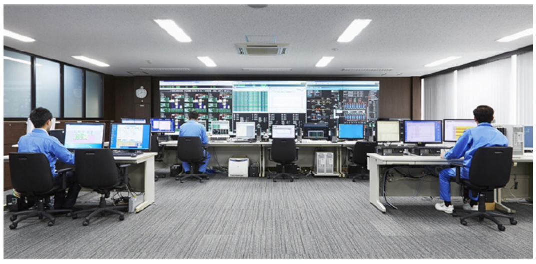
Advancements of Predictive Diagnosis System for Power Generation Engines



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Mitsubishi Heavy Industries Engine & Turbocharger, Ltd. (MHIET) has been engaged in developing predictive diagnosis systems to further help customers realize the stable operation of their power-generating facilities. When it comes to engines for power generation, the application of commonly-used predictive diagnosis techniques has been considered to be difficult, because the power output of these engines is not constant owing to their operating patterns. We developed a new predictive diagnosis system by taking the following three approaches: "the statistical method (i.e., vector quantization clustering or VQC)," "big data analysis" and "the utilization of knowledge from past abnormalities." The developed system is now in operation. By the end of 2018, we obtained solid outcomes indicating a high likelihood of achieving a practically-sufficient correct prediction rate. The predictive diagnosis service will be made available commercially in 2019.

1. Introduction

We remotely monitor more than 450 power generation engines from the Remote Monitoring Center at the Sagamihara Machinery Works (Sagamihara RMC), which was established in 2014. The initial purpose of the center was to support the quick recovery of the power generation facilities of clients after the occurrence of abnormalities. However, to further contribute to the stable operation of such facilities, a commercially-available predictive diagnosis system has become essential. Power generation engines are often used for private power generation, and therefore in many cases, the operation is limited to weekday daytime high-load hours for their facilities while shutting down during the night and weekends. If an imminent abnormal event of the equipment can be accurately predicted 1 or 2 weeks before it happens, the equipment concerned can be examined/repaired when it is placed out of operation such as on weekends, which then will inflict no economic loss on the customer due to the down time. On the other hand, power generation engines are also used to curb peak demand in many cases. As the power output is naturally inconstant, the measurement values (temperature and pressure) obtained from each part of the engine can vary substantially according to the power output fluctuations. Although commonly-used statistical techniques for predictive diagnosis such as the Mahalanobis-Taguchi (MT) method can capture subtle changes in measurement values, their direct application to power generation engines is difficult because of the reasons mentioned above. We therefore developed a new predictive diagnosis system by taking the following three approaches: "the statistical method (i.e., VQC)," "big data analysis" and "the utilization of knowledge from past abnormalities." The developed system is now in operation. **Figure 1** is a configuration diagram of the entire system including both remote monitoring and predictive diagnosis. This report summarizes each of the subsystems of our predictive diagnosis system, and describes the challenges we face when operating the system and our future direction.

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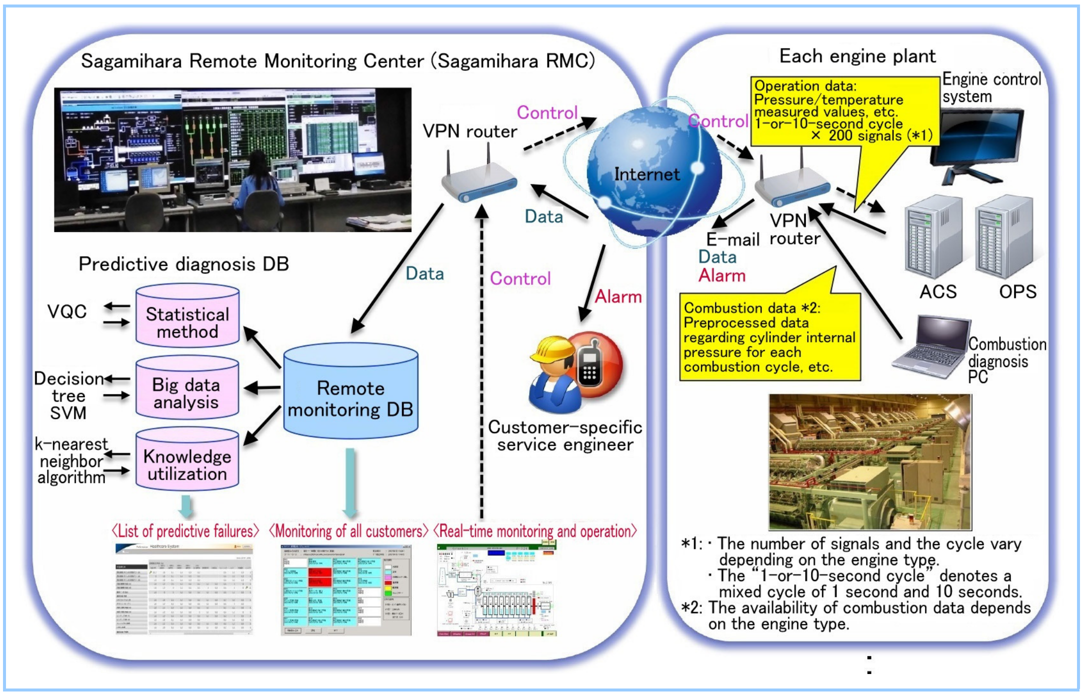

Figure 1 Configuration diagram of entire system

2. Statistical method (VQC)

Since December 2013, a VQC-based predictive diagnosis system has been in use for our power generation engines. Having been developed by Hitachi Power Solutions Co. Ltd. (Hitachi PS), it is known as the Hitachi Power Anomaly Measure Pick-up System or “HiPAMPS.”* As of February 2019, we monitor 70 medium class engines with 500-2000 kW of output in Japan with each being equipped with 40 sensors, as well as 40 large class engines with 5000-7500 kW of output (31 units in Japan and 9 units overseas) with each being equipped with 100 sensors.

VQC is summarized in **Figure 2**. In VQC, machine learning of the sensor data under normal conditions is performed. Using the deviation of monitoring data from the normal data groups as an indicator, whether the monitoring data is either “the same as usual” or “different from usual” will be determined.”[1] The diagnosis is made while the engine is in operation. The “predictive failure” will be reported as an imminent stage of engine failure, when the status of “different from usual” continues for 30 minutes or longer.

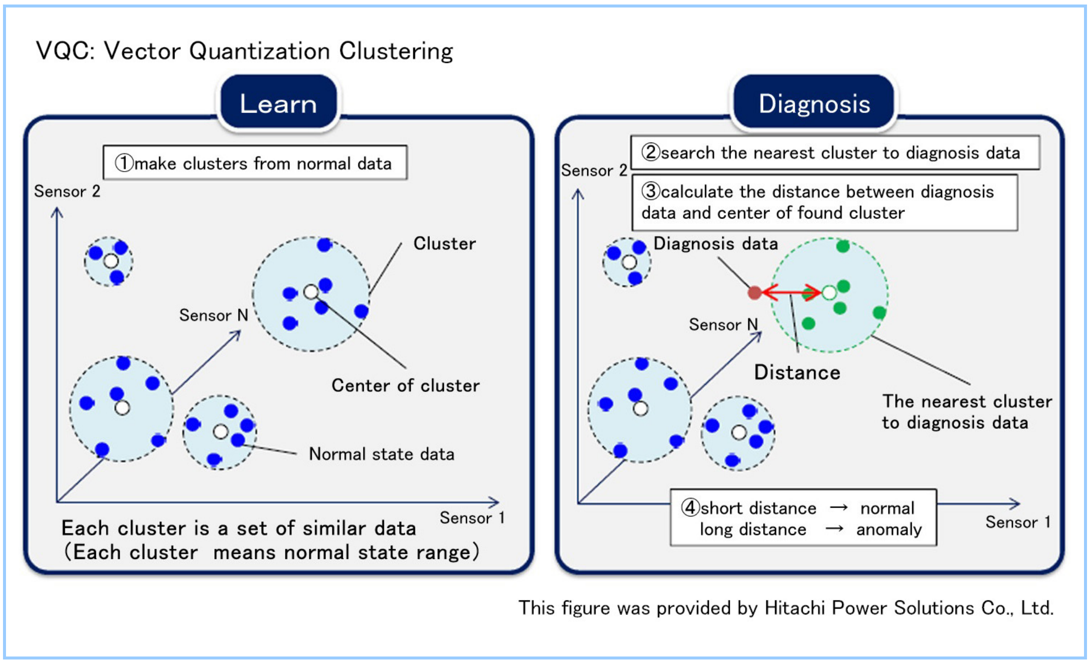

Figure 2 Summary of VQC

In the beginning of the operation of the system, predictive failures were reported almost every day, but most of them did not lead to abnormal events (hereafter referred to as unwanted reports). We therefore reviewed the system settings including the number of clusters by considering (1) the customer's engine operation patterns, (2) engine type in use, (3) narrowing down of abnormal events to be reported and (4) the removal of the effects caused by the seasonal temperature fluctuations. After the reported predictive failures were screened accordingly by the service personal, the issuance of unwanted reports was reduced to a frequency of once a week. As a result, during the period between July and December 2018, about 30 imminent abnormal events were successfully reported, which include (1) decrease/increase in the cylinder outlet temperature, (2) decreased lubricant oil pressure, (3) decreased primary cooling water pressure, (4) increased cooling water temperature, (5) increased pressure in the crankcase and (6) disconnection of sensors. Of these 30 events, three had the potential to lead to an unscheduled engine shutdown. Our service personnel were promptly informed of these events, thus successfully preventing unscheduled engine shutdowns in all the three cases. The measurement data in two of these cases are shown in **Figures 3** and **4**.

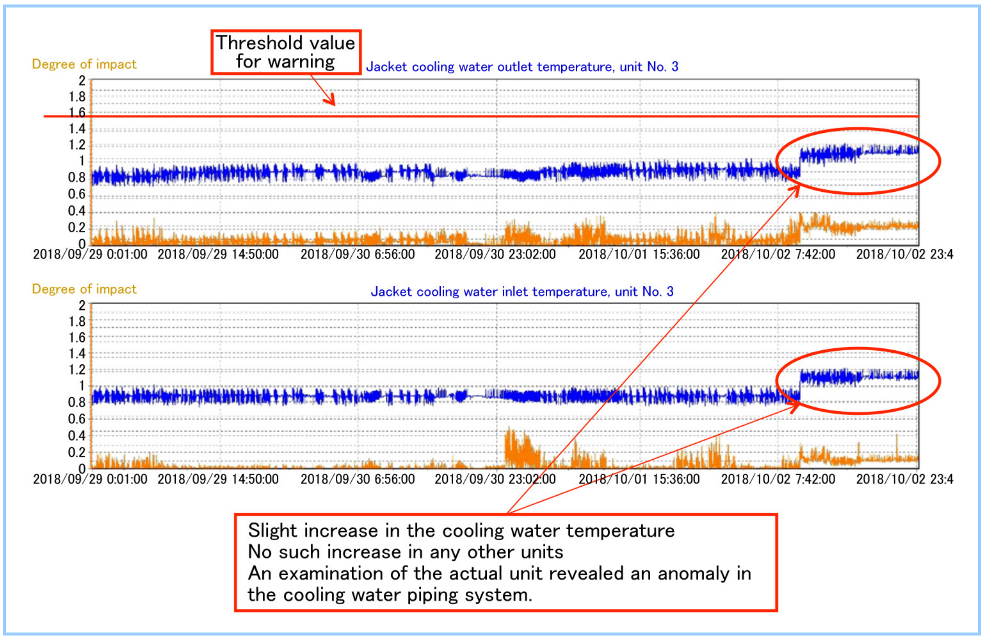

Figure 3 Predictive failure report example 1

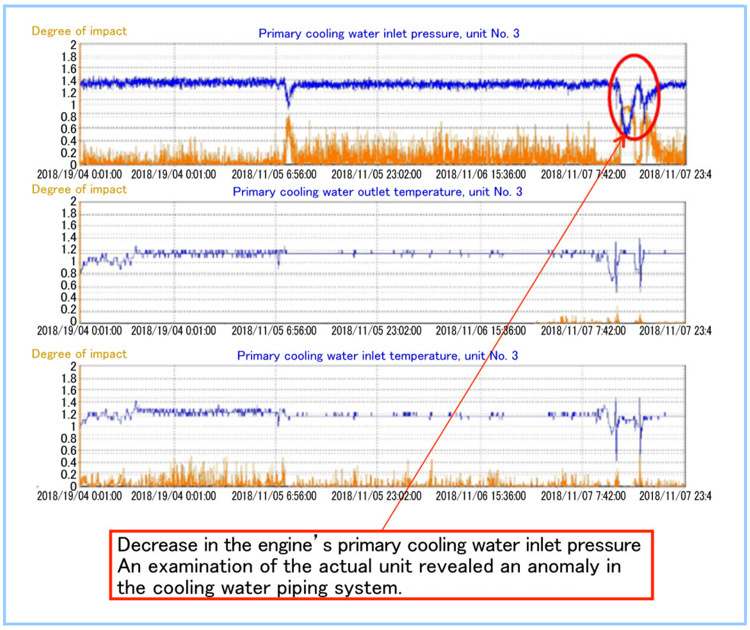

Figure 4 Predictive failure report example 2

To assess the accuracy of predictive diagnosis, we examined the system in terms of the condition of predictive failure reporting and the actual warnings issued for engine anomalies (including cases where the occurrence of the predicted failures was prevented by informing the relevant sites) during the period between July and December 2018. Specifically, we calculated the rate of correct prediction (obtained by dividing the number of actual warnings issued among the reported predictive failures by the total number of reported predictive failures) and the rate of overlooked events (obtained by dividing the number of warnings issued without predictive failure reports by the total number of actual warnings issued). The results indicated a correct prediction rate of 55% and a rate of overlooked events of 15% under the condition of "diagnosis by the system + screening by service personnel." Please note that the results were obtained when the anomalies concerned were limited to those of the engine itself.

To make the predictive diagnosis service commercially feasible, there are two challenges: (1) the realization of a higher correct prediction rate without screening by service personnel and (2) the prediction of failures that can be made beyond the engine itself.

In 2019, we will attempt to improve the correct prediction rate of this subsystem and lower the rate of overlooked events through analysis of all the reported predictive failures using AI, machine learning and the automatic extraction of abnormal conditions.

3. Big data analysis to estimate the probability of abnormal events

In 2013, the Technology & Innovation Headquarters of Mitsubishi Heavy Industries, Ltd. (the current ICT Solution Headquarters and Research & Innovation Center) developed a data mining technique by combining two methods (i.e., support vector machine (SVM) and decision tree), which is summarized in **Figure 5**. Using this technique-based analytical system, we analyzed seven years of big data obtained from 130 large class engines with 5000 kW of output containing 200 parameters (various types of hourly measured data). Regarding the selected three abnormal events (i.e., startup failure, misfire and decrease in the primary cooling water pressure), the relationships were extracted to show the association with conditions during operation. Based on the patterns leading to the abnormal events, we predicted (quantified) the abnormal events that were likely to occur in the coming three months. When compared with the actual occurrences of such events in the past six months, the rate of correct prediction (which is obtained by dividing the number of actual warnings issued among the reported predictive failures by the total number of reported predictive failures) in the coming three months was approximately 30%. However, when limiting the duration for prediction to the coming week, it turned out that the rate fell to 0-10%.

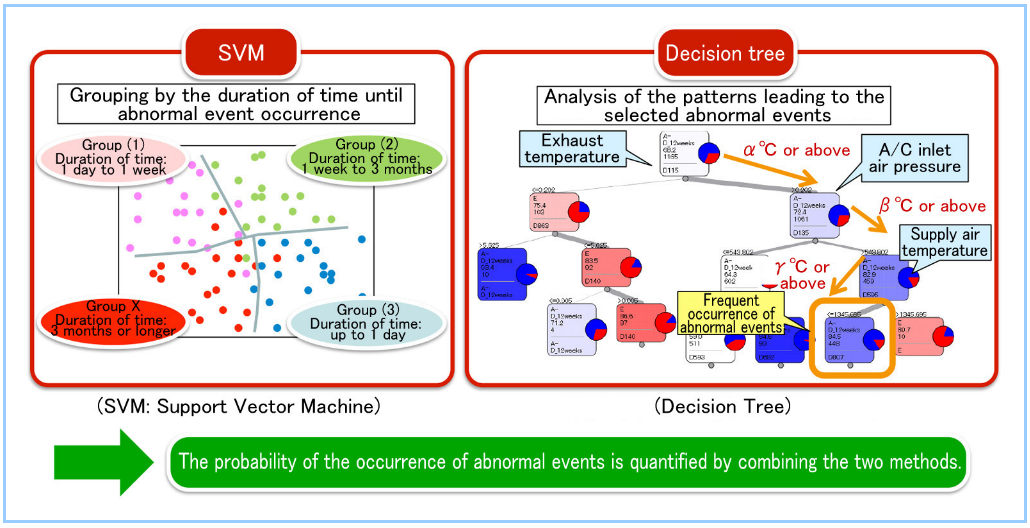

Figure 5 Outline of developed data mining technique

In 2017, the number of predictable abnormal event types was increased to 20. Setting the duration for prediction to the coming week, we set out to improve the system with a target rate of correct prediction of 80% and a target rate of overlooked events of 20% (which is obtained by dividing the number of abnormal events that actually occurred when no such events were predicted by the total number of abnormal events that actually occurred). The 20 types of predictable abnormal events were those that can cause considerable damage to the engine or substantially affect the duration of shutdown for repairs (e.g., bearing anomaly and abnormal exhaust temperature), including the three events mentioned earlier. The following three major steps were taken to improve the correct prediction rate: (1) improve the accuracy and quality of data for use, (2) increase the density of measurement data and (3) add combustion data to the data sets for learning. For (1), we removed false warnings and abnormal events during post-maintenance test operations from the supervisory abnormal event data and corrected data errors/missing information in the measurement data. It turned out that a problem was found in more than 10% of the data. With respect to (2), the measurement data sampling cycle was changed from 1 hour to 1 minute. Regarding (3), the combustion data including cylinder internal pressure for every combustion cycle were conventionally stored in the on-site computers (130 units in total). As the volume of such data was extremely large, it was difficult to transfer them to the central computer and use the data for the predictive diagnosis system. Therefore, we preprocessed the data of each site and only the downsized data were forwarded to the central computer, thus making the information usable by the predictive diagnosis system. As a result, the rate of correct prediction was improved as shown in **Figure 6**, which compares the system developed in 2013 (System 2013) with the system upgraded in 2017 (System 2017) under the same conditions. Specifically, using the data in 2014 and 2015 for learning, the prediction results were checked with the abnormal event occurrences in 2016. Using System 2017, the correct prediction rate in the coming week was increased to roughly 50%, when considering the three abnormal events that are predictable by System 2013.

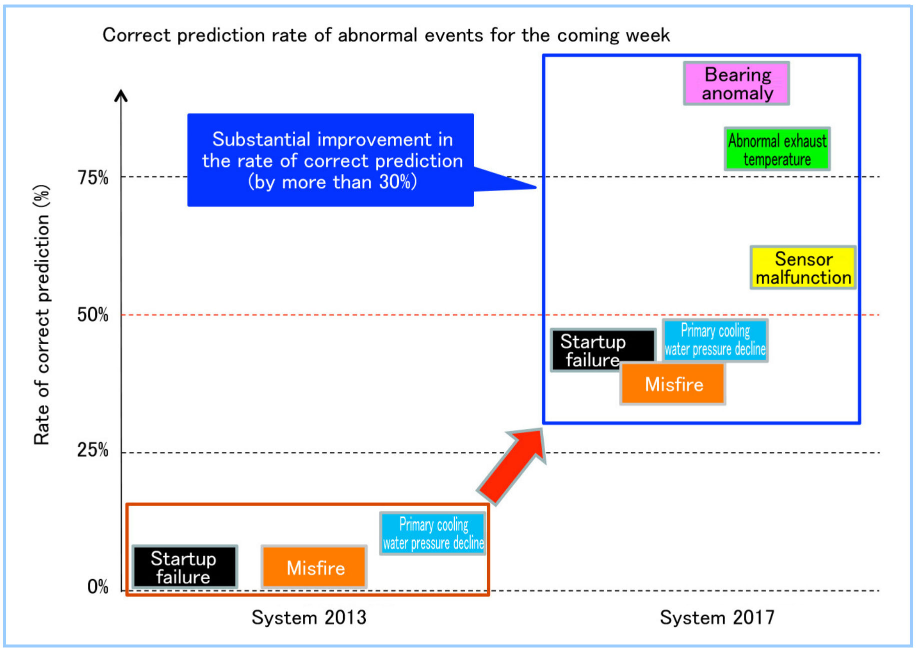

Figure 6 Rate of correct prediction after the system was upgraded

In 2018, to further improve the correct prediction rate, we (1) increased the density of combustion data by reviewing the preprocessing procedure and (2) assessed an ensemble using models with different algorithms or data processing conditions. The latter is based on the concept that the accuracy is increased when the assessment is conducted simultaneously using segmented data (those obtained during the engine's rated operation, shutdown, etc.), rather than using all the data in a single model. As a result, we expect to achieve a rate of correct prediction of about 70% and a rate of overlooked events of about 30%. We will further improve the correct prediction rate through the operation of the system.

4. Utilization of knowledge from past abnormalities

It has been known that several abnormal events that may severely damage the engine (e.g., main-bearing burnout and intake/exhaust valve damage) can be detected by devising a method to observe changes in the tendencies of the exhaust temperature or compression pressure in the cylinder, and therefore the occurrence of these abnormal events has often been successfully prevented. The example given in **Figure 7** is a typical case. However, whether such data knowledge can be of use greatly depends on the data analysis and interpretation skills of service personnel, resulting in inconsistent detection accuracy. Because even similar damage (no matter how small the dissimilarity might be) tends to produce different data changes, such variations have often gone unnoticed. Since 2018, in an attempt to overcome this problem, we have been systematizing the data on main-bearing burnout and intake/exhaust valve rod damage by utilizing the accumulated knowledge coupled with machine learning (k-nearest neighbor algorithm). We will continue to gather and systematize this knowledge.

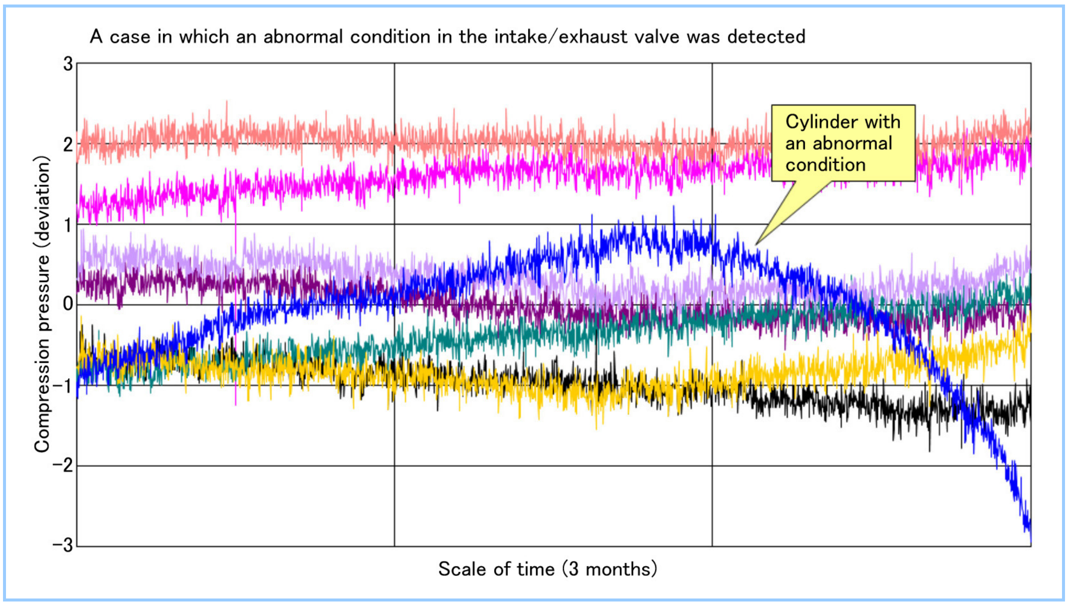

Figure 7　An example of detected abnormal conditions in the intake/exhaust valve

5. Conclusion

Table 1 lists the characteristics and improvements of the predictive diagnosis system. As each subsystem of the predictive diagnosis system has strengths and weaknesses, the effective use of these characteristics makes it possible for the subsystems to complement each other, enabling the predictive diagnosis system to more accurately predict (high correct prediction rate) and minimize the number of signs that go unnoticed (low rate of overlooked events).

As solid outcomes that indicate a high likelihood of achieving a practically-sufficient correct prediction rate have been obtained by the developments so far, we will first make the predictive diagnosis service commercially available for selected engine types in 2019. The price and service ranges are currently being considered.

Table 1　Characteristics and improvements of predictive diagnosis system

	Statistical method (VQC)	Big data analysis	Knowledge utilization
Diagnostic approach	"Something different from usual" is expressed in the form of degree of deviation.	The subsystem deduces "laws" from the "conditions during past operations" and "warnings issued," and estimates the probability of occurrence based on the degree of coincidence with the "conditions of the current operation."	Humans deduce "laws" from the "conditions during past operations" and "warnings issued," and estimate the degree of imminence based on the degree of coincidence with the "conditions of the current operation."
Strengths	The signs of "imminent abnormal events" can be detected from tiny changes in data.	With regard to the selected 20 abnormal events, the correct prediction rate is relatively high.	With regard to some of the selected abnormal events, the correct prediction rate is high.
Weaknesses and countermeasures	Screening by humans is required. → Apply AI and machine learning	The rate of correct prediction is not satisfactory at this point in time. → Make improvements through the operation of the system	• Successful detection depends on judgement by humans. → Combine with machine learning • The number of predictable abnormal events is small. → Mathematize and make use of the existing accumulated knowledge

While further improving the accuracy of the predictive diagnosis system, we will also apply this technology to the assessment of the remaining life of parts, which enables us to offer a more advanced service menu, operation and maintenance (O&M) support services, etc.

* "HiPAMPS" is a registered trademark of Hitachi PS.

References

(1) Tadashi S., et.al., An Anomaly Detection System for Advanced Maintenance Services, Hitachi Review Vol.63 No.4(2014) p.178～182