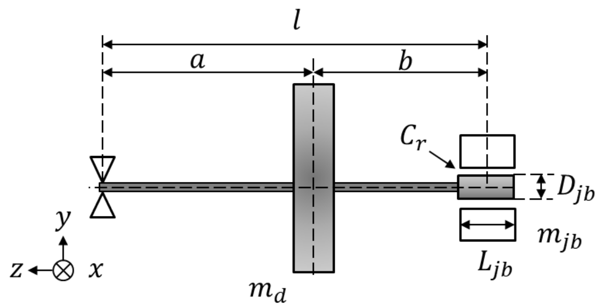

Figure 3. Horizontal rotating shaft model with two disks.

The equation of motion for the horizontal rotating shaft model (Figure 3) is shown in Eq. (1).

$$
\begin{aligned}
&\mathbf{M}\ddot{\mathbf{q}} + \mathbf{C}\dot{\mathbf{q}} + \mathbf{K}\mathbf{q} \\
&= \mathbf{F}_{unb} + \mathbf{F}_g + \mathbf{F}_{cont} + \mathbf{F}_{RD} + \mathbf{F}_{rnd} \\
&\mathbf{M} = diag[m_d \quad m_d \quad m_{jb} \quad m_{jb}], \\
&\mathbf{C} = diag[c \quad c \quad 0 \quad 0], \\
&\mathbf{K} \\
&= \begin{bmatrix} k_1 & 0 & -k_1\left(\frac{a}{l}\right) & 0 \\ 0 & k_1 & 0 & -k_1\left(\frac{a}{l}\right) \\ -k_2\left(\frac{l}{a}\right) & 0 & k_2 & 0 \\ 0 & -k_2\left(\frac{l}{a}\right) & 0 & k_2 \end{bmatrix}, \qquad (1) \\
&\mathbf{F}_{unb} = \begin{bmatrix} m_d e\omega^2 \cos \omega t \\ m_d e\omega^2 \sin \omega t \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{F}_g = \begin{bmatrix} 0 \\ -m_d g \\ 0 \\ -m_{jb} g \end{bmatrix}, \\
&\mathbf{F}_{cont} = \begin{bmatrix} 0 \\ 0 \\ F_{contx} \\ F_{conty} \end{bmatrix}, \quad \mathbf{F}_{RD} = \begin{bmatrix} 0 \\ 0 \\ F_{RDx} \\ F_{RDy} \end{bmatrix}, \\
&\mathbf{F}_{rnd} = \begin{bmatrix} 0 \\ 0 \\ F_{rndx} \\ F_{rndy} \end{bmatrix}, \quad \mathbf{q} = \begin{bmatrix} q_{dx} \\ q_{dy} \\ q_{sx} \\ q_{sy} \end{bmatrix}
\end{aligned}
$$

where $\mathbf{F}_{cont}$ is the contact force at the journal bearing, $\mathbf{F}_{rnd}$ is a random excitation force considering the effect of slurry water at the journal bearing, and $\mathbf{F}_{RD}$ is the fluid force. $\mathbf{F}_{RD}$ is obtained by integrating the pressure distribution in the journal bearing. This pressure distribution is derived by solving the Reynolds equation in Eq. (2)

$$\frac{1}{R^2}\frac{\partial}{\partial\theta}\left(\frac{H^3}{12\mu}\frac{\partial p}{\partial\theta}\right)+\frac{\partial}{\partial z}\left(\frac{H^3}{12\mu}\frac{\partial p}{\partial z}\right)=\frac{\omega}{2}\frac{\partial H}{\partial\theta}+\frac{\partial H}{\partial t} \quad (2)$$

The oil film thickness $H(\theta)$ is defined by Eq. (3).

$$H(\theta) = C_r(1+\varepsilon\cos(\theta-\phi)) \quad (3)$$

Gumbel boundary condition is used in the analysis.

In this paper, wear development was expressed as an increase in clearance C_r. In practice, the stator bore of journal bearing is no longer a perfect circle due to wear, and the amount of wear is not uniform in the axial direction. Therefore, this model is very approximate. The clearance is varied from 1.0 to 1.6 times the design value by 0.1 increments, and time history displacement data was obtained by simulation. The range of the clearance size in the simulation corresponds to the average value of the amount of wear in the experiment, just prior to peeling. Considering that the excitation force is random, the time history displacement data was obtained five times for each clearance case.

The parameters used in the simulations are listed in Table 1.

Table 1. Parameters of the mathematical model**.**

Shaft length -a	a
Shaft length -b	b
Disk weight	m_d
Unbalance amount	e
Journal bearing diameter	D_{jb}
Journal bearing length	L_{jb}
Journal bearing weight	m_{jb}
Damping coefficient	c
Spring constant 1	k_1
Spring constant 2	k_2
Clearance	Cr
Young's modulus of the shaft	E
Viscosity	μ
Rotor spinning velocity	ω
Eccentricity	ε
Attitude angle	ϕ
Angle in circumferential direction	θ

3. Analysis and evaluation of features of experimental and simulation data

3.1. Analysis and selection of features

From both the experimental and simulation data, the features commonly used in condition monitoring are obtained (Caesarendra, & Tjahjowidodo, 2017), (Li, Dong, & Yuan, 1999). Average and coefficient of variation (CV) of each of RMS value, kurtosis, and skewness of displacements in x and y directions, and 1~4th order discrete wavelet transforms (DWT) in each direction, a total of 20 features were obtained.

The features used in this paper are listed in Table 2.

Table 2. Features used in this paper

x-direction, RMS, average
x-direction, RMS, coefficient of variation
x-direction, kurtosis, average
x-direction, kurtosis, coefficient of variation
x-direction, skewness, average
x-direction, skewness, coefficient of variation
y-direction, RMS, average
y-direction, RMS, coefficient of variation
y-direction, kurtosis, average
y-direction, kurtosis, coefficient of variation
y-direction, skewness, average
y-direction, skewness, coefficient of variation
x-direction, 1st order DWT
x-direction, 2nd order DWT
x-direction, 3rd order DWT
x-direction, 4th order DWT
y-direction, 1st order DWT
y-direction, 2nd order DWT
y-direction, 3rd order DWT
y-direction, 4th order DWT

Goto, Inoue, Hori, Yabui, Katayama, Tomimatsu and Heya (2023) used these features for fault diagnosis of journal bearing and showed their effectiveness. Then, SVM models were built using the features of the experimental and simulation data respectively and interpreted. To build each SVM model, the first 9 data, which were in the early stages of wear, were used as normal, and the last 9 data, which were after wear development, were used as abnormal training data. The rest of the data in the middle part were used as test data.

The Fisher Score (Sun, Wang, Ding, Xu, & Lin, 2021) and Wrapper method (Maldonado & Weber, 2009) were used for interpretation, and the features are arranged in order of importance for diagnosis.

Some of the features, listed in order of importance for both the experiment and simulation, are shown in Table 3.

Table 3. Some important features for diagnosis in each data.

Experiment	Simulation
Kurtosis Average y	RMS CV y
Skewness Average y	Kurtosis CV x
	RMS Average y

In Table 3, there were no feature which were common to both the experiment and simulation. Therefore, among the features shown in Table 3, the features which show the same trend of change relative to the wear development were considered to be essentially important. As a result, the CV of the kurtosis of the x displacement was selected.

In the following, only the CV of the kurtosis of the x displacement is used to diagnose the experimental data.

3.2. SVM model training based on simulation data

The SVM model was built using the CV of the kurtosis of the x displacement obtained from the simulation data as training data. As in section 3.1, among the simulation data, the first 9 data, which were in the early stages of wear, were used as normal, and the last 9 data, which were after wear development, were used as abnormal training data.

3.3. Validation of experimental data with SVM model

Using the SVM model trained on the simulation data, wear diagnosis of the journal bearing in the experimental data was conducted. Results of the diagnosis using all features and using only the CV of the kurtosis of the x displacement are shown in Figure 4.

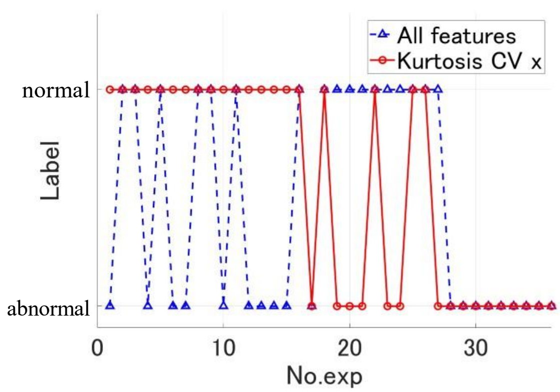

Figure 4. Evaluation of experimental data using SVM model and wear diagnosis of the journal bearing - Comparison of results for difference in selected features.

When all the features were used, the wear condition of the journal bearing even in the early stages of wear was diagnosed as abnormal. On the other hand, when only the CV of the kurtosis of the x displacement was used, the initial stage of wear was correctly diagnosed as normal and after wear developing as abnormal.

4. Conclusion

In this paper, the important features for diagnosis were compared for experimental and simulated data. Then, the feature showing same trend in both the experimental and simulation data was chosen, and the wear diagnosis was demonstrated for the experimental data using the SVM model learned by the simulation data. The following conclusions are obtained:

Among the features for diagnosis, the CV of the kurtosis of the x displacement indicated the same trend for both the experimental and simulation data.

The wear of journal bearing was not predicted by SVM model which used all features in its training. However, it was diagnosed correctly when the CV of the kurtosis of the x displacement was used.

In the future, multiple experiments will be conducted using the same experimental apparatus to verify the reproducibility of changes in the features due to the wear development. In addition, the model will be improved by considering the shape change of the journal bearing, and the effect of this on the features will be evaluated.

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BIOGRAPHIES

Masaki Goto was born in Aichi, Japan, on August 30, in 1999. He received his Bachelor of Engineering from Nagoya University in 2023. He is currently a master's student in the Graduate Department of Mechanical Systems Engineering, Nagoya University (Japan). He is a student member of the Japan Society of Mechanical Engineers. His research interests on wear diagnosis of journal bearings.

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