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ADVANCED GAS TURBINE DIAGNOSTICS USING PATTERN RECOGNITION

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ABSTRACT

Power plant owners require their plants' high reliability, availability and also reduction of the cost in today's power generation industry. In addition, the power generation industry is faced with a reduction of experienced operators and sophistication of power generation equipment.

Remote monitoring service provided by original equipment manufacturers (OEMs) has become increasingly popular due to growing demand for both improvement of plant reliability and solution of experienced operator shortage. Through remote monitoring service, customers can benefit from swift and appropriate operational support based on OEM's know-how.

Before implementation of remote monitoring, the customer and OEM often required repeated interchanges of information about operation and instrumentation data. These interchanges took a lot of time. Data analysis and estimation of deterioration were time-consuming. Remote monitoring has enabled us, OEMs, not only to access to a plant's real-time information but also to trace the historical operation data, and therefore the required time of data analysis and improvement has been reduced.

Mitsubishi Heavy Industries, Ltd. also embarked on around-the-clock remote monitoring service for gas turbine plant over a decade ago and has increased its ability over time. At present, the application of remote monitoring systems have been extended not only into proactive maintenance by making use of diagnostic techniques carried out by expert engineers but also into building a pattern recognition system and an artificial intelligence system using expert' knowledge.

Conventional diagnostics is only determining whether the plant is being operated within the prescribed threshold levels. Pattern recognition is a state-of-the-art technique for diagnosing plant operating conditions. By comparing past and present conditions, small deterioration can be detected before it needs inspection or repair, while all the operating parameter is within their threshold levels.

Mahalanobis-Taguchi method (MT method) is a technique for pattern recognition and has the advantage of diagnosing overall GT condition by combining many variables into one indicator called Mahalanobis distance. MHI has applied MT method to the monitoring of gas turbines and verified it to be efficient method of diagnostics.

Now, in addition to the MT method, automatic abnormal data discrimination system has been developed based on an artificial intelligence technique. Among a lot of artificial intelligence techniques, Bayesian network mathematical model is used.

INTRODUCTION

With increase in interest for environmental issues, electrical power generation plants are required to have a high efficiency and high reliability [1]. MHI has been developing Gas Turbine Combined Cycle (GTCC) plants where gas and steam turbines are combined for higher efficiency and reduction of environmental load.

Since the 90's, MHI has strived to offer the long term service agreement (LTSA), a long-term total service package, as a new maintenance service for GTCC plants, in response to the global demand. Parts supply, repair and dispatch of technical advisers for periodic inspection are available within the scope of the LTSA. Also a resident engineer at power station and remote monitoring service are available as optional services to meet customers' individual needs.

The LTSA has become popular for GTCC plants overseas to minimize risk of maintenance cost fluctuation. To meet the demand for high reliability, MHI provides 24-hour remote monitoring service for GTCC plants supplied by MHI.

For that purpose, Takasago remote monitoring center (RMC) was established in 1999. Afterwards in 2001, Orlando RMC was established by Mitsubishi Power Systems Americas, Inc. (MPSA), MHI's group company, in Florida, the USA in order to cover the remote monitoring of power plants located in North and Central America. Thereafter the number of remote monitoring users has gradually increased. Now the two centers above provide the remote monitoring service for more than 50 gas turbines worldwide with a total power output equal to 15 million kW. (Fig. 1)

At present, in order to improve the monitoring service for early detection of abnormality and quick diagnosis of root-cause, the application of remote monitoring systems have been extended into building a pattern recognition system and an artificial intelligence system using expert's knowledge[2][3].

A lot of pattern recognition-based monitoring methods have been studied. Artificial Neural Networks(ANNs) like multilayered Perceptron or Kohonen's Self-Organizing Map are actively applied to plant monitoring [4][5]. These techniques are useful for discriminating the normal pattern from abnormal patterns which consist of a lot of monitoring parameters without preparing any strict mathematical model of normal operations. However, after detecting the abnormality, these models require some additional analytical method if you want to know which monitoring parameters show the abnormality.

Another technique is to use statistical models. A multi regression method is used for the estimation of normal monitoring parameter values under the current operational condition using the training parameters collected from the normal operation conditions. This method tells which parameters show the largest deviation from the normal operation. However, we have to check all monitoring parameters for the abnormality detection every time.

Mahalanobis Taguchi method, another sophisticated statistical method can show the abnormality by a single value called Mahalanobis distance, and also it can tell which monitoring parameters are closely related with the largest abnormality by "SN ratio"[6][7]. Now MHI RMC use Mahalanobis Taguchi method for automatic abnormality detection.

Diagnosis of root-cause of abnormality is another important process for the monitoring. For this diagnosis, there are also a lot of "soft computing methods". ANN or fuzzy logic has been studied for this purpose [8][9]. ANNs have some difficulty to combine experts' root-cause knowledge with the neural network structure explicitly. Fuzzy logic better represents the expert's knowledge. However the quantitative connections of observed conditions and possible root-cause should be defined by experts' subjective opinions as fuzzy functions, which do not necessarily agree with objective probabilities based on collected operation data.

Bayesian Network (BN) model is based on the root-cause knowledge model with Bayesian probability. This model is used actively in the diagnosis fields [10][11]. Successful gas turbine monitoring using BN model has been reported[12]. MHI RMC also use BN model for the diagnosis. Root-cause analysis for Blade Path temperature (BPT) high was firstly implemented with over 1,000 BPT events.

This paper presents an overview of the Mitsubishi's 24x7 Remote Monitoring Center capabilities and experience. Then, examples of RMC Information processing technologies such as trend monitoring system, abnormality detection using Mahalanobis Taguchi method, and failure root-cause analysis using Bayesian Network model are described. Effects and advantages of these techniques are shown based on the field examples.

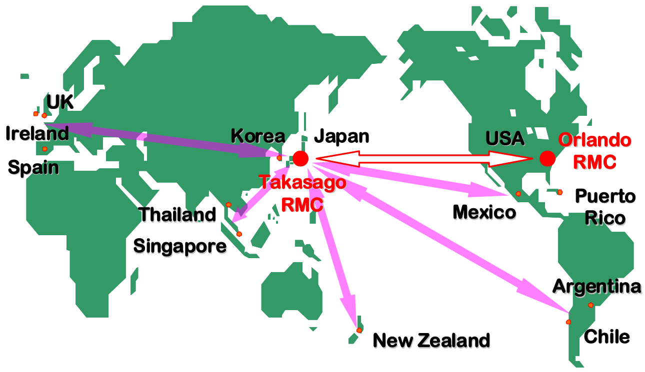

Fig. 1 Two remote monitoring centers and worldwide users

1. REMOTE MONITORING SYSTEM CONFIGURATION

Configuration of the Takasago's remote monitoring system (RMS) is shown in Fig. 2. The RMS enables us to monitor plant operational conditions by extracting operation data from the plant control equipment into the local data server and transmitting it to the RMC.

1.1. Local Data Server

First, operational data consisting of analogue and digital values are transmitted from the plant control equipment to the local data server installed for the remote monitoring systems. Then, it is transmitted to the RMC in almost real time (approximately three second intervals) as "real-time data" and also stored temporarily in the local data server at one second intervals. The one second interval data is sampled to one minute interval data and is stored in the data storage server as "historical data".

1.2. Web Server & Client, Data storage

The "real-time data" transmitted from the local data server at three second intervals via the MPLS-VPN or the Internet is stored temporarily in the web server located in the RMC, the monitoring terminals in the RMC are updated on a real-time basis from this server.

The one minute interval “historical data” is stored in the data storage server located in the RMC and all the monitored power plants’ operation data is stored away there for an unlimited duration. The stored operation data is able to be downloaded from the data storage server at anytime as required.

1.3. Sampling and monitoring items

The main GT operational parameters recorded by the RMS are;

(1) GT Speed and generator output
(2) Control signal output
(3) Fuel gas temperature, flow and control valve position
(4) Compressor inlet, outlet air temperature and pressure
(5) Blade path temperature and exhaust gas temperature
(6) NOx emissions
(7) Combustion pressure fluctuations
(8) Bearing vibration and metal temperatures
(9) Rotor cooling air temperature and disc cavity temperatures.

In addition to these analogue data points, digital data points (alarm and event signals) are also recorded. The main items cover the rest of the plant including steam turbine and heat recovery steam generator are also collected. Total number of monitoring items reaches up to 2,000 points at each monitoring cycles.

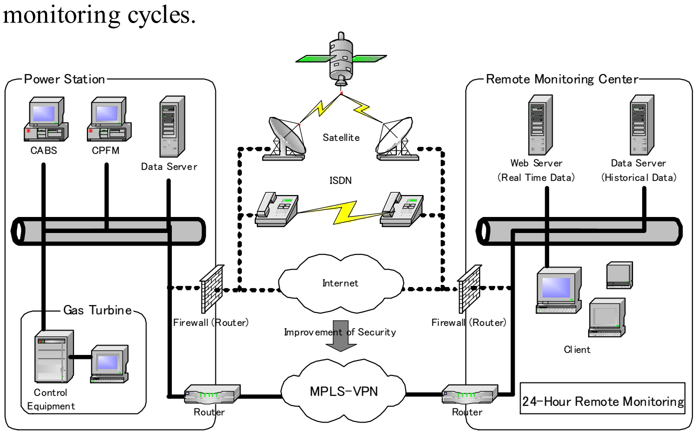

Fig. 2 Configuration of remote monitoring system

2. RMC’S MONITORING FUNCTIONS AND PLANT OPERATION SUPPORT

Remote monitoring system can display data in various ways, such as trend graphs, schematic diagrams and alarm summaries which are the same as the power plant’s control screens. These displays are used for observing the plant operational conditions and identifying alarms as standard real-time monitoring. In addition to this, the RMS has a data file writing function, which enables us to download operation data from the data storage server. This operational data can be used for various analyses, such as root-cause analysis of problems and performance evaluations.

2.1. Trend Graph Screen Display Function

On the trend graph screen as shown in Fig. 3, the progression of any specified parameter is viewable. The graph can be traced back 365 days. The time interval and the span are selectable. A cursor is available to read instantaneous data values.

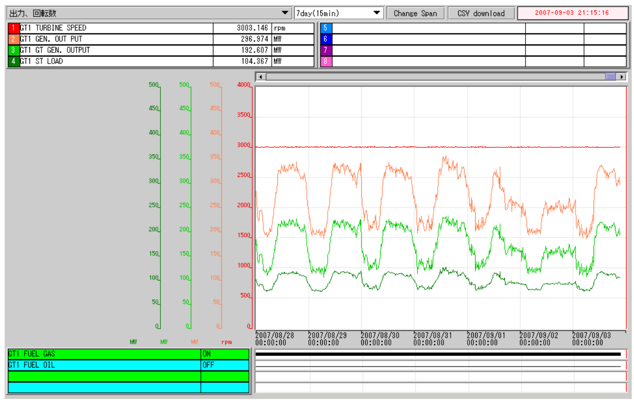
Fig. 3 Trend graph screen

2.2. Schematic Diagram Screen Display Function

The control block display is shown in Fig. 4. The current operational status of each system (such as fuel gas system, air flow system, lubrication system, bearing vibration and exhaust gas temperature distribution) can be easily understood from the schematic diagram screens.

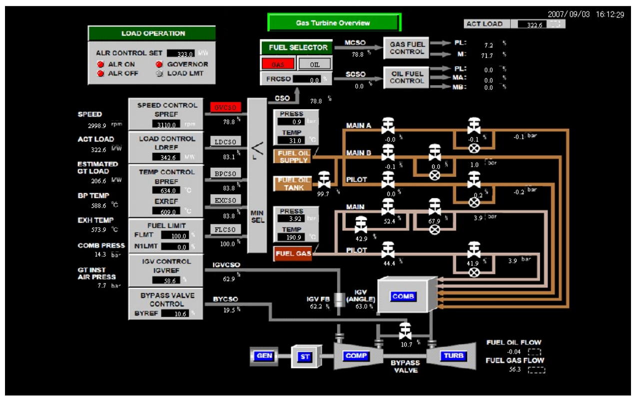
Fig. 4 Schematic diagram screen (control block)

2.3. Alarm Summary Display Function

From the viewpoint of protecting the equipment, an acceptability threshold is set for each operational parameter, such as temperature and pressure. These are the criteria which limit plant operation. If an operational parameter exceeds the threshold level, an alarm is activated which notifies us of some abnormality with the plant. The RMC above mentioned also receives various event signals, such as valve's open and closed signals, along with the alarm signals. The summary of alarm and event signals is displayed on a dedicated screen.

2.4. Plant operation support

RMC engineers monitor plant operational conditions around-the-clock in three shifts providing the operational support services, such as troubleshooting, tuning support, answering inquiries and diagnosing a root-cause of abnormality. (Fig. 5)

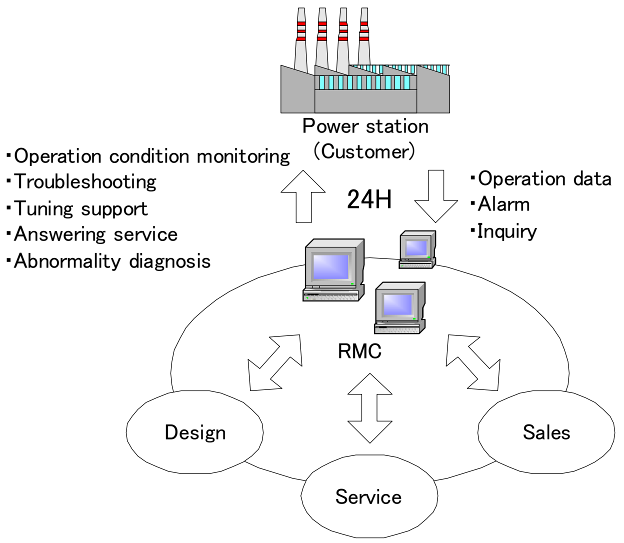

Fig. 5 Operation support service

The RMC has prepared various templates of graphs for the purpose of data discrimination. Therefore, the required time for discrimination has been remarkably reduced regardless of the plant's location (Fig. 6) so that unplanned outages are minimized. This will increase the plant reliability which is the greatest advantage of the remote monitoring center.

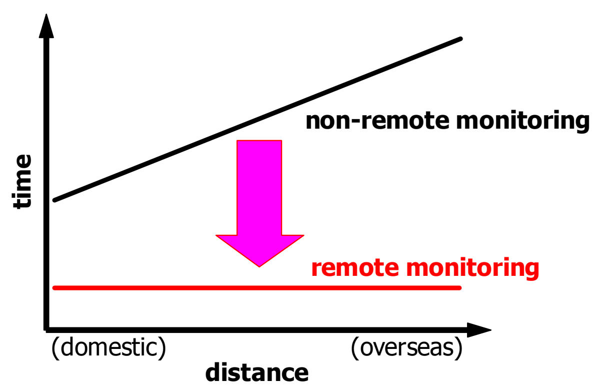

Fig. 6 The required time for data discrimination

3. ABNORMALITY DIAGNOSIS

The key of abnormality diagnosis is early detection. To protect the equipment from damages, the alarm threshold level can independently be set to each operation parameter, such as temperature and pressure. These alarms notify the RMC of some abnormality of the equipment when the parameter exceeds the threshold level.

In some cases, however, the proper action should be taken before the instrumentation data exceeds the alarm threshold. Even though the instrumentation data is within the threshold level, indications of a problem may appear as "small" change in that parameter (as shown in Fig. 7) and when the alarm is generated, the equipment may have already suffered damage.

It is, therefore, important to detect small changes which are symptomatic of an initial problem, before the alarm is generated. The monitoring items of gas turbine unit, however, cover a broad range of physical parameters and are subject to vary depending on many factors, such as atmospheric conditions and operation condition. Therefore it is not easy to detect such small changes by traditional operational monitoring.

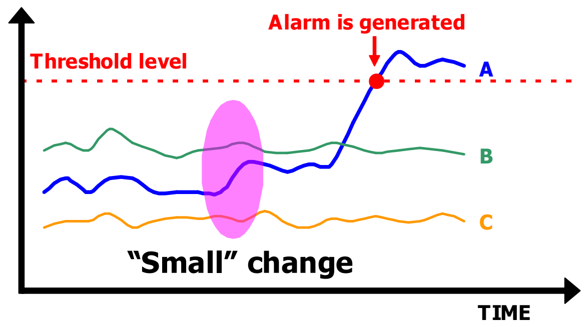

Fig. 7 Indication of initial problem

For the diagnosis of abnormality, we focus on two types of differences from standard patterns. Fig. 8 shows the two typical differences of a combination of parameters "X" and "Y". One is an abnormality which exceeds the alarm limit, which was discussed above. The standard custom alarm method is applied for detecting this type of abnormality at an earlier stage. The other shows a deviation from the normal relationship between the correlative parameters. The fact that the pattern is different from the standard operational patterns suggests an initial problem. Trend monitoring methods and Mahalanobis Taguchi method are useful in this type.

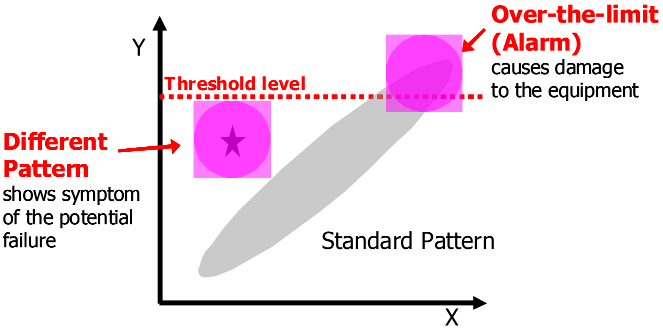

Fig. 8 Two types of abnormalities

3.1. Custom Alarm

The RMC sets a pre-alarm separate from the permanent alarm. Pre-alarm level is set closer than the permanent alarm for the purpose of early detection. Even if each unit has individual patterns of the same parameter, the threshold level of the permanent alarms are common to each unit. However, the RMC's custom pre-alarm is able to be set arbitrarily and individually for each unit as shown in Fig. 9. Therefore, custom alarm is very useful as an early warning system.

In addition to the pre-alarm based on arbitrary threshold level, the differential alarm and the variation rate alarm are able to be set arbitrarily.

(1) Threshold level pre-alarm
(2) Differential alarm
(3) Variation rate alarm

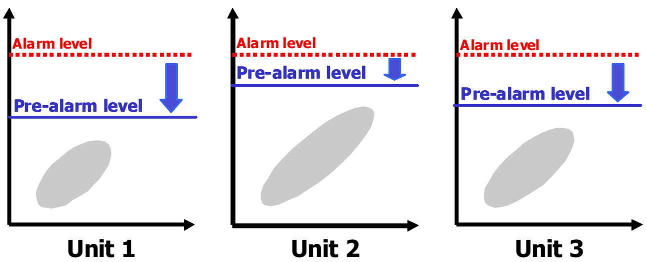

Fig. 9 Custom pre-alarm

3.2. Trend Monitoring

There are some cases where a small change cannot be detected early even if custom pre-alarms are used. For detecting these abnormalities, monitoring the trend of the pattern is useful.

An example of trend monitoring of the blade path temperature (BPT) deviation is shown in Fig. 11. Combustion gas temperature is one of the most important operational parameters of gas turbine, but turbine inlet gas temperature is too high to be measured. Therefore the temperature downstream of turbine final row blades called "BPT" is used to monitor the combustion condition. Fig. 11 is an example of the MHI 701F-type gas turbine witch has 20 combustors. Each deviation from the average temperature is important because its distribution can tell us something about the combustion condition of each combustor. (Fig. 10)

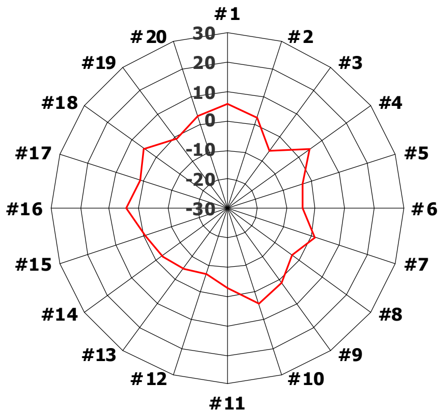

Fig. 10 Distribution of BPT deviation

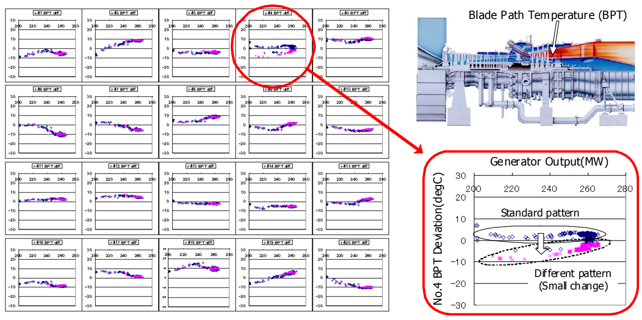

Fig. 11 Trend monitoring of BPT deviation

Fig. 11 shows scatter diagrams of BPT deviation (deg. C). on the Y axis and the generator output (MW) on the X axis. The blue points show a 10 day scatters and pink points show the latest one day scatter. The correlation between the two parameters is clearly visible here. Since each BPT deviation has individual patterns of correlation with generator output, by monitoring changes in such patterns, it is possible to detect changes in operational parameters even if it is a small change.

The latest one day pattern of No.4 BPT deviation varies from the standard pattern, even though it is a "small" change. This "small" change was actually detected before an alarm was generated. From this an inspection was carried out and No. 1 combustor was found to have initial light damage. Heavy damage was avoided because of early detection. The light damage caused a reduction in airflow into No. 1 combustor and this caused No. 4 BPT corresponding to No.1 combustor to decrease. Like the above example, trend monitoring enables us to detect such a small change before they become big changes, which could prevent damage in the time passed.

3.3. Mahalanobis Taguchi Method

Trend monitoring is a useful method for detecting differences in pattern early on. However, because of the large number of sensors on a modern GT, there are many monitoring parameters. Mahalanobis Taguchi method (MT method) is an advanced method of analysis which has the advantage of making diagnosis using only one index.

The MT method is one of several methods of the Mahalanobis Taguchi system and has a feature to identify the major factors in causing the difference. Also, MT method is a popular method used for pattern recognition. It is considered applicable to abnormality diagnosis to investigate whether the current operation condition is normal or abnormal in comparison with the previous condition.

The standard pattern consisting of multiple variables is created using a large number of data collected during normal operation. The distance between the standard pattern and the sample pattern is calculated based on the Mahalanobis distance(MD), where the variance of collected normal data is taken into account for the distance computation. Whether the operation condition of sample pattern is normal or abnormal is determined depending on this distance (Fig. 12).

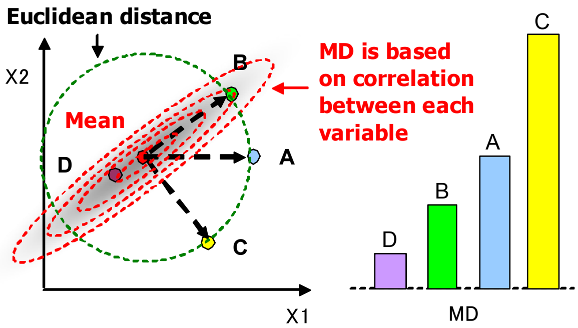

Fig. 12 Euclidean distance & Mahalanobis distance

The MD is calculated from the gas turbine's operation pattern consisting of more than 150 parameters considering correlations between each parameter as shown in Fig. 13.

The process of MT method consists of three major steps: (1) Preparation for MD calculation by defining correlation matrix, (2) Calculation of MD, (3) Calculation of SN ratio of each monitoring parameter.

Correlation matrix R is defined as follows:

$$R = \begin{bmatrix} & & \\ & r_{ij} & \\ & & \end{bmatrix} \cdots (1)$$

where $r_{ij} = E[u_i \cdot u_j]$. $E[\bullet]$ is the average of training data that are collected from the normal operation, and $u_i = \left(\dfrac{x_i - m_i}{\sigma_i}\right)$. m_i, σ_i are the mean and the standard deviation of i-th monitoring parameter of training data set $\{x_i\}$ respectively.

Mahalanobis Distance MD is defined as follows:

$$MD = \sqrt{\frac{1}{k}\sum_{i,j=1}^{k} \alpha_{ij}\left(\frac{x_i - m_i}{\sigma_i}\right)\left(\frac{x_j - m_j}{\sigma_j}\right)} \cdots (2)$$

Here, k is number of monitoring parameters. α_{ij} is i,j component of R^{-1}.

If the correlation matrix is an identity matrix, the training data have uniform distribution along all parameters. In this case, MD is equivalent to Eucledian distance.

Basic idea of SN ratio of i-th monitoring parameter is the difference of Mahalanobis distance of abnormal operation between the two cases: the case where i-th parameter is used and the case where i-th parameter is not used. In order to calculate this SN ratio effectively, the experimental design with orthogonal representation is used in Mahalanobis Taguchi method[6][7].

Since Mahalanobis distance indicates how the monitored operation is different from the normal operation with one parameter, we can detect any abnormality without looking at a lot of variables, such as generator output, control signal output, fuel gas flow, compressor inlet air temperature and exhaust gas temperature, etc.

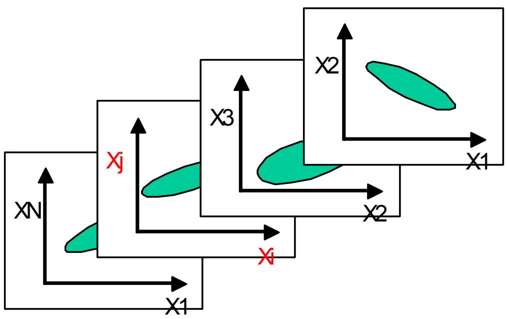

Fig. 13 Correlations between each parameter

If the sample pattern is diagnosed as "abnormal", the signal-to-noise ratios (SN ratios) of each variable used for the calculation of MD are estimated. Looking at the SN ratios, it is possible to identify which parameters are the major factors causing the large MD.

The RMC has developed special software for making abnormality diagnosis calculations based on the MT method. Since 2008, we have successfully detected more than 20 potential problems at an early stage.

One example of successful detection is shown here. The MD value shown rapid change and had large values (Fig. 14).

The SN ratios showed a specific fuel gas pressure control valve to be the major factor of this abnormality (Fig. 15). Looking at the CV position of this value, small position changes were repeatedly observed which were within the pre-alarm level (Fig. 16), during normal operation, this value should be stable. At the earliest possible inspection, the corresponding servo card and servo valve were exchanged. If this “small” abnormality was not detected, continuous operation might have caused a Gas turbine trip due to the high control deviation.

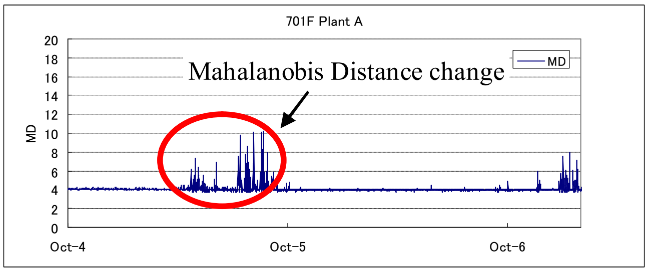

Fig. 14 Mahalanobis distance change

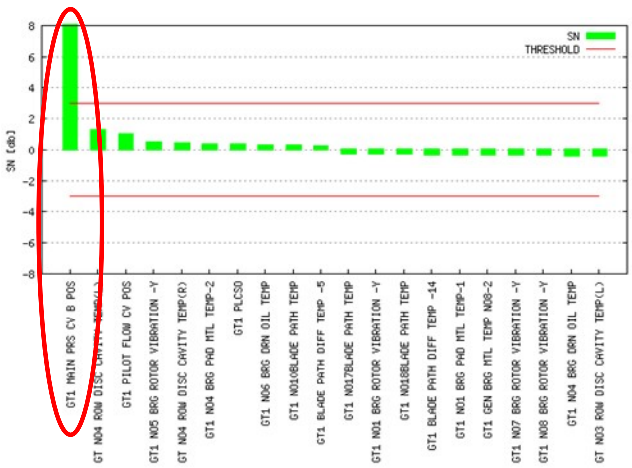

Fig. 15 SN ratio

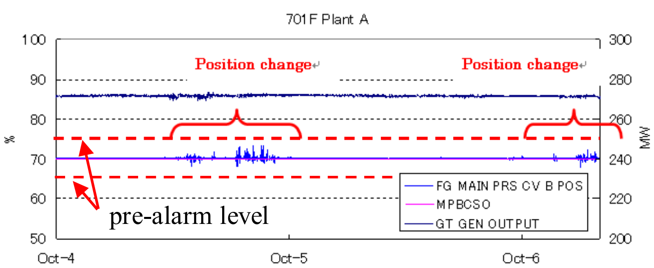

Fig.16 Unusual position change observed on the specific valve

4. ROOT CAUSE ANALYSIS

4.1. Bayesian network model

Now the RMC is developing the root cause analysis system based on an artificial intelligence technique. The Bayesian network can make reasonable inferences on the possible root causes using mathematical probability models.

Fundamental Bayesian theory is described first. Let $x=(x_1,...,x_n)$ be observed monitoring parameters and $y=(y_1,...,y_m)$ be operational condition parameters like fuel type or ambient temperature. Let z be possible root-cause. From accumulated operation data, conditional probability that z is the root-cause under the condition where $x=X$ and $y=Y$ can be calculated as follows:

$$P(z\mid X,Y)=\frac{P(z)P(X,Y\mid z)}{\sum_{x,y}P(z)P(x,y\mid z)} \quad \cdots(4)$$

Here, $P(X,Y\mid z)$ can be calculated by measured data collected from the cases where parameters are X and Y under the root-cause z. $P(z)$ is the probability of root-cause z through the whole operation. $\sum_{x,y}$ is the summation of all possible combination of x and y.

The Bayesian network is a probabilistic graphical model which represents a set of variables, their causal relationships and the conditional probability between variables via directed acyclic graph whose nodes have conditional probability tables. To avoid the explosions of computation steps, probability propagation method is used [13]. Based on these probabilities, the components to be inspected can be limited to a minimum so that the time and the cost for restoring the equipment to working order are reduced.

This model is constructed by accumulating the actual results of causes and incidents. It can represent their causal relationships quantitatively as conditional probabilities. Accordingly, in the Bayesian network, an unknown cause can be inferred from previously observed incidents.

4.2. Applied results of Bayesian Network model

Here, a real field example how Bayesian network successfully estimated the root cause of abnormality is described. On April 2010, MT distance alarm was generated. By the SN analysis, a #4 BPT deviation was found to be changing slowly. BPT signal and trend graph are shown in Fig. 17. Mahalanobis distance graph is shown in Fig. 18.

The Bayesian network model for BPT was activated. Necessary information for the inference such as the magnitude of deviation, number of BPT sensors which shows the large deviation and times of deviation occurred, etc. are input to the Bayesian network system. The Bayesian network system estimated with probability 67% that the root cause of #4 BPT large deviation might be damage to a spring clip (Fig. 19).

After inspecting the corresponding combustor basket, the suggested spring clip damage was observed . Since we prepared the repair parts before the inspection based on the

Bayesian network analysis, this damage was quickly rectified and the GT was successfully restarted after a short stoppage.

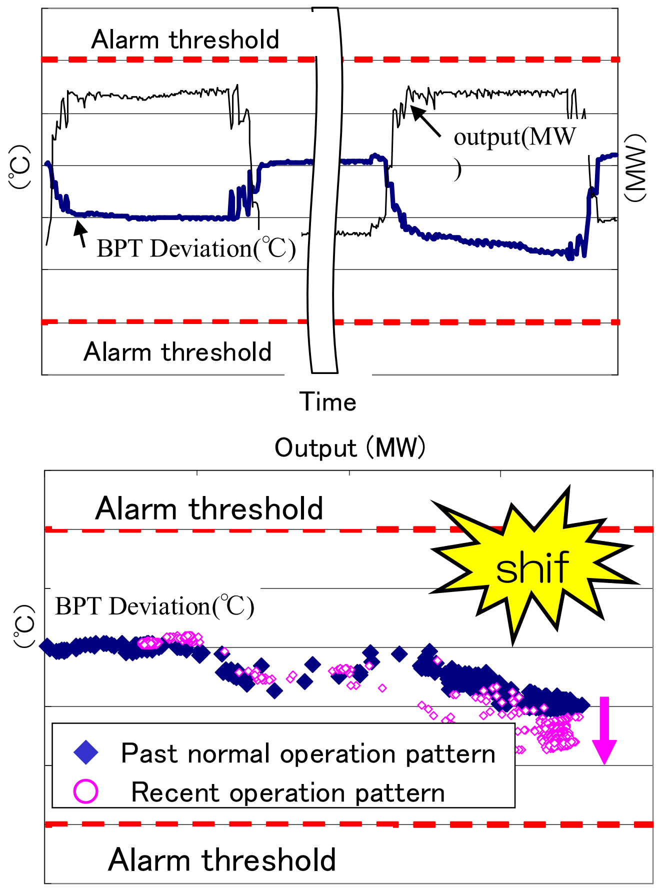

Fig. 17 BPT signal trend and trend graph

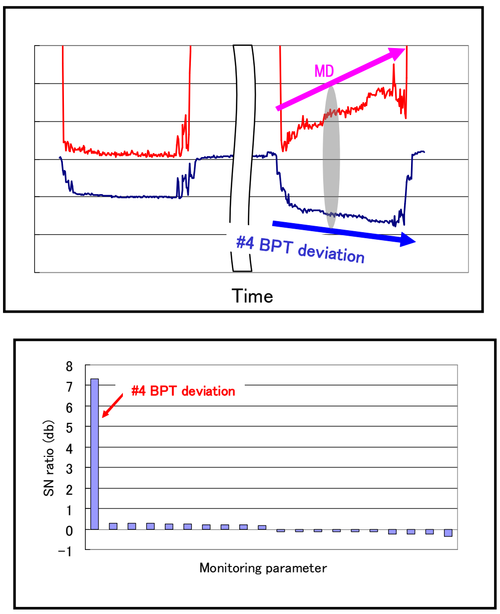

Fig. 18 Mahalanobis distance increased

	Possible damaged parts	probability
1	Spring clip of combustor basket	67.478%
2	Control value/controller	39.020%
3	Electrical equipments	35.850%
4	Cables	31.937%
5	Atmosphere air condition	18.014%
6	Fuel gas condition change	10.630%
7	Cogging of fuel nozzle	0.796%
8	Fuel pipe	0.447%
9	Transition piece	0.003%
10	Bypass/link equipment	0.003%
11	Atomize nozzle	0.001%

Fig. 19 Bayesian Network analysis result

The accuracy of inference of the Bayesian network model depends on the quantity of actual results used for the construction of the model. Furthermore, the Bayesian network has a learning function and its model repeats reconstruction based on the result of inference. The RMC has many actual results on the basis of more than 10 years' remote monitoring, and collection of actual results is ongoing.

5. CONCLUSIONS

One of an important responsibilities of power producers is stable supply of energy. To achieve this goal, OEMs must provide more reliable machines and also optimum operation support service. The RMS is a powerful tool to provide effective and reliable operational support.

Through utilization of the RMS, the RMC provides advanced abnormality diagnoses, so that the outage of the plant is minimized by detecting small symptom before the deterioration becomes a problem. Also, in case of abnormal data deviation, the RMC provides swift and valuable approach, such as root-cause analysis including cause probabilities. Therefore, remote monitoring plays a big part in maintaining safe and stable operation, thereby high reliability of the monitored power plant. This will improve further advances in IT and the monitoring technology.

However, our goal cannot be reached only by advance of remote monitoring tools. Extensive experience and know-how our engineers have gained are essential in providing operational support.

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