Selection of Sensors that Influence Trouble Condition Sign Discovery based on a One-class Support Kernel Machine for Hydroelectric Power Plants

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Abstract: Trouble conditions rarely occur in the equipment of hydroelectric power plants. Therefore, it is important to find indicator signs for trouble conditions. In a previous study, we proposed a trouble condition sign discovery method, which consists of two detection stages. In the first stage, we can discover trouble condition signs, which are different from the usual condition data. In the second stage, we can monitor aging degradation, with plant experts confirm these trouble condition signs in daily operations. Hence, there is a need to detect these trouble condition signs using a small number of sensors. In this paper, we propose a method for narrowing down the sensors used in trouble condition sign discovery. This paper shows the experimental results of trouble condition sign detection for bearing vibration based on the collected data from different sensors using our proposed method and our previously proposed method. The experimental results show that even if the number of sensors is reduced, our proposed method can find trouble condition signs, which are different from the usual condition data. Therefore, the proposed method may be useful for trouble condition sign discovery in hydroelectric power plants.

1 INTRODUCTION

In order to realize efficient maintenance and reduce its cost, electric power companies recently began attempting to shift from a time-based maintenance (TBM) to condition-based maintenance (CBM) for electric equipment management (Yamana et al., 2005), (Jardine et al., 2006). With TBM, equipment is checked and changed based on the manufacturer's guarantee period. In contrast, with CBM, equipment is checked, repaired and changed based on the state of the equipment. This state consists of the actual condition of the equipment, its operation period, the operational load, etc.

It is important for electric power companies to collect equipment data to realize CBM. In particular, it is necessary to collect and analyze the previous trouble condition data to discover trouble condition signs for the power equipment. For instance, this might include the discovery of trouble condition signs for bearing vibration from the sensor information of the hydroelectric power plant and the discovery of trouble condition signs from the operation data of the power generation plant. Trouble conditions rarely occur in power equipment in Japan. Moreover, it is difficult to construct an experimental power generation plant to collect trouble condition data.

Thus, Kyushu Electric Power Co.,Inc. and Central Research Institute of Power Industry are investigating a detection method for the trouble condition signs of bearing vibration in hydroelectric power plants. In our research, we consider that the trouble condition signs can be given by an increase in the occurrence of special unusual condition data, because we can only measure the normal condition data during the regular operation of a hydroelectric power plant.

Thus, we are developing a detection method for the occurrence of unusual condition data in the regular condition data, along with a management method for trends in the generation of special unusual condition data related to bearing vibration from the regular condition data for a hydroelectric power plant (Onoda et al., 2009). This method consists of two detection stages. In the first stage, we can discover trouble condition signs, which are different from the usual condition data. In the second stage, we can monitor aging degradation. Our proposed method is based on a one-class support vector machine (one-class SVM) and a normal support vector machine (SVM).

In the first stage, the detection method determines

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the relevance between the degree of an unusual condition and various pieces of sensor information using the weights of the one-class SVM. However, it is difficult for plant experts to evaluate whether or not sensors that have weights close to zero affect an unusual condition. If our detection method is introduced in an actual plant, plant experts will have to confirm the trouble condition signs in daily operations. Hence, there is a need to be able to confirm the trouble condition signs using a small number of sensors.

In this paper, we propose a method for narrowing down the sensors that influence an unusual condition. This method is based on the one-class support kernel machine (one-class SKM).

In Section 2 of this paper, we briefly explain our proposed method for discovering a trouble condition sign. We briefly describe the previously proposed method to detect unusual condition data, and we propose a new method for the selecting sensors that influence an unusual condition. The experimental results are shown in Section 3. Finally, we present conclusions in Section 4.

2 PROPOSED METHOD

In this section, we give an outline of the trouble condition sign discovery method using the *special unusual condition data*. In addition, we explain the previously proposed method for detecting an unusual condition pattern. Finally, we propose a new method for combining the unusual condition pattern detection and the sensor reduction.

2.1 Trouble Condition Sign Discovery Approach

Generally, the discovery of a trouble condition sign relies on the detection of a peculiar case that appears only before an existing trouble condition by comparing the regular condition data and trouble condition data. However, it is a fact that the trouble condition data for electric power equipment are limited, because electric power plants are designed with the high safety factors and are appropriately maintained. Currently, our bearing vibration data for hydroelectric power plants also do not include trouble condition data. Therefore, it is impossible to discover a peculiar case before the occurrence of trouble condition data, because it is difficult to obtain trouble condition data, and it is impossible to compare regular condition data with trouble condition data. Thus, we believe that the relation between a peculiar condition before the occurrence of trouble condition

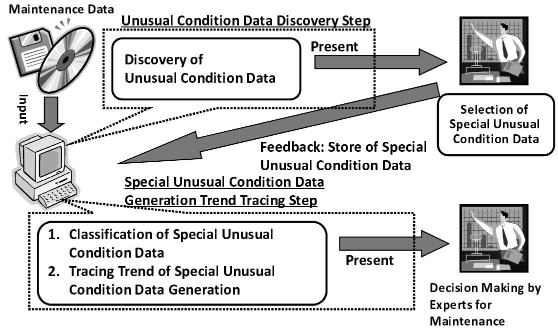

Figure 1: Image of Trouble Condition Sign Discovery.

data (hereafter, we call this the trouble condition sign) and *special unusual condition data* is as follows.

The trouble condition sign $\approx$
A strong rise in the occurrence
of special unusual condition data.

It is possible to change the discovery of the trouble condition sign to the detection of the *special unusual condition data* in the regular condition data. In other words, we suppose that the *special unusual condition data* with a low probability of existing in the regular condition data has a high probability of being a trouble condition sign.

For the condition-based maintenance of hydroelectric power plants, it is very important to discover trouble condition signs. Our proposed trouble condition data discovery method integrates the detection method for *special unusual condition data* and a method of tracing the trends for the generation of *special unusual condition data*.

Figure 1 shows an image of the trouble condition sign discovery for the condition based maintenance of hydroelectric power plants. Our proposed trouble condition sign discovery method is an interactive method. Our system mainly consists of two methods.

The first method is a selection method for the *special unusual condition data*, which relate to the trouble condition sign. This method consists of two phases. The first phase is an unusual condition pattern detection phase based on the one-class SVM or one-class SKM. The next phase is the *special unusual condition data* selection. The detected unusual condition data may include unusual condition data generated by sensor faults and so on.

In our method, human experts detect strange data such as the data generated by sensor faults using their expertise, operation reports, etc., and then select the data related to a trouble condition sign in the unusual condition data. This selected unusual condition data are defined as the *special unusual condition data*.

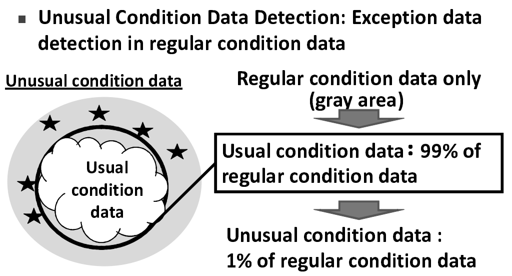

Figure 2: Image of Unusual Condition Data Detection.

The other method is the generation trend tracing method based on a normal SVM. The unusual condition data detection method detects some rare case data in the regular condition data and displays these patterns to experts. From the displayed patterns, the experts select some data that may indicate a trouble condition sign and teach them to the computer.

After this, the computer has the regular condition data and the selected unusual condition data. Now, the computer can generate an optimal hyperplane, which can classify the two classes, by using an SVM. The hyperplane classifies unseen data and finds some data that are similar to the selected unusual condition data. Therefore, the computer can trace the trend for the generation of *special unusual condition data*.

2.2 Unusual Condition Pattern Detection

Figure 2 shows the concept for the detection of unusual condition data in the regular condition data. In this figure, the gray area denotes the regular condition data area. In this research, the unusual condition data are detected from this regular condition data. From Figure 2, if we can find a hyper-sphere, that can cover 99% of the regular condition data, we can consider the other 1% to be unusual condition data. This 99% of the regular condition data are called "usual condition data." In Figure 2, the inside of a circle shown by a solid black line is the usual condition data area, and the black stars denote the unusual condition data. Therefore, if we can correctly find the boundary for an area of α% in the regular condition area, it is possible to detect the unusual condition data that do not belong to this α% area of the regular condition data. We adopt a one-class SVM or one-class SKM to correctly find this boundary.

2.3 One-class Support Vector Machine

Schölkopf et al. suggested a method of adapting the SVM methodology to a one-class classification problem (Schölkopf et al., 2000). Essentially, after transforming the feature via a kernel, they treat the origin as the only member of the second class. By using "relaxation parameters," they separate the image of the one class from the origin. Then, the standard two-class SVM techniques are employed.

One-class SVM (Schölkopf et al., 2000) returns a function f that takes the value -1 in a "small" region, capturing most of the training data points, and $+1$ elsewhere.

Let the training data be $x_1,\ldots,x_N$, belongs to one class X, where X is a compact subset of R^N, and N is the number of observations. Let $\Phi : X \to H$ be a kernel map that transforms the training examples into a feature space. The dot product in the image of Φ can be computed by evaluating some simple kernels,

$$k(\mathbf{x},\mathbf{y}) = (\Phi(\mathbf{x})\cdot\Phi(\mathbf{y})). \tag{1}$$

Then, in order to separate the data set from the origin, one needs to solve the following quadratic program:

$$\begin{aligned} \min_{\mathbf{w},\xi,\rho} \quad & \frac{1}{2}\|\mathbf{w}\|^2 - \nu N\rho + \sum_N \xi_i \\ \text{subject to} \quad & (\mathbf{w}\cdot\Phi(\mathbf{x}_i)) \geq \rho - \xi_i, \\ & \xi_i \geq 0. \end{aligned} \tag{2}$$

Using multipliers $\alpha_i,\beta_i \geq 0$, we introduce a Lagrangian

$$\begin{aligned} L(\mathbf{w},\xi,\rho,\alpha,\beta) = {} & \frac{1}{2}\|\mathbf{w}\|^2 - \nu N\rho + \sum_i \xi_i \\ & - \sum_i \alpha_i((\mathbf{w}\cdot\Phi(\mathbf{x}_i)) - \rho + \xi_i) - \sum_i \beta_i\xi_i \end{aligned} \tag{3}$$

and set the derivatives with respect to the primal variables $\mathbf{w},\xi_i,\rho$ equal to zero, yielding

$$\mathbf{w} = \sum_i \alpha_i\Phi(\mathbf{x}_i), \tag{4}$$

$$\alpha_i = 1-\beta_i \leq 1,\ \sum_i \alpha_i = \nu N. \tag{5}$$

Substituting Eqs. (4) and (5) into Eq. (3), we obtain the dual problem:

$$\min_{\alpha} \quad \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j\Phi(\mathbf{x}_i)\cdot\Phi(\mathbf{x}_j) \tag{6}$$

$$= \min_{\alpha} \quad \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j k(\mathbf{x}_i,\mathbf{x}_j) \tag{7}$$

$$\text{subject to} \quad 0 \leq \alpha_i \leq 1,\ \sum_i \alpha_i = \nu N \quad . \tag{8}$$

All patterns $\{\mathbf{x}_i : \alpha_i > 0, i = 1\ldots N\}$ are called support vectors. These patterns correspond to the hyperplane. From Eq. (8), $\nu \in (0,1)$ is an upper bound on the fraction of outliers, and a lower bound on the fraction of support vectors. The decision function

$$f(\mathbf{x}) = \mathrm{sgn}((\mathbf{w} \cdot \Phi(\mathbf{x})) - \rho) \tag{9}$$

will be positive for most examples of $\mathbf{x}_i$ contained in the training set, while the fraction of support vectors will still be small. The actual trade-off between these two is controlled by ν. For a new point $\mathbf{x}$, the value of $f(\mathbf{x})$ is determined by evaluating which side of the hyperplane it falls on. One can show that at the optimum, the two inequality constraints of Eq. (2) become equalities if $0 < \alpha_i < 1$. Therefore, we can recover ρ by exploiting the fact that, for any such α_i, the corresponding pattern $\mathbf{x}_i$ satisfies

$$\rho = \mathbf{w} \cdot \Phi(\mathbf{x}_i) = \sum_j \alpha_j k(\mathbf{x}_j, \mathbf{x}_i) \tag{10}$$

2.4 One-Class Support Kernel Machine

One-class SKM was developed based on support kernel machine (SKM) (Bach et al., 2004). SKM is a kind of the multiple kernel learning problem defined by Lanckriet et al. (Lanckriet et al., 2004). SKM is able to combine feature selection and optimization.

Eq. (6) is transformed into

$$\min_{\alpha} \sum_j (\sum_i \alpha_i \Phi(\mathbf{x}_{i,j}))^2. \tag{11}$$

This square sum is transposed to maximize the square

$$\min_{\alpha} \max_j (\sum_i \alpha_i \Phi(\mathbf{x}_{i,j}))^2, \tag{12}$$

and transposed to maximize the absolute value

$$\min_{\alpha} \max_j |\sum_i \alpha_i \Phi(\mathbf{x}_{i,j})|. \tag{13}$$

Eq. (13) is transformed into

$$\begin{aligned} \min_{\alpha} \quad & \mathbf{w}_0 \\ \text{subject to} \quad & |\mathbf{w}_j| = |\sum_i \alpha_i \Phi(\mathbf{x}_{i,j})| \leq \mathbf{w}_0 \\ & 0 \leq \alpha_i \leq 1,\ \sum_i \alpha_i = \nu N. \end{aligned} \tag{14}$$

Eq. (14) is a linear programming problem and leads to a sparse $\mathbf{w}$ with good generalization properties. Therefore, this equation can be solved quickly and it selects efficient features. Here, the decision function of the one-class SKM is the same as Eq. (9).

3 EXPERIMENT

In this section, we describe our experiment. In particular, we briefly introduce the measurement data, our experimental setup, experimental results, and the evaluation.

Table 1: Outline of Ooyodo River First Hydroelectric Power Plant.

Generated Output		13,500kW
Working Water		$42m^3/s$
Effective Head		38.40m
Turbine Type		Vertical Shaft Francis Turbine
Rated Revolutions Per Minute		200rpm
Bearing Type	Upper Bearing	Oil Self Contained Type Segment Bearing (Oil Feeding)
	Bottom Bearing	Oil Self Contained Type Cylindrical Bearing (Natural Cooling)
	Turbine Bearing	Oil Self Contained Type Segment Bearing (Natural Cooling)
	Thrust Bearing	Oil Self Contained Type Michell Bearing (Natural Cooling)

3.1 Measurement Data

Table 1 shows the outline of the Ooyodo River First hydroelectric power plant. This hydroelectric power plant has various sensors to measure data related to bearing vibration. The measured operation data were collected from the hydroelectric power plant and analyzed using our proposed method. The measured operation data related to bearing vibration were collected from June 14, 2006, to January 31, 2008, at the Ooyodo River First hydroelectric power plant.

One data set was composed of the sensor and weather information from 38 measurement items for a measurement interval of 5 s. All of the measurement data were regular condition data and did not include the trouble condition data.

3.2 Experimental Setup

Our experiment analyzed the measurement data, which were explained in 3.1. The measurement data were composed of 38 measurement items. However, in order to detect the unusual condition data for bearing vibration, we extracted the measurement items related to the bearing vibration from all of the measurement items. Therefore, 16 measurement items were selected based on the bearing vibration knowledge of the experts to analyze the unusual condition data. Table 2 shows these selected 14 measurement items.

The power generator operation consists of the starting condition, parallel condition, parallel off condition and stopping condition. The number of starting condition data points and parallel off condition data points was relatively very small in our dataset. The number of parallel operation condition data points was very large. If we analyzed all of the measurement data to detect the unusual condition data, the detected condition data consisted of the

Table 2: Measurement Items.

A. Generated Output (MW)	B. Revolutions Per Minute
C. Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	D. Turbine Bearing Oil Temp. (°C)
E. Thrust Bearing Temp. (°C)	F. Bottom Oil Tank Oil Temp. (°C)
G. Bottom Bearing Inlet Air Temp. (°C)	H. Turbine Shaft Vibration (X axis) (μm)
I. Upper Bearing Vibration (Perpendicular) (μm)	J. Upper Bearing Vibration (Horizon) (μm)
K. Bottom Bearing Vibration (Perpendicular) (μm)	L. Bottom Bearing Vibration (Horizon) (μm)
M. Wheel Cover Vibration (Perpendicular) (μm)	N. Wheel Cover Vibration (Horizon) (μm)

Table 3: Number of Data Points for Each Condition.

Group	The number of data points
Stopping condition	2,430,295
Starting condition	6,629
Parallel operation condition	4,346,259
Parallel off condition	672
Total	2,804,113

starting condition data or the parallel off condition data, which were different from the parallel operation condition data. This was not a good situation for our analysis. Therefore, all of the measurement data were divided into the following four groups based on the expertise of the experts.

Starting condition:
Generator Voltage (V-W) $<$ 10kV, Guide Vane Opening $\geq$ 10% and Revolutions per Minute $\geq$ 200 rpm.

Parallel operation condition:
Generator Voltage (V-W) $\geq$ 10kV and
Revolutions per Minute $\geq$ 200 rpm.

Parallel off condition:
Generator Voltage (V-W) $<$ 10kV, Guide Vane Opening $<$ 10% and Revolutions per Minute $\geq$ 200 rpm.

Stopping condition:
Otherwise.

These groups were defined by the experts. Table 3 shows the number of data points in each group.

In the stopping condition group, the bearing does not rotate. Moreover, only one or less than one parallel off condition data point was found for each actual parallel off condition. Therefore, these data groups were omitted from the analyzed data. In other words, the unusual condition data were detected in the other group, which were the starting condition and parallel operation condition. We use a linear kernel in our experiments because it is impossible to tune the kernel parameters using only the regular condition data. In order to ignore the different measurement units and define the unsafe condition, the measurement data were normalized using the following equation for each measurement item for the one-class SVM.

$$\text{value} = -\frac{\text{actual value} - \text{min. value}}{\text{max. value} - \text{min. value}} + 1$$

For the hydroelectric power plant, a high value for any sensor denotes an unsafe condition. Therefore, our method adopted the normalization.

The one-class SKM is equivalent to a one-class SVM that applies *optimized scaling*. Therefore, the measurement data were normalized to maintain the variances of the features, and the origin became the high value of each sensor. Additionally, the measurement data points were multiplied by -1.

3.3 Unusual Condition Discovery Experiment

The unusual condition data were discovered in the starting condition data and the parallel condition data by applying the one-class SVM or one-class SKM. This experiment used the operation data measured from June 14, 2006, to May 31, 2007, to find the special unusual condition data. The discovered unusual condition data were determined to be *special unusual condition data* based on the knowledge of human experts. In the starting condition, 0.1% of the starting operation condition data was determined to be unusual condition data. In the parallel condition, 0.002% of the parallel operation condition data was determined to be unusual condition data. Tables 4 and 5 show the detected unusual condition data from the starting operation condition data from the Ooyodo River First hydroelectric power plant. The unusual condition data that were detected by our system were presented to experts to identify *special unusual condition data*. These human experts pointed out a special feature of the detected data. This feature was that unusual values were detected in data point no. 15 of Table 4 and data point no. 10 of Table 5. The human experts checked the daily operation report for this day and found the following fact. Oil leakage at bearing was found and repaired on this day. This was a very rare case and showed a trouble condition sign.

3.4 Discussion

Figures 3 and 4 show the monthly distributions of unusual condition data. From these figures, the results

Table 4: Detected Unusual Condition from Starting Operation Condition using One-class SVM.

Data Point No.	1(1)	2	3	4	5(2)	6(3)	7	8	9(6)
Revolutions Per Minute	197.0	198.8	199.7	196.6	199.8	200.2	199.0	196.1	198.7
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	13.8	10.8	12.4	12.0	12.7	13.4	11.3	12.6	13.4
Turbine Bearing Oil Temp. (°C)	52.4	46.0	48.5	49.8	49.8	50.1	46.6	50.4	47.9
Thrust Bearing Temp. (°C)	50.2	45.0	50.2	49.1	50.1	51.5	49.1	49.9	.48.6
Bottom Oil Tank Oil Temp. (°C)	43.9	40.8	45.8	45.8	45.8	45.9	45.2	46.0	43.3
Bottom Bearing Inlet Air Temp. (°C)	29.8	29.1	31.0	30.6	30.1	29.8	30.8	31.2	27.6
Turbine Shaft Vibration (X axis) (μm)	190	146	139	140	152	155	145	156	139
Upper Bearing Vibration (Perpendicular) (μm)	6	20	8	13	11	9	9	13	16
Upper Bearing Vibration (Horizon) (μm)	19	21	20	18	20	21	20	19	20
Bottom Bearing Vibration (Perpendicular) (μm)	12	14	13	12	13	13	13	12	14
Bottom Bearing Vibration (Horizon) (μm)	1	1	13	12	1	14	14	1	2
Wheel Cover Vibration (Perpendicular) (μm)	2	2	3	6	2	2	2	29	2
Wheel Cover Vibration (Horizon) (μm) 28	23	0	0	28	0	0	0	24	

Data Point No.	10	11(7)	12	13	14(8)	15(10)	16	17	18
Revolutions Per Minute	196.3	197.0	202.5	198.2	198.5	198.8	195.6	196.3	196.2
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	13.9	13.8	14.0	14.6	14.7	21.9	22.2	22.4	22.4
Turbine Bearing Oil Temp. (°C)	48.8	48.5	48.6	48.8	38.5	40.0	42.4	43.5	43.8
Thrust Bearing Temp. (°C)	48.0	48.8	46.0	47.2	41.0	41.3	50.0	49.8	49.8
Bottom Oil Tank Oil Temp. (°C)	44.4	44.4	43.0	43.1	36.5	34.0	35.3	36.2	36.3
Bottom Bearing Inlet Air Temp. (°C)	27.8	27.5	27.0	26.5	21.1	13.9	16.2	16.1	16.0
Turbine Shaft Vibration (X axis) (μm)	162	155	133	140	130	126	251	280	278
Upper Bearing Vibration (Perpendicular) (μm)	15	22	3	21	27	22	32	28	29
Upper Bearing Vibration (Horizon) (μm)	18	18	18	19	16	15	21	20	19
Bottom Bearing Vibration (Perpendicular) (μm)	12	13	12	14	15	16	13	13	13
Bottom Bearing Vibration (Horizon) (μm)	2	2	1	2	1	8	1	1	1
Wheel Cover Vibration (Perpendicular) (μm)	2	2	25	2	22	4	2	2	2
Wheel Cover Vibration (Horizon) (μm)	24	26	1	20	0	0	2	2	2

Note: The data point numbers from Table 5 are shown in parentheses.

Table 5: Detected Unusual Condition from Starting Operation Condition using One-class SKM.

Data Point No.	1(1)	2(5)	3(6)	4	5	6(9)	7(11)	8(14)	9
Revolutions Per Minute	197.0	199.8	200.2	198.5	199.1	198.7	197.0	198.5	197.2
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	13.8	12.7	13.4	12.8	11.5	13.4	13.8	14.7	21.5
Turbine Bearing Oil Temp. (°C)	52.4	49.8	50.1	50.1	46.8	47.9	48.5	38.5	39.8
Thrust Bearing Temp. (°C)	50.2	50.1	51.5	50.0	50.0	.48.6	48.8	41.0	40.8
Bottom Oil Tank Oil Temp. (°C)	43.9	45.8	45.9	46.3	44.8	43.3	44.4	36.5	33.9
Bottom Bearing Inlet Air Temp. (°C)	29.8	30.1	29.8	30.8	31.2	27.6	27.5	21.1	14.1
Turbine Shaft Vibration (X axis) (μm)	190	152	155	168	140	139	155	130	130
Upper Bearing Vibration (Perpendicular) (μm)	6	11	9	7	7	16	22	27	15
Upper Bearing Vibration (Horizon) (μm)	19	20	21	20	21	20	18	16	14
Bottom Bearing Vibration (Perpendicular) (μm)	12	13	13	24	26	14	13	15	15
Bottom Bearing Vibration (Horizon) (μm)	1	1	14	2	1	2	2	1	1
Wheel Cover Vibration (Perpendicular) (μm)	2	2	2	0	0	2	2	22	16
Wheel Cover Vibration (Horizon) (μm)	28	28	0	2	2	24	26	0	3

Data Point No.	10(15)	11	12	13	14	15	16	17	18
Revolutions Per Minute	198.8	198.7	196.0	203.3	199.1	200.7	198.7	199.0	197.2
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	21.9	23.7	22.2	20.5	13.8	16.1	15.4	11.3	11.2
Turbine Bearing Oil Temp. (°C)	40.0	37.9	42.2	43.9	29.2	35.7	43.0	28.8	27.8
Thrust Bearing Temp. (°C)	41.3	40.5	50.1	43.1	37.2	42.8	45.9	39.8	39.3
Bottom Oil Tank Oil Temp. (°C)	34.0	31.8	35.2	35.8	30.2	35.2	39.3	32.6	31.9
Bottom Bearing Inlet Air Temp. (°C)	13.9	11.4	16.2	17.2	17.9	19.8	22.3	22.9	23.8
Turbine Shaft Vibration (X axis) (μm)	126	120	295	135	73	86	111	65	72
Upper Bearing Vibration (Perpendicular) (μm)	22	14	23	4	6	22	9	8	14
Upper Bearing Vibration (Horizon) (μm)	15	12	20	14	14	16	15	14	15
Bottom Bearing Vibration (Perpendicular) (μm)	16	16	14	15	19	17	17	29	29
Bottom Bearing Vibration (Horizon) (μm)	8	0	1	9	1	1	11	1	1
Wheel Cover Vibration (Perpendicular) (μm)	4	14	2	3	19	20	2	0	0
Wheel Cover Vibration (Horizon) (μm)	0	2	2	0	2	0	0	1	1

Note: The data point numbers from Table 4 are shown in parentheses.

for the one-class SVM (OCSVM) were highly biased in summer. On the other hand, the one-class SKM (OCSKM) reduced this bias.

Tables 6 and 7 show the weight factors **w** for the starting condition data and parallel condition data. In OCSKM, the turbine bearing oil temperature, thrust bearing temperature, and bottom oil tank oil temperature are zero. These temperature features reach high values in summer. Therefore, the unusual condition data of OCSVM increase in summer.

4 CONCLUSIONS

There are two kinds of trouble condition signs. The first indicates an accidental trouble condition, where the data are different from the usual condition data. The other kind of trouble condition sign indicates

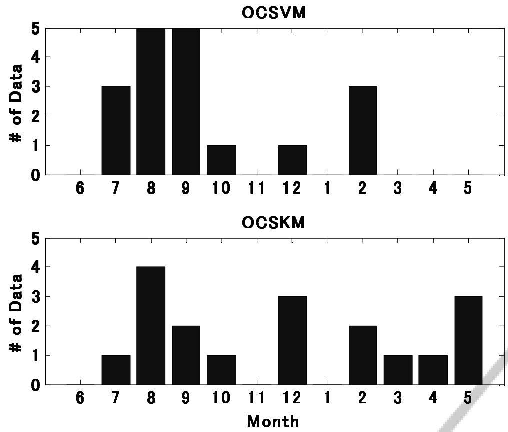

Figure 3: Monthly Distribution of Unusual Condition Data (Starting Operation Condition).

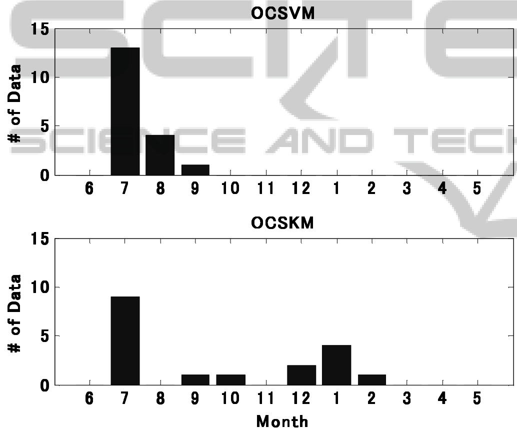

Figure 4: Monthly Distribution of Unusual Condition Data (Parallel Operation Condition).

aging degradation. If aging degradation occurs in a hydroelectric power plant, then this second kind of trouble condition sign increases year by year. In our method, we identified this second kind of trouble condition sign using special unusual condition data, which were discovered by an interaction between computers and human experts. However, it is difficult for human experts to evaluate whether or not sensors with weights of nearly zero affect an unusual condition. If our detection method is introduced in actual plant, human experts will need to confirm the trouble condition signs in daily operations. Hence, there is a need to be able to confirm trouble condition signs using a small number of sensors. In this paper, we proposed a method for narrowing down the sensors that indicate an unusual condition. This method was based on a one-class SKM.

Our unusual condition discovery experiment showed that the one-class SKM found the trouble condition signs in a hydroelectric power plant by using a

Table 6: Weighting Factors for Starting Operation Condition.

	OCSVM	OCSKM
Revolutions Per Minute	8.13	0.54
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	9.16	0.72
Turbine Bearing Oil Temp. (°C)	2.62	0
Thrust Bearing Temp. (°C)	2.02	0
Bottom Oil Tank Oil Temp. (°C)	2.38	0
Bottom Bearing Inlet Air Temp. (°C)	4.22	0
Turbine Shaft Vibration (X axis) (μm)	7.70	1.68
Upper Bearing Vibration (Perpendicular) (μm)	9.22	0.29
Upper Bearing Vibration (Horizon) (μm)	3.45	0
Bottom Bearing Vibration (Perpendicular) (μm)	10.33	2.98
Bottom Bearing Vibration (Horizon) (μm)	11.81	2.15
Wheel Cover Vibration (Perpendicular) (μm)	13.23	2.45
Wheel Cover Vibration (Horizon) (μm)	10.86	2.20
ρ	52.72	10.71

Table 7: Weighting Factors for Parallel Operation Condition.

	OCSVM	OCSKM
Generated Output (MW)	1.58	0.09
Revolutions Per Minute	3.34	1.26
Upper Bearing Oil Temp. − Oil Cooler Inlet Air Temp. (°C)	9.83	3.35
Turbine Bearing Oil Temp. (°C)	0.73	0
Thrust Bearing Temp. (°C)	1.20	0
Bottom Oil Tank Oil Temp. (°C)	1.49	0
Bottom Bearing Inlet Air Temp. (°C)	2.09	1.72
Turbine Shaft Vibration (X axis) (μm)	7.72	0.75
Upper Bearing Vibration (Perpendicular) (μm)	9.68	1.20
Upper Bearing Vibration (Horizon) (μm)	6.17	0.24
Bottom Bearing Vibration (Perpendicular) (μm)	9.80	1.36
Bottom Bearing Vibration (Horizon) (μm)	10.50	1.37
Wheel Cover Vibration (Perpendicular) (μm)	10.59	1.39
Wheel Cover Vibration (Horizon) (μm)	9.76	1.27
ρ	48.65	11.95

large quantity of usual condition data. In addition, a one-class SKM was found to reduce the extraction bias in summer for the one-class SVM.

In future work, we plan to apply our method to evaluate the soundness of real hydroelectric power plants in Japan and verify the effectiveness of our method for risk management in hydroelectric power plants.

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