

Growth and Evolution of Plant Anomaly Detection in TOMONI[®]/ΣSynX[®]



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Stable operation of power plants requires early detection of equipment anomalies and appropriate response decisions. This report summarizes the development of anomaly monitoring technologies used by Mitsubishi Heavy Industries, Ltd. in remote monitoring services for power plants. First, anomaly detection based on correlations among operating parameters has enabled monitoring to advance from conventional threshold-based approaches to statistical methods, allowing changes to be identified more effectively while improving monitoring efficiency. The incorporation of past cases has also enhanced cause estimation and response decision-making. More recently, MHI has been exploring highly versatile monitoring methods that use generative AI to automate various operational processes associated with anomaly monitoring, including analysis and evaluation. These developments indicate a promising direction for the further advancement of anomaly monitoring technology.

1. Introduction

In recent years, an upward trend in power demand has been observed against the background of the expanding demand for data centers accompanying the explosive evolution of generative AI, and progress in electrification. Furthermore, while responding to fluctuations in supply and demand along with the expanding introduction of renewable energy, flexible and sophisticated operation of power plants is demanded. In such an operating environment, preventing equipment anomalies before they occur and reducing unplanned outages is even more important.

Power plants are social infrastructure facilities that are operated over a long period of time, and inherently possess risks of nonconformity associated with aging deterioration and changes in operating conditions. Therefore, anomaly monitoring technology that continuously tracks equipment conditions, and detects and addresses early signs of abnormalities is indispensable as a foundation for supporting stable operation and maintenance optimization.

On the other hand, human resources responsible for operation and maintenance (hereinafter referred to as O&M) are in short supply and skilled engineers are getting older, resulting in technology transfer and maintenance of response capabilities becoming key challenges. Faced with these conditions, the importance of data utilization through remote monitoring and operation support using digital technologies is increasing.

Mitsubishi Heavy Industries, Ltd. (hereinafter referred to as MHI), as a manufacturer responsible for everything from the development and manufacturing of power generation equipment including gas turbines to after-sales services, has continuously developed and applied remote monitoring and anomaly monitoring technology. These initiatives have been organized as TOMONI[®]/ΣSynX[®] and are evolving as monitoring and diagnostic technologies that utilize operations data and field expertise. Furthermore, in recent years, new initiatives are being developed, such as the cross-sectional utilization of technical documentation and past cases using generative AI, as well as support for interpreting monitoring results.

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This report reviews the history of MHI's plant anomaly monitoring technology and describes its growth as well as the deepening of the technology through the utilization of generative AI. Building on monitoring data and technical expertise accumulated through years of field application, it focuses on how generative AI can be incorporated into monitoring operations to support the process from anomaly detection through judgment and response, and presents the concept of next-generation anomaly monitoring within TOMONI®/ΣSynX®.

2. History of plant anomaly monitoring in MHI

Since the 1990s, Long-Term Service Agreements (hereinafter referred to as LTSAs) were adopted as a form of maintenance for large gas turbines, and have now become common, especially in overseas projects. LTSAs supply high-temperature parts and consumables, conduct repairs, and dispatch engineers over the long term, and remote monitoring services have also been introduced as an optional menu. A mechanism where operations data is collected from remotely located power generation equipment and the condition of the equipment is continuously monitored was constructed, and development of the monitoring system was advanced. In 1999, a remote monitoring center (TOMONI HUB) was first established in Takasago Machinery Works (Japan), and another remote monitoring center was established in Orlando, Florida, USA two years later in 2001. As of 2026, the monitoring area has expanded worldwide, and more than 200 gas turbine units in total are monitored by both centers.

A major characteristic in monitoring large gas turbines is the large number of monitoring points and the large impact in case of trouble. Therefore, to avoid equipment shutdowns, it is important to detect early signs of trouble from a wide range of monitoring parameters and take appropriate preventive maintenance actions based on assessments such as "continued operation until the next scheduled inspection is possible," "remedial action is required at the next available shutdown opportunity," or "immediate shutdown and remedial action are required." However, when the remote monitoring services were initiated, the monitoring method was based on whether various operation parameters were within specified operation limits (threshold-based monitoring), and detecting changes that signaled trouble was difficult.

Subsequently, as the number of units that are monitored increased and operational data and know-how accumulated, as well as the analysis of past cases progressed, more advanced monitoring methods have been introduced. For example, anomaly sign detection using the Mahalanobis-Taguchi method (hereinafter referred to as the MT method) based on quality engineering can be cited. In this method, correlations among multivariate data under normal conditions are used as reference and deviations are quantitatively evaluated therefrom, and subtle changes that were previously difficult to detect can be observed. In this way, earlier identification of anomalies and improved monitoring efficiency has been sought.

In addition to such data analysis technology, development of operation processes responsible for field monitoring and diagnosis has also advanced. At the aforementioned remote monitoring centers, equipment conditions are evaluated by combining multiple monitoring methods under a 24-hour, 365-day monitoring system. Furthermore, expertise obtained in the monitoring process and records of event responses are accumulated as equipment maintenance records, which are then utilized in referencing past cases and sharing know-how. Through such mechanisms of operation and knowledge accumulation, construction of a reproducible monitoring system that does not depend on the experience of individual monitoring staff, has been advanced.

Since the 2010s, these initiatives for remote monitoring and data utilization have been systematized and deployed as the digital solution TOMONI®. TOMONI® integrates operation data collected from power generation equipment operating globally, analyzes them in a cloud environment, and provides them in the form of various applications such as anomaly monitoring, performance diagnosis, and operation support. This framework plays an important role as a foundation to support stable operation and planned maintenance of equipment covered by after-sales service contracts as typified by the LTSA.

Furthermore, in recent years, the scope of application has been expanded to include not only gas turbines but also steam power plants and related equipment, which represent the evolution of energy-domain-wide monitoring technology. Regarding anomaly monitoring technology described

in the next chapter, although originally developed for gas turbines, it can now be used for various products throughout the company as a general-purpose anomaly detection system. In this manner, MHI's anomaly monitoring technology has expanded its application domain while progressively developing data analysis technology, operation processes, and knowledge utilization, starting from the introduction of remote monitoring.

Through many years of initiatives as described above, MHI has accumulated anomaly monitoring technology based on actual unit data and field expertise. This serves as the foundation for the advancement of conventional technologies described in the next chapter and the subsequent development of monitoring technology that utilizes generative AI.

3. Advancement of anomaly monitoring by conventional technologies

Among gas turbine operation parameters, there are many correlations, such as fuel gas flow rate and gas turbine output, or valve opening command and actual opening. The relationship between two correlated parameters, X and Y is shown in **Figure 1**. In state (a), although there is no anomaly (change) in the correlation between X and Y, the value of Y exceeds the operation limit. In (b), the value of Y gradually increases due to deterioration or other factors and exceeds the operation limit. Continuous operation in a state where the operation limit is exceeded (where an alarm is triggered) is not acceptable as it leads to equipment damage, and careful operation so the alarms are not initiated is required. On the other hand, what about the state of (c)? Because the operation limit is not exceeded, conventional threshold-based monitoring judges operations as normal. However, the relationship between X and Y clearly deviates from the normal correlation, and can be called an anomaly. This is the very sign mentioned above, and if left unaddressed, may lead to serious trouble.

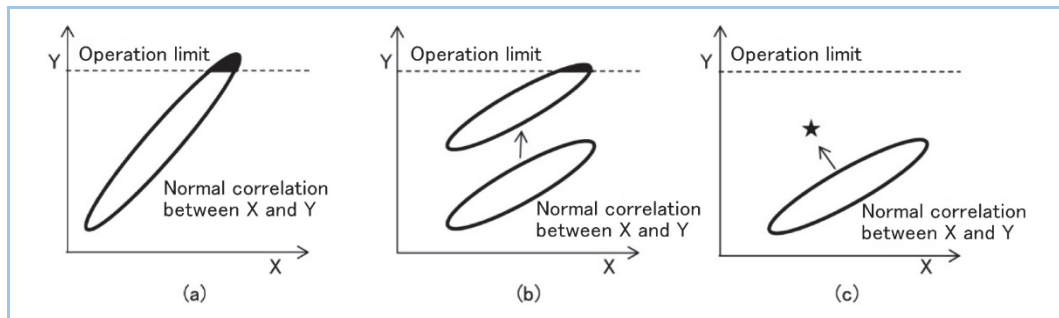


Figure 1 Correlation between operation parameters

To detect these anomalies at an early stage, two monitoring methods are used in combination. One is to detect when an operational parameter has approached the operation limit at an early stage so that it does not exceed the limit in cases like (a) and (b), or to detect sudden changes regardless of the magnitude of the value (by assigning arbitrary thresholds to the "magnitude of the value" or the "rate of change" with regard to time for various operation parameters). At MHI's remote monitoring centers, this is called a "focused monitoring alarm," which is distinguished from control device alarms initiated when design-specified operation limits are exceeded, and is handled with a unique set of thresholds for each piece of equipment.

The other is to detect deviations (changes) in the correlations among operation parameters in cases like (c), for which the introduction of statistical methods played a major role. There are also multiple approaches within statistical methods, including methods which are suitable for monitoring the deviation between actual and predicted values of specific parameters such as multiple regression analysis and those which are suitable for comprehensively monitoring the correlations among various operation parameters like the MT method (**Figure 2**), and each has its own advantages and disadvantages. MHI's remote monitoring centers, which monitor a large number of gas turbines centrally, adopt the MT method which is of significant benefit from the viewpoint of monitoring efficiency.

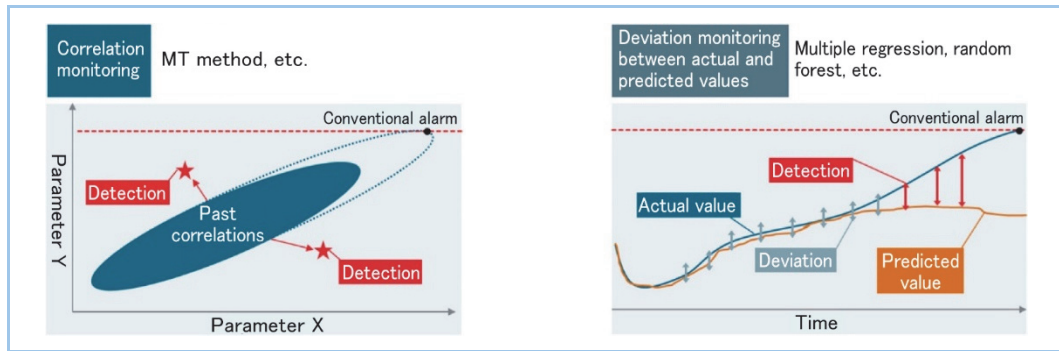


Figure 2 Methods to detect deviations in correlations among operation parameters

The MT method uses correlations among multivariate data under a normal state as reference and evaluates the degree of deviation as a single indicator, and can detect subtle changes (deviations in correlations) that are difficult to observe by conventional trend monitoring or threshold-based monitoring. In addition, consideration of each correlation of a wide range of monitoring parameters is not needed and correlations among a huge number of parameters are monitored by replacing them with a single assessment indicator called the Mahalanobis distance, remarkably improving monitoring efficiency (Figure 3).

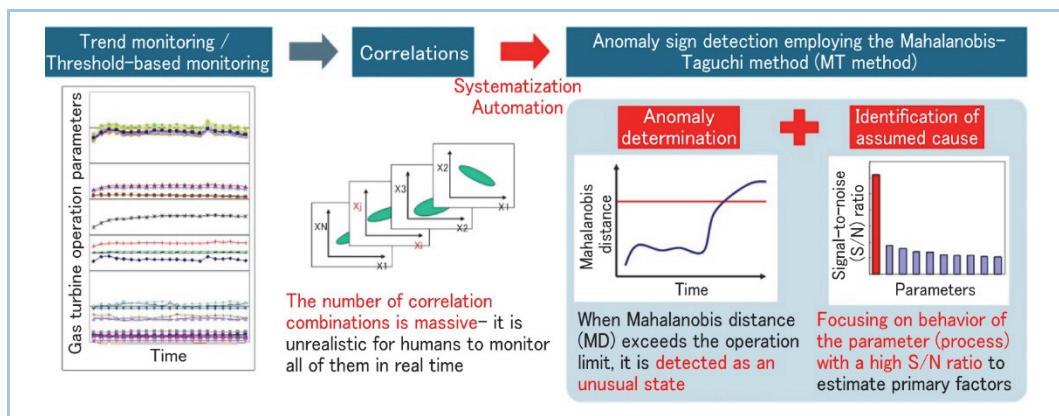


Figure 3 Evolution of anomaly monitoring methods

On the other hand, how to update the reference normal state, that is, how to make the system learn the latest operating state, was a challenge. When this method was first introduced, learning was performed at specific time intervals, which caused problematic bias in the learning state. Therefore, an algorithm designed to facilitate the learning of change points in operating conditions has therefore been developed and implemented.

Furthermore, by combining these statistical evaluations with the experience of the monitoring staff and expertise based on past cases, estimation accuracy of anomaly factors has been improved. That is, by combining data-driven detection and human knowledge, advancement of a series of monitoring processes from early anomaly detection to response has been sought, achieving practical field-tailored anomaly monitoring.

In this manner, MHI's conventional anomaly monitoring technology has developed by combining various aspects of statistical analysis methods, human knowledge, and operation processes, serving as the foundation for anomaly monitoring technology that uses generative AI as described in the next chapter.

4. Next-generation anomaly monitoring in the generative AI era

In recent years, the use of generative AI in routine and common operations such as document summarization, translation, technical document search, and referencing past cases has increased, and its application to specialized operations is also expanding progressively. In the O&M field of power plants, its effectiveness continues to be confirmed for cross-reference of technical information such as reports, manuals, past cases, and inspection records to quickly access necessary information. It is also applied to information searching and knowledge utilization, which

conventionally depended on highly experienced engineers. Consequently, a certain degree of effect in improving operation efficiency and standardizing the quality in anomaly monitoring operations is shown.

Based on such usefulness, generative AI is expected to be applied to plant anomaly monitoring in combination with time-series data in the future. However, for actual application, clearly defining its role and application scope, and sufficiently examining the division of roles and limitations with existing methods are needed. One critical matter requiring examination is the division of roles in quantitative anomaly determination. In the process to quantitatively determine the presence or absence of anomalies from time-series data, statistical methods and machine learning methods are suitable as conventionally implemented, and substituting this with generative AI alone is not appropriate. In particular, the method of inputting time-series data into a Large Language Model (LLM, a form of generative AI), for processing as they are would present challenges: long-term and high-frequency operation data would cause an increase in the number of tokens, and furthermore, when handling subtle changes in values and correlations, interpretations that do not match actual data, so-called hallucinations, may occur. For this reason, as practical anomaly monitoring, a configuration where numerical processing is delegated to an external numerical processing engine and the LLM handles calling the engine, organizing and interpreting the results, is effective.

In contrast, in the actual operations of anomaly monitoring, a series of analytical processes is required, such as selecting monitoring targets, confirming related signals, comparison with past cases, formulating factor hypotheses, and organizing response policies. MHI focuses not on "anomaly detection" itself, but on a mechanism to support the operation processes of "anomaly monitoring and analysis" using generative AI, delegating most of them to an AI agent.

In conventional anomaly monitoring, focus is centered on methods to understand state changes of specific monitoring targets or specific components using the MT method, etc. In contrast, next-generation anomaly monitoring utilizing generative AI aims to proceed with monitoring and analysis, not by depending on fixed monitoring items, but by allowing the AI agent to flexibly search for areas which are to be focused on according to operating states and detection results, while cross-referencing related signals, events, past cases, and technical documents. That is, in contrast to the quantitative anomaly sign detection performed by conventional technology, generative AI handles the subsequent roles of information integration, context understanding, hypothesis generation, and judgment support.

Based on this concept, MHI adopts a configuration that links the LLM with an external numerical processing engine. The numerical processing engine features statistical processing and machine learning processing on given time-series data and visualizing the results in the form of graphs or schematic diagrams. On the other hand, the LLM handles the actual analysis processes, such as extracting target periods, selecting related signals, comparing trends, and evaluating differences before and after events. That is, LLM formulates an analysis plan, instructs the numerical processing engine on necessary processing, and then, based on the results, organizes the situation, presents related information, and generates factor hypotheses, thereby supporting the entire analysis process. With this configuration, achieving both numerical accuracy and analytical flexibility is possible (**Figure 4**).

Furthermore, in the practical application of generative AI, a clear indication of the basis for judgment and visualization of the judgment processes are indispensable. For this reason, applying Retrieval-Augmented Generation (RAG) to refer to technical documents and past cases in order to make the sources of answers traceable is needed. In addition, a mechanism where data and evaluation conditions used for the analysis are clearly indicated to allow engineers to confirm its validity must be constructed.

To apply these technologies to actual operations, MHI is proceeding with the identification of specific applications in actual plant anomaly monitoring and conducting initial verifications. As an example, the results of application to a pump vibration anomaly event in a steam power plant are shown below. In this case, triggered by the detection of exceeding an operation limit through conventional threshold-based monitoring, the engineer in charge provided a group of signals considered to be related to the target equipment to the AI agent. The AI agent autonomously

selected signals necessary for analysis from these using LLM, and calculated and presented statistical quantities, correlation coefficients, and time trends using the external numerical processing engine. Based on these results, the AI agent further recognized state changes in the equipment by comparing the behaviors of multiple signals, and determined the nature of the event, which was "load-dependent high vibration," by checking the correlation structure against the mechanical characteristics of the target pump equipment. Based on this determination, the situation where vibration gradually decreased within the period but still continued to exceed operation limit was integrally evaluated by LLM as the current status, stating that "although there is a decreasing trend, risk of it rising again during high-load operation still remains." Then, everything from enumerating factor candidates to organizing immediate and planned responses with priorities was seamlessly executed. This series of processes to interpret quantitative analysis results, understand context, and generate hypotheses conventionally depended on the experience and judgment of the engineer in charge. Through this verification, the division of roles, where conventional monitoring handles "anomaly detection" and the AI agent supports the subsequent "monitoring and analysis" operation processes, was confirmed to function in the context of actual operations. Furthermore, by incorporating MHI's domain knowledge, sophistication of judgment and response by the AI agent into those tailored to the context of the monitoring target is expected. In this manner, by organizing analysis processes from the perspective of engineers who actually handle anomaly monitoring operations, and based thereon, examining the suitability and effects of AI application, technology development emphasizing practicality is progressing.

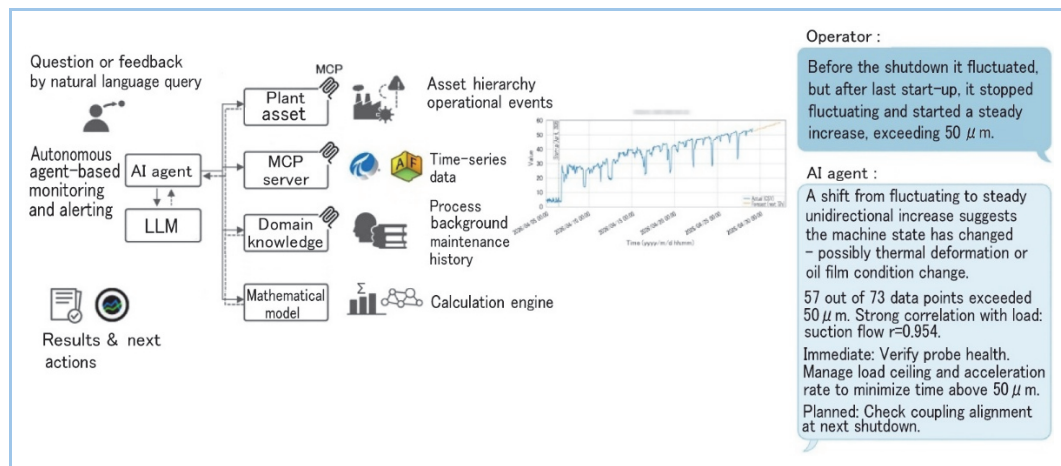


Figure 4 New anomaly monitoring mechanism that utilizes generative AI

Here, MHI's strength lies in the fact that the engineering team responsible for actual plant trouble response and routine monitoring is positioned close to the digital team that designs and develops systems aimed at solving challenges in engineering team activities. By closely linking on-site challenges and technology development, utilization of generative AI in a form tailored to operations can be considered and implemented.

The utilization of generative AI tends to lean toward the evaluation of system-side matters such as model performance and tool functions. However, MHI performs evaluations from the perspective of "value creation in actual business" through anomaly monitoring operations in actual plants. That is, a key feature of this approach is that validity of technology introduction is verified using practical operational effects as indicators, such as improvement in monitoring operation efficiency, homogenization of judgment quality, and shortening response time.

As described above, the evolution of anomaly monitoring in the generative AI era must be advanced, not merely as technology introduction, but in a form that is integrated with operation processes. MHI aims to realize next-generation anomaly monitoring that achieves both practicality and reliability through a functional configuration based on monitoring and analysis expertise cultivated with conventional technologies, while considering the characteristics of generative AI.

5. Future prospects and business impact

It is important to promptly complete the Proof of Concept (hereinafter referred to as PoC) of the next-generation anomaly monitoring technology described in this report and move on to application in actual operations. By doing so, MHI aims to improve the quality of services provided to customers through the advancement of anomaly monitoring. It is particularly important to realize an environment where engineers can concentrate on essential operations such as anomaly factor analysis and response judgments by organizing and reducing auxiliary tasks that occurred incidentally in conventional monitoring operations.

Regarding application, remote monitoring of gas turbines will continue to be the primary target field, and focus will be placed on how to contribute to improving the availability of customer equipment. In the future, the number of gas turbines newly delivered and operated will increase significantly. Under such circumstances, MHI needs to provide monitoring and maintenance services with higher quality than conventional services in order to continue offering highly reliable power generation equipment to our customers. The technology described in this report is considered to be an effective means to meet these demands.

Furthermore, application of this technology is not limited to power plants. From the perspective of enhancing operation processes in anomaly monitoring and analysis, deployment to various machinery and plant products offered by MHI is considered fully possible. By utilizing operation data and technical expertise accumulated in individual business domains in a cross-sectional manner, development of more advanced monitoring and diagnostic technologies can be expected.

Such initiatives are based on the "Smart Connections" concept advocated by Σ SynX[®]. In other words, individually accumulated data and expertise are linked by digital technology to create new values. This technology is an example of practical implementation thereof, and plays an important role in supporting the advancement of MHI's various businesses, including the power plant business, through evolving digital technologies.

Next-generation anomaly monitoring that utilizes generative AI goes beyond simply introducing technology, but reforms the operation processes themselves, contributing to the realization of an environment where engineers can focus on essential operations such as high-level judgment and analysis. As a result, this is expected to become a foundational technology that promotes further enhancement of value provided to MHI customers.

6. Conclusion

This report reviewed the history of MHI's plant anomaly monitoring technology, and presented its growth based on the accumulation of conventional technologies and the direction of its evolution through the utilization of generative AI. Anomaly monitoring is increasingly important, not simply as a detection technology but as a foundational technology that supports the entire operation and maintenance activities.

Monitoring technology based on conventional statistical methods and human expertise has steadily become more sophisticated through its application to actual equipment. However, with the introduction of generative AI, reconfiguring the entire monitoring and analysis process, and sophistication of information integration and judgments support is becoming possible.

The approach described in this report aims to realize anomaly monitoring in a form that can handle application to actual operations by combining the reliability of numerical analysis with the flexibility of generative AI.

Moving forward, along with the verification of effectiveness through PoCs, further improvement in terms of accuracy, responsiveness, and operability in order to proceed to implementation in actual operations is needed. In addition, regarding application of generative AI, operation design premised on participation by engineers remains important from the perspectives of ensuring transparency in the basis for judgments and maintaining quality.

Through these initiatives, MHI will continue to advance anomaly monitoring technology, and reform operation processes to realize an environment where engineers can focus on essential operations, thereby contributing to greater value provided to customers.

TOMONI® is a registered trademark of Mitsubishi Heavy Industries, Ltd. in Japan and other countries and regions.

ΣSynX® is a registered trademark of Mitsubishi Heavy Industries, Ltd. in Japan and other countries.

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