Generator Maintenance Data Collection by IoT and Failure Sign Diagnosis

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Abstract

Along with the development of Internet of Things (IoT) and Machine to Machine (M2M) technologies, it has become possible to easily and continually collect data from sensors installed in infrastructure facilities. The basis of maintenance of infrastructure facilities currently has changed from former Time Based Maintenance (TBM) to Condition Based Maintenance (CBM) mode.

In Fiscal 2015, we began data collection and verification for customers' facilities to improve availability. As such, we developed a sensing system for operating hydropower generating plant. This system is intended to collect, accumulate, and analyze the status data continuously from the key components of each generator. All sensors on these generators are newly mounted by refitting work. These units work completely independently from existing facilities. The state of the generator's operation data are always collected by taking pictures of the generator output meters on the switchboard and analyzing pictures obtained from the network camera. For this verification, a machine learning approach is applied to the post-analysis of vibration data collected near the shaft bearings. As a result, a sign-emergence timing of mechanical failures could be detected about 12 days before the occurrence of an actual failure.

1 Preface

If our major products of infrastructure facilities stop functioning due to a sudden system failure, enormous and economical losses could occur. To prevent such a serious failure, it is indispensable to reinforce technologies for facility diagnosis. In conventional diagnostic approach, Time Based Maintenance (TBM) was mainstream where maintenance for facilities was carried out periodically. Nowadays, however, the technologies of Internet of Things (IoT) and Machine to Machine (M2M) were developed and status data ("maintenance data" hereafter) can be collected easily and continually from the key parts of a generator. They are gathered by sensors mounted in an infrastructure facility. As such, it is possible to carry out maintenance by Condition Based Maintenance (CBM) services with due consideration to the operating state of our supplied products and facility management status.

This paper introduces our programs to improve the facility availability.

(1) We put various sensors on water turbine gen-

erator facilities under operation to collect, store and analyze maintenance data on a continuous basis. (2) It aims to detect signs of facility failure (difference from regular conditions) in early stages to take adequate countermeasures.

2 Building Sensing System

To collect maintenance data from operating facilities, we began gathering field test data ("field test" verification hereafter) in Fiscal 2015 in our customer's facilities. The main purpose was to improve facility availability. We selected two hydropower generating plants using our generator as field test project site. We built a sensing system on the project site facility.

2.1 Sensing System

Fig. 1 shows a basic configuration of the sensing system. Various sensors are mounted on the generator and the data collected by these sensors are sent through a wired network and tentatively stored in the data gathering Personal



The basic configuration is the same at any hydro power station.

Computer (PC). After primary diagnosis, data are sent to the cloud system via the wireless mobile telephone network. The cloud system stores and analyzes the data. The maintenance data are collected once every hour at a waveform data for a duration of five seconds. This system is completely independent of the existing facilities, as every sensor is a custom installation.

Considering the difficulty of permanently placing sensors in all facilities and key parts, we established a simplified system for off-line telemetry by combining a set of similar sensors and a data-gathering PC. We use this simplified system at various project sites for our maintenance service activities.

2.2 Applicable Sensors

Table 1 shows the sensors applied to this field test. To grasp working conditions of the generator, it was necessary to obtain information about generation output and other essential data. If such information is taken from the sensors connected to the existing system in the site, however, some modifications were necessary.

This system went digital by using image analysis. We collected image data of the generation output analog meter on the switchboard by a network camera. To detect mechanical failure around the bearing, a vibration sensor, an acoustic sensor, an infrared sensor, and a thermocouple were installed. In addition, a current sensor was installed on a grounding wire to monitor the state of insulation deterioration. Installation of thermal and hygroscopic sensors were indispensable to analyze the correlation between the operating conditions at the site and facility failures. **Fig. 2** shows installation status of the various sensors.

3 Failure Sign Diagnosis on Generators

Generators and such electrical facilities come in a variety of types and ratings. Since these facilities are composed of various components and parts, causes of failures are by many factors. For this reason, it is difficult for many people to define a process or set of rules to be followed in identifying and deciding the root cause of the failure. In this field test, we tried to detect a sign of a mechanical failure from vibration data gathered around the shaft bearing.

Table 1 Applicable Sensors

This table shows the purpose of installation, specifications, and external appearance of various sensors applied to this verification.

Sensor	Purpose of Installation	Specifica- tions	External appearance
Network camera	Analog meters data (kW, etc.) of target facilities are digitized to grasp the opera- tion status.	Attached with color night view mode of approx. 1.3 million pixels	
Vibra- tion	Vibration near the bearing was meas- ured to detect the presence of mechan- ical failures and flaws in the main shaft and the bearing and imbalance.	Magnet base in 3 axial direc- tions of X, Y, and Z	
Acoustic (micro- phone)	Noise around the bearing was meas- ured (frequency analysis) to detect a ground fault, short- circuit fault, insula- tion breakdown, and mechanical failures (metallic sound).	Microphone preamplifier	
Infrared rays	Surface tempera- tures around bear- ings and the main shaft (exposed parts) were measured.	Thermopile type (non-contact)	
Thermo- couple	Surface temperature near the bearing was measured to analyze the correlation to the vibration and sound. It also became pos- sible to monitor a trend of temperature difference by meas- uring the surface temperature at the inlet and outlet of the cooling water piping.	Length: 10m Measuring range: 0~ 200°C	
Environ- ment (tem- perature and humidity)	Temperature and humidity on the site were measured to analyze the correla- tion to vibration, sound, and surface temperatures. It also became pos- sible to grasp the risk of dew condensation by making compari- son with surface temperatures.	Measuring range: -20~80°C/ 0~100%RH	er Transis Base
Electric current	Mounted on the grounding wire. A leakage current was detected which was generated due to insulation deteriora- tion.	Rated current: ±1000mA	

3.1 Detection of Failure Sign at Power Station A

The water turbine generator at the Power Station A is of the horizontal axis type. During a period of about one month after the start of meas-



 (a) Vibration, acoustic, and infrared sensors installed near the bearing



(b) Current sensor mounted on the grounding wire



(c) Temperature and hygroscopic sensors and sensor terminals





(d) Analog values were digitized from the images of the generation output meter through the network camera.

ig. 2 Installation Status of Various Sensors

The vibration sensor was fixed with a magnet. Microphone stands were used to install acoustic and infrared sensors.



A vibration sensor was installed at the top of the load-side bearing.

urement, a failure (damage in the bearing) occurred. Fig. 3 shows the installation position of the sensor and Fig. 4 shows the transition in generation output. In Fig. 4, generation output (kW) is shown on the axis of ordinates and the lapse of days (minimal unit: 1 hour) after the start of measurement is shown on the axis of abscissas.

The data obtained during the seven days after the start of measurement service as the benchmark



Variations in generation output are shown monitored during the data measuring period (approx. one month).



The abnormality rate is shown on the assumption that a period of

7 days after the start of measurement is defined as the learning period.

data and the abnormality rate is calculated based on the benchmark data. Fig. 5 shows the timeseries graph of the abnormality rate. The abnormality rate (%) is shown on the axis of ordinates and the lapse of days after the start of measurement is shown on the axis of abscissas. Judging from this graph, the abnormality rate seems to increase about 12 days before the occurrence of a failure. In other words, a vibration pattern appeared in the different patterns form the benchmark data and this irregularity can be considered as a sign of failure occurrence. When focused on the generation output in Fig. 4, however, the period when the abnormality rate was high was caused while the generation output is continued at a low level of about 1000kW. For this reason, it is important to review if the collected benchmark data are insufficient or not.

3.2 Selection of Learning Period at the Power Station B

The water turbine generator at the Power Station B is of the vertical axis type. It operated normally for about 4 months after the start of measure-



(%) 10 (%)



Variations in generation output are shown monitored during the data measuring period (approx. 4 months).



Fig. 8 Case 1

The abnormality rate is shown on the assumption that a period of one month after the start of measurement served as the learning period. The abnormality rate seemed high.

ment. Fig. 6 shows the installation position of the sensor, Fig. 7 shows the transition in generation output, and Fig. 8 shows the transition in the abnormality rate. The data obtained during the month after the start of measurement (initial benchmark data collection period) served as the original col-



The abnormality rate is shown on the assumption that a period of the subsequent month served as the learning period. The condi-

tions of high abnormality rate improved.

lected data and the abnormality rate was calculated based on these benchmark data. About 90 days after the start of measurement, there was a tendency of high abnormality rate despite no occurring failure. When focused on the generation output in **Fig. 7**, the generation output during the period of high abnormality rate was about 12MW. This generation output is not included in the data during the data collection period.

Consequently, we changed the benchmark set of data. The data include the generation output around 12MW during the subsequent month. It has a large amount of data. Fig. 9 shows the new benchmark data. Including the data around the 90th day, the overall data show a low abnormality rate. Judging from this result, the data of the learning period covers almost all vibration patterns during the evaluation period.

4 Postscript

In this field test, we investigated the method of failure sign detection by using a data driven type approach like machine learning. We studied a method to detect the failure sign from the vibration data measured at the water turbine generator. Although this approach made it possible to detect a sign of timing for mechanical failures, it is still necessary to deepen our further study on the period for benchmark data and data coverage. These points greatly affect the analysis results.

Going forward, we will improve the sign diagnostic accuracy for mechanical failures occurring in a variety of types and ratings of a rotating machine. This is a study based on correlation among multiple data and through acoustic data analysis, not limited to only vibration data. For example, new sensors such as a displacement sensor will be adopted. Further, we will work on cost reduction (on specifications and prices) of sensors to be applied. We will provide continuous monitoring services, and will implement the feedback to our maintenance service business.

Lastly, we would like to express our sincere gratitude to the customers of the field test projects and the related university people for their supports on the related technical development.

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