An Anomaly Detection System for Advanced Maintenance Services

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OVERVIEW: Combining maintenance service expertise with data mining technology, Hitachi has developed an anomaly detection system to make appropriate diagnoses in accordance with equipment status changes. The system enables automation of equipment status diagnoses that previously required engineers with specialist knowledge. The system's highly accurate anomaly detection helps prevent losses from unexpected production facility shutdowns, and improves availability. Carrying out maintenance appropriately in line with equipment status can also lower the time and cost of maintenance management. Expanding the scope of application of the system is expected to enable advanced maintenance services.

INTRODUCTION

NOW that recent advances in information and communication technology (ICT) are making it easy to collect and store massive amounts of operation records data and sensor data, such log data are being saved for a large number of devices and systems. But in many cases, the saved electronic data are not being used effectively. The large volume of saved data (big data) contains various types of information about the devices and systems that the data came from. Effective use of this data can provide advance knowledge of device status changes and problems, and create highly reliable operation.

Seeking to enable more advanced maintenance services, Hitachi Power Solutions Co., Ltd. has developed the anomaly detection system, a system designed to provide advance knowledge of changes to abnormal hardware statuses by using data mining technology to extract significant information from among big data.

This article provides an example of how this big-data-driven anomaly detection system was applied to compact gas engine generators (see Fig. 1), and discusses future applications of the system.

ANOMALY DETECTION SYSTEM FUNCTIONS

The developed anomaly detection system automatically gathers data from dozens of sensors for parameters such as temperature, pressure, and engine speed. It stores the data in a database, then automatically executes a diagnosis process using two functions—a remote monitoring function and a data mining function. The diagnosis result can be communicated to maintenance service personnel using a list screen of color-coded statuses for each piece of equipment (see Fig. 2).

The remote monitoring function is a physically based diagnosis function that detects status changes after upper/lower threshold values and rate-of-change evaluation criteria for each sensor signal gathered from the equipment have been set from operator experience and knowledge. Evaluations are made by setting an abnormal detection threshold value for each sensor. Each sensor signal has a single evaluation threshold value and vice versa, making it easy to explain generated errors and failures, but making it difficult to detect status changes involving multiple sensor signals. When there are seasonal variations or differences in equipment installation environments, separate settings are also needed for each of the changing conditions. When there are many different failure types, each will

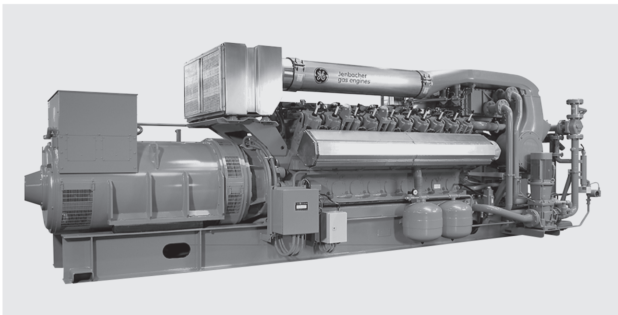

Fig. 1—Compact Gas Engine Generator.
A type of generator used in facilities such as offices, hospitals, and shopping malls, with a generation output of 300 to 2,400 kW.

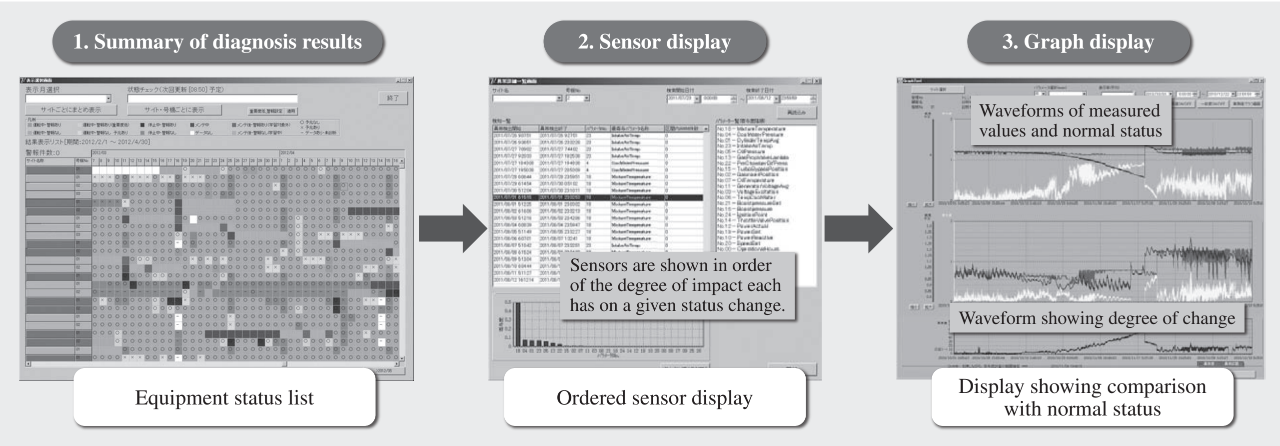

Fig. 2—Checking Status from Diagnosis Result Display.
Color-code displays show various equipment statuses giving the user a visual representation of them.

have a different occurrence frequency, so it may not always be possible to determine the optimum setting value. Another difficulty is that even among failures of the same type, the process leading to the failure or the cause of the failure might be different in each case, making it impossible to determine a single setting value for each failure type.

The data mining function is an example-based diagnosis function that is trained with normal-status data to learn statistical reference points. It detects equipment status changes on the basis of the distance between the measurement point in the statistical data space, and the reference point. The data mining function has higher sensitivity than the remote monitoring function, so could enable early detection of status changes. But a drawback of conventional data mining functions is that causes are difficult to explain when diagnosis results are derived from complex sensor signal correlations. This system has been designed to assist status monitoring and cause analysis by outputting an ordered list of the sensor signals responsible for a detected status change.

Configuration Overview

The anomaly detection system consists of a data gathering unit that receives sensor signal data from the equipment (a pre-existing data gathering mechanism can be used if present), a data storage unit that stores the gathered data, a diagnosis process unit that analyzes the stored data, and a display unit that outputs the analysis result (see Fig. 3).

Since the equipment in this example did not necessarily require a large computer system, the entire system was constructed using a computer to handle all three functions (data gathering, diagnosis, and storage).

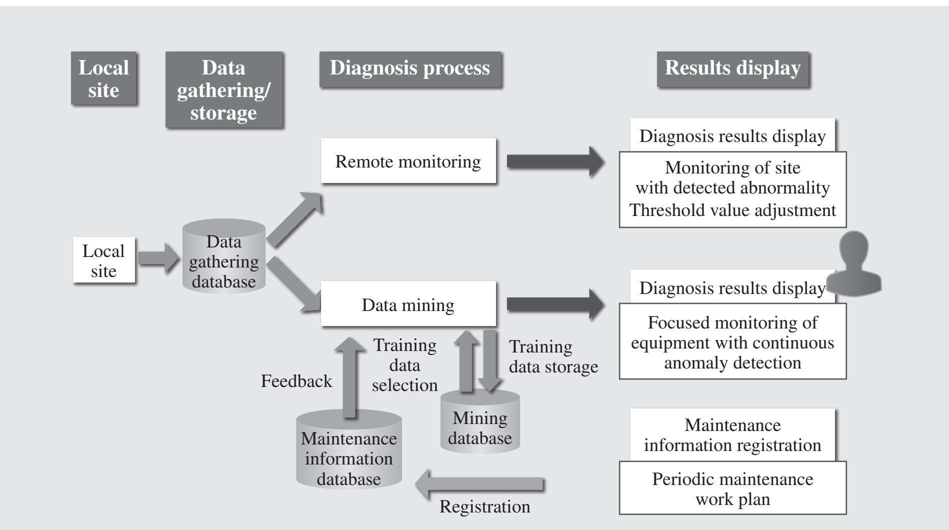

Fig. 3—Anomaly Detection System.
The anomaly detection system gathers and stores data, executes diagnosis processes, and displays the results. It enables early discovery of status changes, assisting inference of causes.

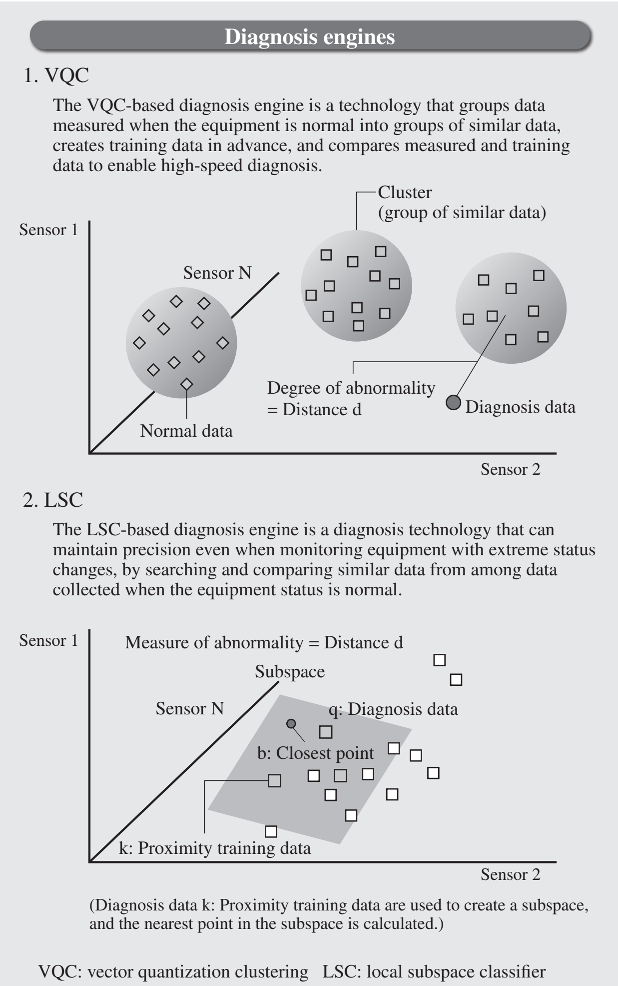

Fig. 4—Data Mining Algorithms.
Equipment operation statuses and sensor signal movements are used to select the optimum diagnosis algorithm, and mount it in the system.

Diagnosis Engines (Algorithms)

Two data mining technologies are used as anomaly detection algorithms—vector quantization clustering (VQC), and local subspace classifier (LSC) (see Fig. 4). Both of these diagnosis engines perform machine learning on normal-status sensor data, create indicators of differences between the data to be monitored and the learned normal data group, and evaluate whether the result is normal (same as the normal data) or abnormal (different from the normal data).

Since the developed diagnosis engines are non-parametric methods, they are resistant to statistical restrictions on sensor data. Methods such as the Mahalanobis-Taguchi (MT) system can only be applied when sensor data has a normal distribution, but the developed diagnosis engines are resistant to being affected by the data distribution. Since the algorithms are model-free, they can respond flexibly without the need for modelconstruction or simulations for each status change, even when there is a major change in a device or system operation status.

The optimum system configuration can be created by using each diagnosis engine separately according to the device or system to be monitored, or to the characteristics of the abnormality to be detected.

SYSTEM EVALUATION AND OPERATION

The Onuma Works of Hitachi Power Solutions (located in Hitachi, Ibaraki prefecture) performs remote monitoring of compact gas engine generators throughout Japan. We evaluated the system by applying it experimentally to about 100 of these monitored generators to verify its effectiveness. We have now increased the number of generators to 120, and perform daily diagnoses of about 30 different sensor signals measured in 30-second cycles. Here we describe an example anomaly that was actually detected by the data mining function (see Fig. 5).

This example is an anomaly that the system started to detect on October 11, and which subsequently continued to increase in degree of abnormality. The abnormality detection interval sensor signal was analyzed. As shown in Fig. 5, the result indicated that Sensor X contributed the most to the abnormality, and the anomaly detection system detected a drop in its measured value. The progress of the abnormality in the equipment was subsequently monitored, and parts were replaced on October 22. A pattern of decreasing Sensor X values led to the estimate that without this corrective action, the equipment would have experienced a trip (sudden shutdown) after about three

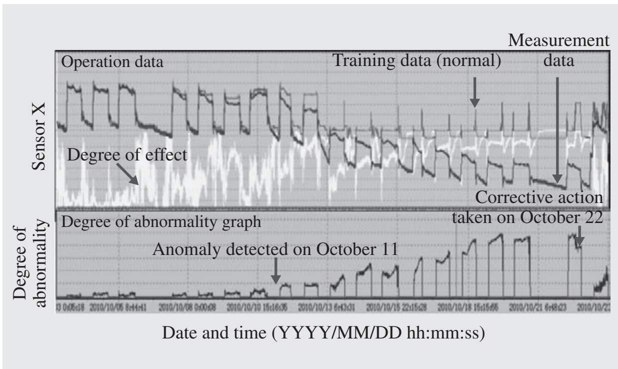

Fig. 5—Anomaly Detection Example.
When monitoring many equipment items, manually checking each output from every sensor is very difficult. The anomaly detection system can automatically diagnose device statuses that are different from the normal data, and notify the monitoring operator of the sensors responsible.

days, and an evaluation by experts also concluded that the system succeeded in detecting the anomaly about 10 days in advance.

Before the anomaly detection system, problems were handled by after-the-fact maintenance once failures had occurred. This approach requires time to coordinate the schedules of the field engineers dispatched to the site and time to allocate replacement parts, leading to adverse effects on equipment availability factors.

Since the use of the anomaly detection system enables steady monitoring of equipment anomaly detection results, the approach to compact gas engine generator maintenance service has now radically changed. Specifically, system diagnosis results are checked daily and also subjected to expert evaluations. The need for maintenance and its appropriate timing are then studied. While not completely comprehensive, this approach enables condition-based maintenance (CBM) in accordance with equipment status before failures occur and enables appropriate allocation of replacement parts (see Fig. 6). Since the system also provides visualization of equipment statuses, it has changed the awareness among maintenance service personnel, and data gathered daily are being used effectively.

ANOMALY DETECTION SYSTEM APPLICATIONS

The anomaly detection system uses sensor data to monitor (visualize) the daily operation statuses of devices and systems, and determines whether each is normal (the same as the normal data) or abnormal (different from the normal data) on the basis of abnormality measurement indicators. It can therefore be used to solve various problems (see Fig. 7).

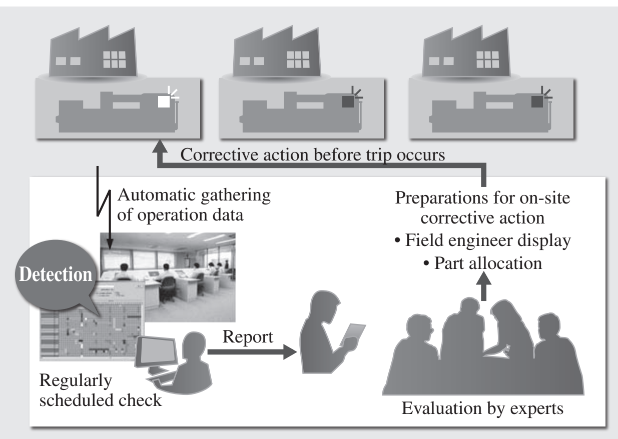

Fig. 6—Operation of Anomaly Detection System.
By checking anomaly detection system results daily, after-the-fact corrective actions can be replaced with advance corrective actions.

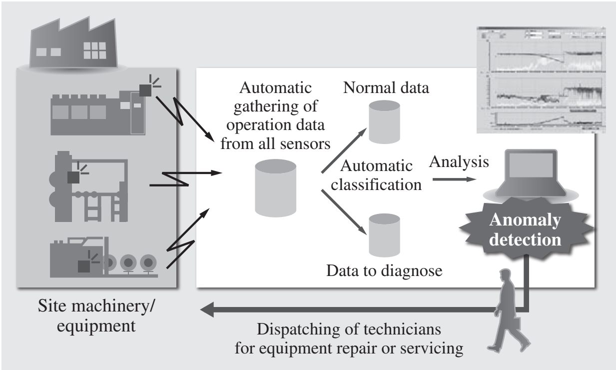

Fig. 7—Avoiding Unplanned Shutdowns of Important Equipment.
Data gathered and analyzed daily can be used to identify statuses that are 'different from always' and take corrective action without waiting for periodic maintenance.

(1) Problems encountered in preventing unplanned shutdowns

(a) The user has signed a maintenance agreement and makes efforts to maintain equipment. Maintenance is done periodically, but the user does not know whether the maintenance cycle and replacement parts are appropriate.

(b) The user puts time and effort into coordinating production and carries out periodic maintenance, but has overlooked failures and coordination errors, and sudden shutdowns have occurred directly after maintenance.

(c) When the user spots failures early on, repairs are just quick-fix part replacements.

(d) The user is unaware of equipment statuses, so daily operations are done with the anxiety of not knowing when a shutdown could occur.

(2) Problems encountered in using gathered data effectively

(a). The user gathers operation data and sensor data for important equipment items, but feels reassured just by gathering the data, and doesn't use it.

(b) The user does not know how to analyze data.

(c) Data are analyzed manually, imposing a large burden on workers.

(d) Data are used for cause analysis when accidents occur but not for preventive maintenance.

(3) Problems encountered in transferring skills and assuring quality

(a) The user relies on highly experienced veteran operators for equipment inspections and failure detection, and skills are not passed on to others.

(b) The user is forced to rely on individual ability for evaluating abnormalities.

(c) Only specific equipment items can receive abnormality evaluations.

(d) The user starts production without noticing that incorrect parameters or conditions have been entered, and produces a large volume of inferior products.

(e) Inferior products are generated even when the production process is the same.

The anomaly detection system greatly helps to solve these problems, and by storing information gathered during maintenance (type of sensor indicating an abnormality, failure cause, replacement part, corrective action) in a maintenance information database, it can provide guidance on the action required (hypothesized cause, possible replacement parts, corrective action) when a previously encountered anomaly is detected. These benefits improve maintenance work efficiency. They should also enable further use of data mining (effective data extraction) to acquire information needed for applications such as optimum part ordering and inventory management driven by replacement-based consumable part management, and needed for repairs and improvements done by identifying frequent failure locations and parts.

CONCLUSIONS

This article has presented an example of how a big-data-driven anomaly detection system was applied to compact gas engine generators, and discussed how its range of applications could be expanded in future.

In future, this system will be used with advanced maintenance technology to grow the O&M (operation and maintenance) service business. The anomaly detection system could also be used to create advanced maintenance services spanning a wide range of areas.

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