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Recent digitization of GIS and sophistication of equipment condition monitoring and diagnosis applying AI technologies

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SUMMARY

In order to improve the economy and working efficiency of substation maintenance work, digitalization of GIS has been started, in which various sensors are mounted on GIS and the monitoring results collected by them are evaluated. Advances in reliable and sensitive instrument diagnostic technologies are essential for the digitization of GIS These technologies are expected to accelerate the transition from conventional TBM (Time Based Maintenance) to CBM (Condition Based Maintenance). In the advancement of diagnosis technology, the technology to comprehensively diagnose equipment status by monitoring results from multiple sensors with different sensing items is important and can improve the reliability of equipment diagnosis. In addition to diagnosis based on threshold values set for each diagnostic item, trend diagnosis, which can detect signs of abnormality based on long-term changes in diagnostic results, is also expected to contribute to the advancement of equipment diagnosis. It is also important for equipment diagnosis systems to be equipped with HMIs (Human Machine Interfaces) that accurately communicate diagnosis results and acquired data to maintenance personnel to encourage them to perform appropriate maintenance at the right time. In order to respond to the further advancement of diagnosis technology, equipment manufacturers are evaluating the possibility of applying AI technology to equipment diagnosis by trial application to the monitoring data they have obtained during equipment development.

KEYWORDS

digitization of GIS, monitoring and diagnosis, AI technology

1. Introduction

In this paper, we introduce advanced technology for equipment condition monitoring and diagnosis applied to the digitalized GIS, which is now in commercial operation at electric power companies in Japan [1]. The monitoring results from multiple sensors are used to comprehensively diagnose the status of the equipment. In addition, the equipment diagnostic unit (EMU), which performs various diagnostic evaluations based on the equipment condition monitoring results, is highly functionalized and equipped with a function to transmit the diagnostic results to the upper-level digital substation system and with an interface that allows maintenance personnel to access the diagnostic results in a user-friendly manner.
In recent years, waveform pattern recognition and AI technologies have been widely used and their effectiveness has been confirmed, so the equipment manufacturers are examining the possibility of applying these technologies to waveforms monitored by GIS and diagnosing equipment based on the acquired waveform information itself. The results are expected to show that AI diagnosis technology can detect signs of abnormalities at an early stage that cannot be detected by diagnosis based on characteristic values extracted from monitoring waveforms. The AI diagnosis technology that we are attempting to apply is expected to be useful for existing switchgear, which is generally highly reliable and for which it is difficult to obtain equipment abnormality data in AI learning stage. There is a possibility that the application of AI technology will lead to further sophistication of switchgear diagnosis.

2. Condition monitoring, diagnosis and evaluation of GIS for CBM

2.1 GIS condition monitoring and condition assessment

In order to accurately diagnose the condition of equipment in the CBM of GIS, multiple sensors with different sensing items need to be mounted on the equipment for condition monitoring. Fig.1 shows an example of sensor mounting implemented in the 300kV GIS digitalization, which started commercial operation in 2021, and it introduces the sensing item and equipment diagnostic evaluation item.

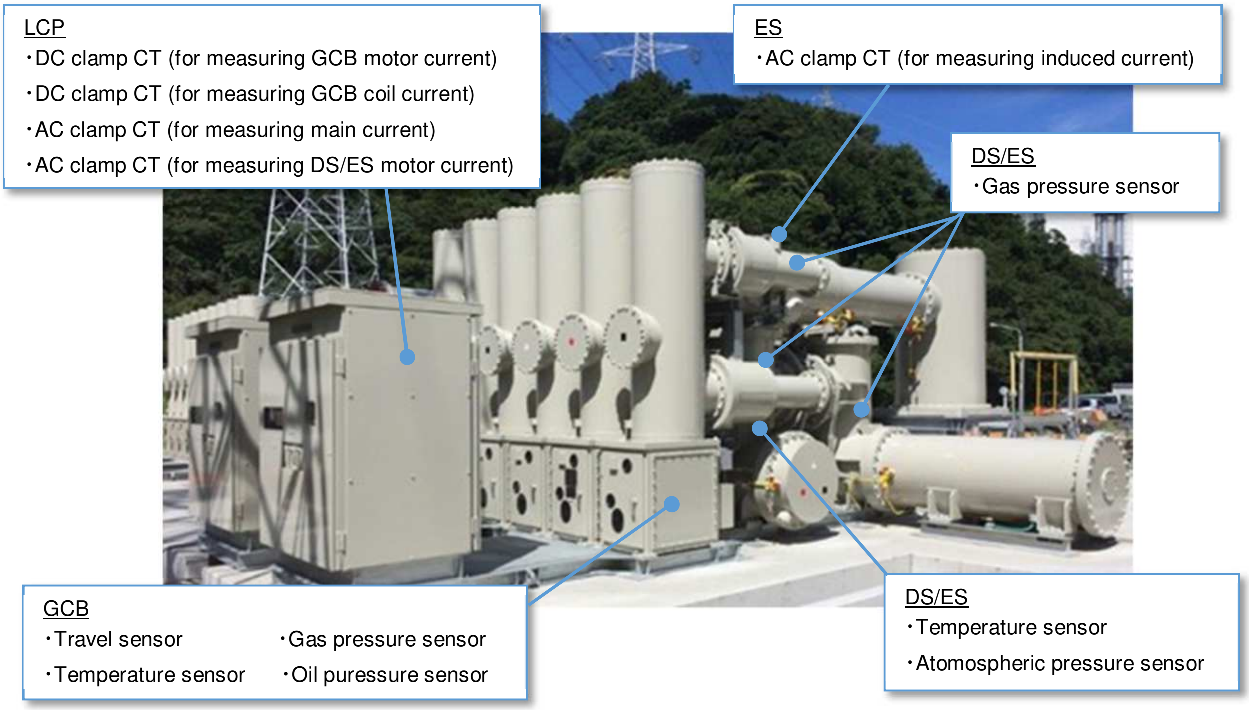


Fig.1.Sensor mounting of 300V GIS

In the CBM of GIS, it is important to have a technology to diagnose the equipment status comprehensively by monitoring results from multiple sensors with different sensing items. For example, the reliability of the diagnosis of the opening /closing time can be improved by evaluating the opening /closing time of the monitored GCB with the changes caused by multiple monitoring results such as the ambient temperature and the control operation voltage at the time of the open/close operation. For better equipment diagnosis, it is preferable to evaluate the results with monitoring results corrected to the standard conditions (like as ambient temperature is 20 °C and control voltage is 100V) of the equipment to remove variations in operating conditions. As an example, Fig. 2 shows that by correcting the closing time of the GCB with the ambient temperature, the bias of the closing time from the average value can be evaluated to a small extent, and a more reliable diagnosis of the equipment status can be made.

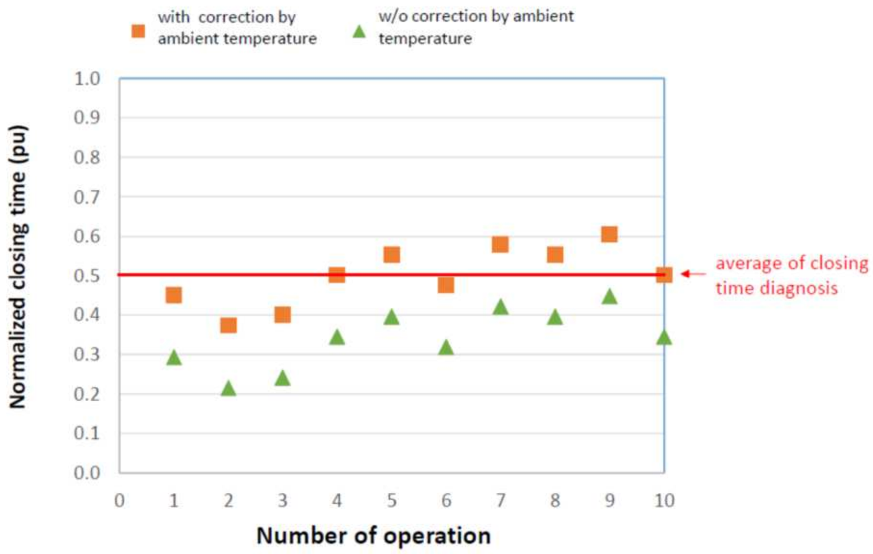


Fig.2 The example of diagnosis with different sensing results.
(Closing time diagnosis with and w/o correction of temperature)

In addition to threshold diagnosis, which is set for each diagnostic item, there is a trend diagnosis method that can detect signs of abnormality based on the fluctuation of diagnostic results, which is expected to contribute to the advancement of diagnosis. One such example is a method for detecting slow leaks of gas in a GIS by adding corrections for gas tank temperature and atmospheric pressure to the monitoring results of the enclosed gas pressure of the GIS and evaluating the trend over a long period of time. [1,2] Since gas pressure sensors detect the differential pressure between atmospheric pressure and measured pressure, atmospheric correction is used to detect more accurate enclosed gas pressure.

An overview of the leak determination method in gas pressure slow leak monitoring is shown in Fig.3. The gas slow leakage detection is performed according to the following procedure.

(1) Monitor the daily gas pressure, atmospheric pressure, and tank temperature.
(2) Calculate the corrected gas pressure by correcting the monitored gas pressure with the atmospheric pressure.
(3) Based on the correlation between the corrected gas pressure and the tank temperature for one year, calculate the corrected gas pressure at 20°C.
(4) An approximate straight line is calculated from 20°C conversion corrected gas pressure for one year.
(5) After calculating the amount of change (%/year) from the slope of the approximate straight line, the determination is made by comparing the determination to the reference value.

Fig.4 compares the results of the time series of the calculated 20°C equivalent gas pressure change rate for long term with and without atmospheric pressure correction on the gas pressure time series data measured for gas leakage free GIS on site. In the case of the gas pressure corrected by the atmospheric pressure, the variation width was reduced by about 40% compared to the case where the gas pressure was not corrected by atmospheric pressure. This is because when the atmospheric pressure correction is performed offset atmospheric pressure fluctuations are offset and the variation in the gas pressure converted at 20°C is smaller than when no correction is performed. It was confirmed that accounting for the corrections of gas pressure by atmospheric pressure in addition to the conventional temperature correction slow leakage can be more accurately determined.

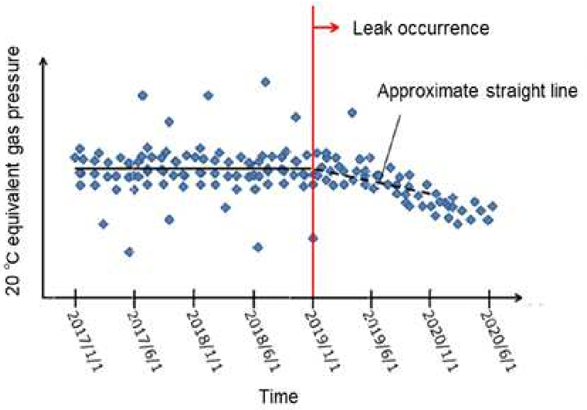


Fig.3. Leakage judgment method for gas pressure slow leakage monitoring

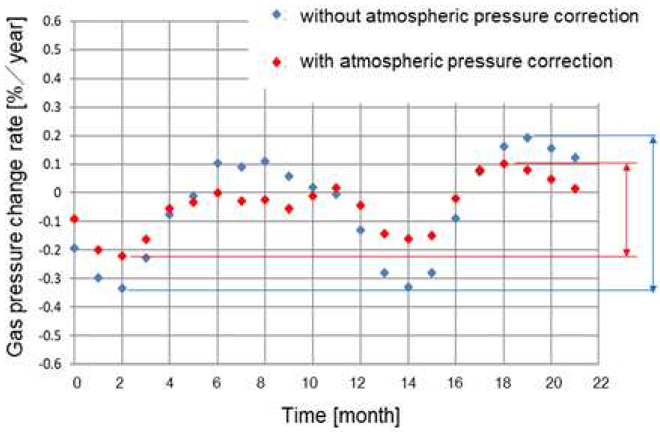


Fig.4 Comparison of long term gas pressure change with or w/o atmospheric pressure correction

2.2 Equipment monitoring, diagnostic systems and effective use of diagnostic information

In order for equipment maintenance managers to make more sophisticated use of monitoring and equipment diagnosis results, it is essential to build the equipment diagnosis systems with information transmission functions.

Fig. 5 shows an example of a system configuration of an equipment monitoring and diagnosis system for monitoring the status of a GIS. The equipment monitoring and diagnosis system consists of sensors, an Equipment Monitoring Unit (EMU), which aggregates and transmits information and performs arithmetic processing as an edge, and a host system that performs remote monitoring and data storage. The signals output from the sensors installed in the equipment shown in Table 1 are inputs to the EMU, and the EMU uses these signals to perform the arithmetic processing necessary to monitor and diagnose the various operating conditions of the equipment shown in Table 2. For example, to diagnose slow leakages by monitoring the trend of SF6 gas, and to predict the life of the equipment, in a GCB, the EMU calculates the amount of contact wearing and tear from the cut-off current and arc time. For a DS, the EMU calculates and evaluates the amount of contact wearing and tear from the loop current.

The EMU has a web server function, and by connecting a PC with a web browser to the EMU, the monitoring and diagnostic results can be displayed in a user-friendly and easy-to-understand manner at the substation. Fig. 6 shows an example of the HMI user interface of the EMU, where Fig. 6 (a) shows the real-time display of the current status of the circuit breaker, disconnector, and grounding switch. Fig. 6 (b) shows the operating waveforms of the circuit breaker (command current, stroke, a/b contact, and main circuit current). The HMI-PC allows the user to manipulate and read the measured values of the operating waveforms. This data can also be downloaded to the HMI-PC in CSV data format for further analysis.

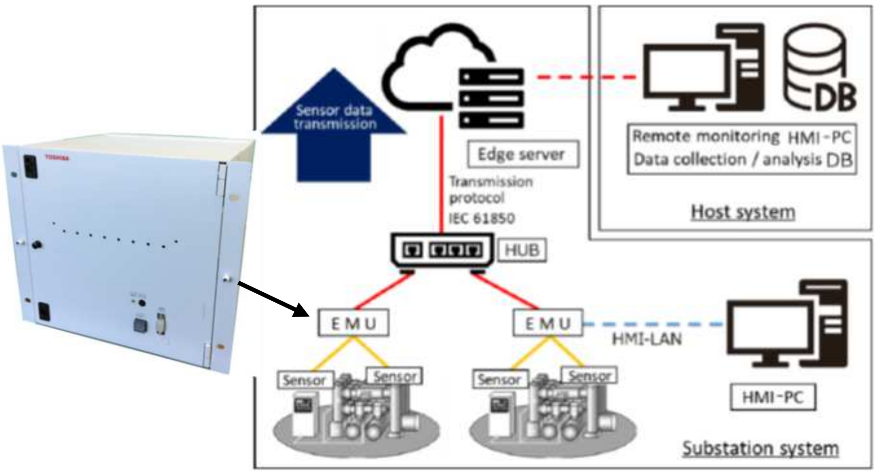


Fig.5 The principal composition of the GIS equipment monitoring system

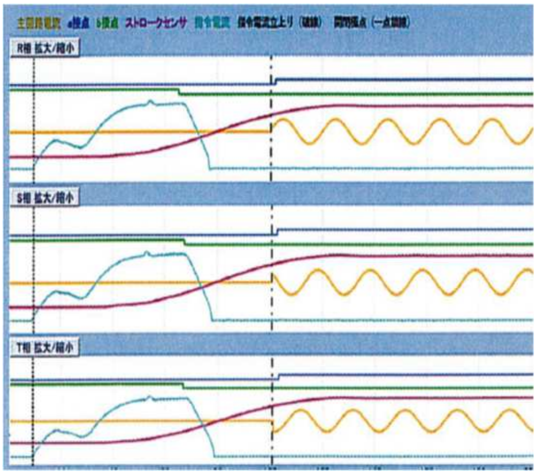
Table 1 EMU monitoring items and sensors

Equipment	Monitoring items	Necessary sensors	Usage data	Purpose		
				Deterioration diagnosis	Life expectancy	Maintenance efficiency
GIS Common	Gas pressure Slow leak monitoring Fault location	Gas pressure sensor Temperature sensor Atmospheric pressure sensor	SF_6 gas pressure GIS tank surface temperature Atmospheric pressure	○	○	○
GCB	Operating characteristic monitoring	DC clamp CT Travel sensor Temperature sensor Auxiliary switch	Control coil current Operation travel Mechanism box temperature Auxiliary switch contact signal	○		○
	Operation mechanism energy storage monitoring	DC clamp CT AC clamp CT Oil pressure sensor	Electric spring motor current Hydraulic pump motor current Oil pressure	○		○
	Contact consumption monitoring	AC clamp CT Travel sensor Auxiliary switch	Main circuit current (Breaking current) Operation travel Auxiliary switch contact signal		○	○
DS／ES	Operating characteristic monitoring	DC clamp CT Operation check switch Temperature sensor	Motor steady current Operation check switch Ambient temperature	○		○
	Contact consumption monitoring	AC clamp CT Operation check switch	Main circuit current (Loop current) Ground wire current (Induced current) Operation check switch contact signal		○	○

Table 2 EMU monitoring and diagnostic functions

Monitoring and diagnostic functions	Details
Gas pressure slow leak monitoring	Correct gas pressure by temperature and atmospheric pressure and evaluate slow leak
Fault location	Identify fault location by detecting increase in gas pressure
Equipment operating characteristics monitoring	Since the operating characteristics change depending on the environmental conditions,it is corrected and evaluated.
Contact consumption monitoring	Calculate contact consumption by monitoring main circuit current
Monitoring of energy storage characteristics of GCB spring operating mechanism	Monitor motor current and diagnose effective current value and operating time
Monitoring of pump operating characteristics and oil pressure of GCB hydraulic operating mechanism	Monitors hydraulic pump motor current and oil pressure, and evaluates the number of pump operations, operating time, oil pressure during operation / stop, and oil pressure drop during GCB operation
Trend analysis function	Evaluate time series data
Failure mode analysis function	If an abnormality occurs in the GIS, the failure part is estimated by analyzing a plurality of diagnostic items.
Monitoring of failure of individual sensor	Diagnose the output of individual sensor
EMU Self-monitoring function	EMU has constant self-monitoring function equivalent to digital relay.

(a) Summary table of equipment status



(b) Operating waveforms of ciruit breaker

Fig.6 The example of HMI-PC indication

Data is transmitted from the EMU to the host system in accordance with the transmission protocol specified in IEC 61850-8-1 (90-3) and is can be displayed on the substation dashboard. The information is stored in a database for data accumulation and analysis and is used to optimize the timing of inspections and patrols according to the condition of the equipment, to perform preventive maintenance, and to present equipment shutdown plans. Fig.7 shows an example of the dashboard screen, where the results of equipment monitoring and diagnosis by the EMU, i.e., the presence or absence of abnormalities in the equipment, SF6 gas pressure, control voltage of the equipment, temperature, and other current values can be remotely displayed. The system is also equipped with functions such as 3D data interconnection of related equipment and document interconnection of drawings, instruction manuals, test reports, etc., which can be used to build an asset management system.

Fig.7 The example of substation dashboard indication

3. **Possibility of further sophistication on equipment diagnosis by applying AI technology**

In the past, the main method of diagnosing substation equipment including GIS has been parameter evaluation, which extracts individual characteristics such as opening/closing time, speed, and operation time from the stroke curve obtained from the measurement (monitoring) results. In recent years, waveform pattern recognition and AI technologies have been widely used and their effectiveness has been confirmed. GIS equipment manufacturer is considering the possibility of applying these technologies to waveforms acquired from GIS to diagnose the equipment status by monitored waveforms themselves.

3.1 AI-based diagnostic methods

In the diagnosis of GIS equipment, it is desirable to apply a method that can detect signs of abnormality with high accuracy at an early stage and also provide a clear explanation for the abnormality in the diagnosis result when it is judged to be an abnormal condition. In recent years, the shapelets machine learning method has been used as a machine learning method for AI diagnosis of time series data which can also provide a rationale for abnormalities in diagnosis results. [3] The shapelets machine learning method automatically learns partial waveform patterns (shapelets), which are effective for diagnosing waveform data from the training data, and can quantitatively show the differences between the waveform data and the waveform data to be diagnosed. In addition, the use of One-Class Learning Time-Series Shapelets (OCLTS) is being considered as a technology that can learn with only normal data and diagnose with high accuracy, whereas the conventional shapelets learning method requires both normal and abnormal data. We are currently conducting a trial application to equipment diagnosis. [4][5] The overview of OCLTS is shown in Fig.8. In OCLTS, the characteristic partial waveform patterns (shapelets) that constitute normal waveform data are automatically learned at the time of training and, at the same time, the region where normal waveform data exists is learned by calculating how similar the normal waveform data is to the shapelets. At the diagnosis mode, by comparing the learned shapelets with the waveform data to be diagnosed, the degree of deviation is presented quantitatively as an abnormality score making it possible to indicate which parts of the waveform data deviate from the normal state. Therefore, this method is also useful for estimating the causes of abnormalities and is suitable to develop the effective countermeasures.

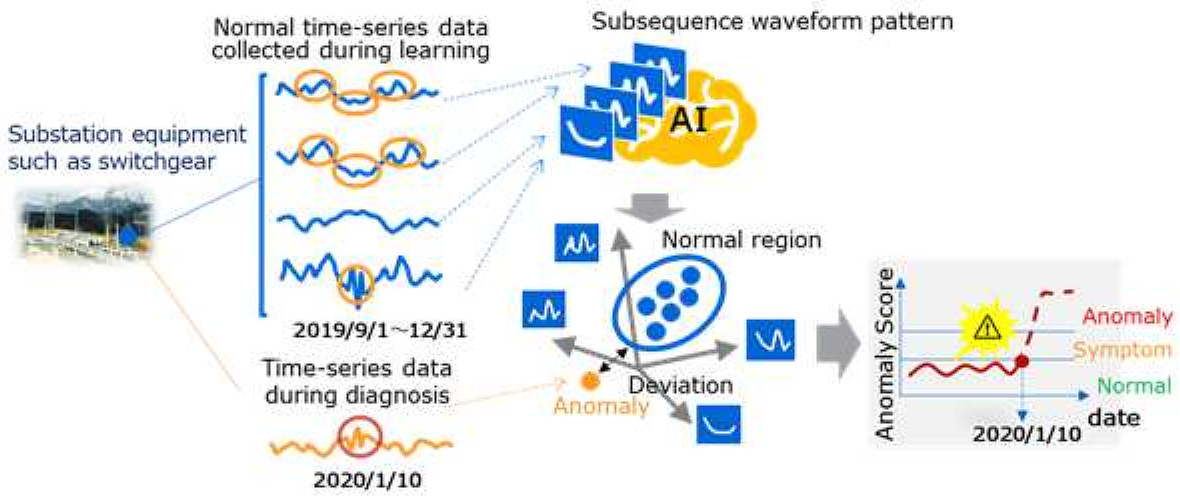


Fig.8 Overview of OCLTS

3.2 AI diagnosis of travel curves and its effectiveness

Fig.9 shows the AI diagnosis results of the abnormalities of the prototype GCB travel curve during the prototype verification process. In this case the parts of GCB gradually deformed over a number of operations and it led to change of travel curve. After the AI was trained with 100 operations worth of normal waveform data for the GCB opening travel curve, the AI was used to determine the score of abnormality for the following 100 operations of normal waveform data and 30 operations of waveform data immediately before the equipment abnormality became apparent. As a result, it can be seen that the abnormality score of the judged normal data is at the same level as the training data, while the abnormality score of the data just before the abnormality increases. At this stage, no equipment abnormality has been detected by the conventional parameter diagnosis such as opening time. For the diagnostic waveforms with high abnormality scores, we checked the areas with the largest differences from the characteristic partial waveform patterns (shapelets) learned by the AI and confirmed that the AI was able to detect slight differences in the waveform of the travel curve. Since the opening speed is expected to increase as the part is deformed, it is considered that the abnormal signs are correctly captured.

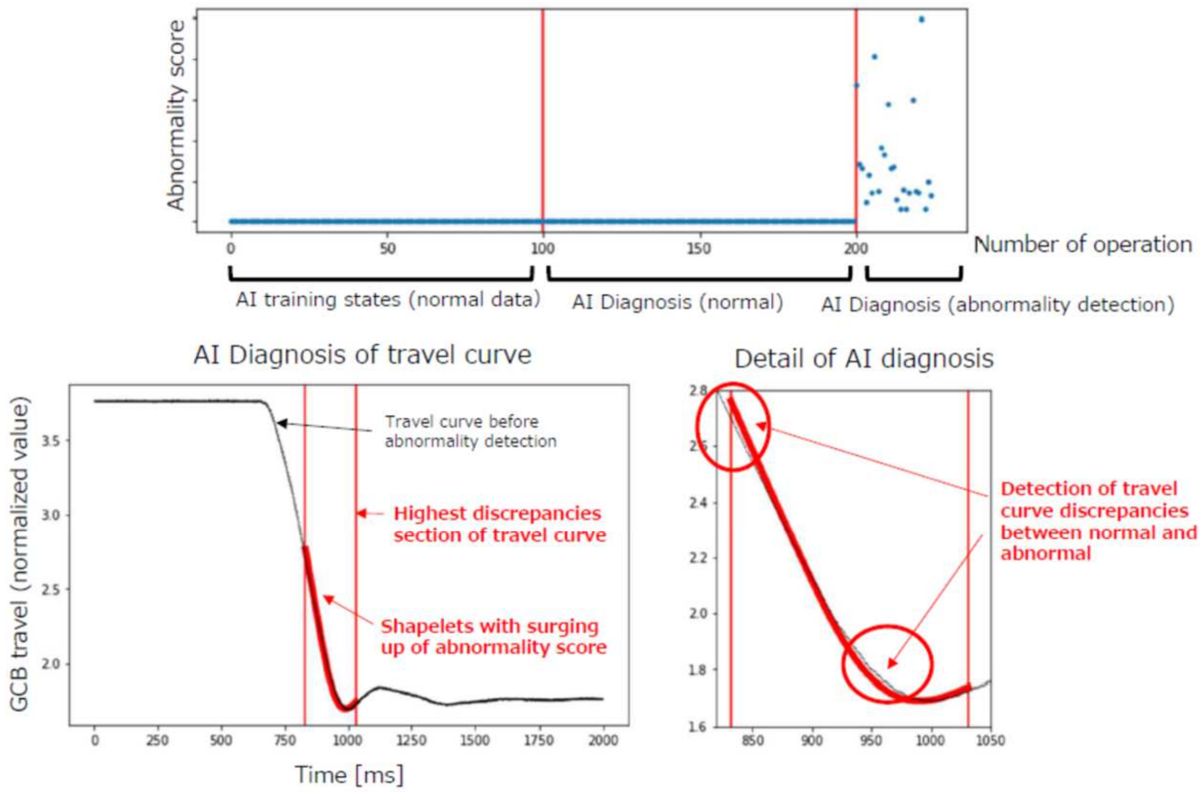


Fig.9 Detection of abnormality of GCB travel curve with AI techonology

Fig.10 shows the results of an AI's diagnosis of the data from 50 opening operations at ambient temperatures of 40°C, -10 °C, and -20°C respectively. This diagnosis occurred after having the AI trained with normal data of 50 operations at an ambient temperature of 10°C. As a result, it was confirmed that the anomaly score increased at different ambient temperatures from that at which the AI was trained, and that the anomaly score increased the most for the data at -20°C. The areas that were judged to have large differences from the characteristic partial waveform pattern (shapelets) at 10°C trained by the AI were as follows. It was confirmed that the AI captured the slight difference in the damping waveform of the travel curve in the latter half of the operation. Based on previous findings, it is known that the damping characteristics of the travel curve of the GCB in the second half of the operation slightly changes depending on the ambient temperature, and this diagnosis result is considered to capture the slight change.

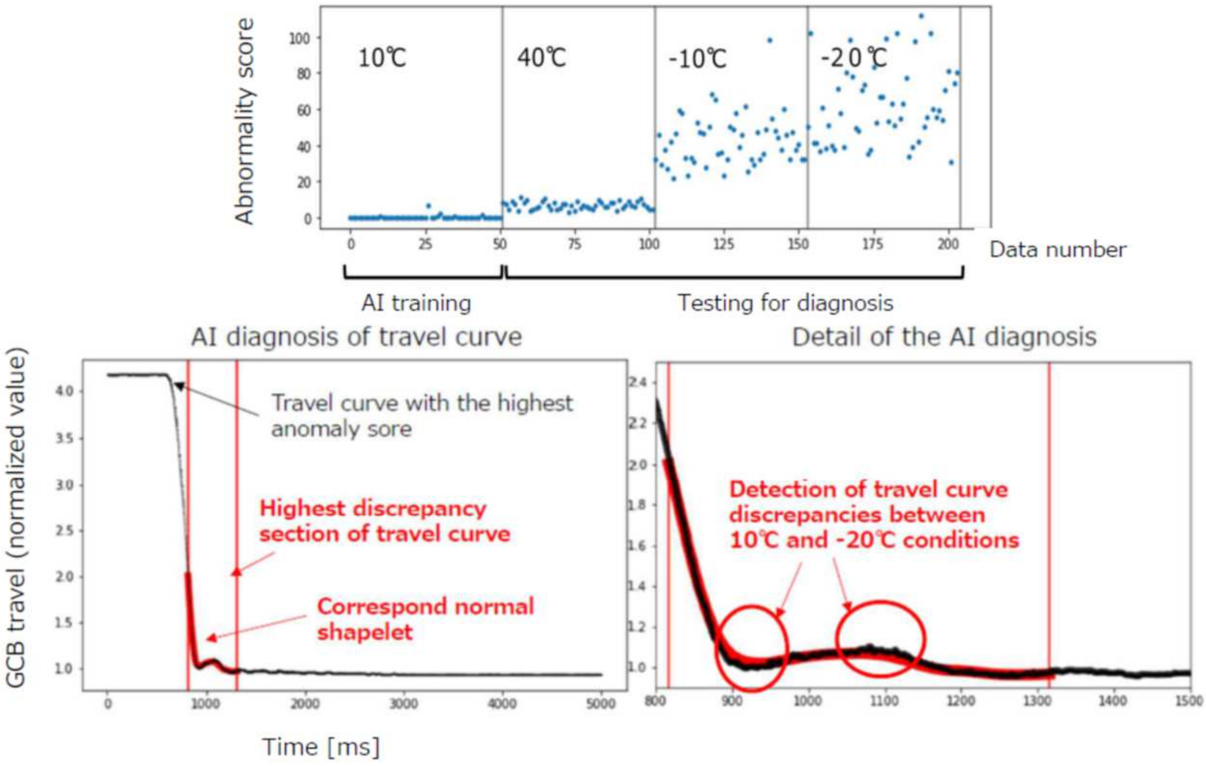


Fig.10 AI diagnostic results for GCB travel curves under different temperature conditions

Considering the above, it is thought that AI diagnosis technology may be able to detect signs of abnormalities at an early stage that cannot be detected by characteristic value management diagnosis using parameters such as opening/closing time and speed, by taking into account appropriate correction processes such as temperature compensation.
Furthermore, since the OCLTS method does not require error data in the AI training process, it is expected to be useful for existing switchgear, which is generally highly reliable and for which it is difficult to obtain equipment error data.

3.3 Challenges for equipment diagnosis using AI technology
The following are issues to be addressed in the future for the application of AI technology to equipment diagnosis.

1) Optimizing the number of training sessions by AI
Some of the older existing equipment for which equipment diagnosis is desired has been in use for a considerable period of time since the equipment was developed so the equipment manufacturer may not be able to prepare sufficient AI training data for such equipment. For this reason, it is necessary to set a certain period of time for AI training after applying it to existing equipment. It is important to shorten the training period until diagnostic results with a certain degree of reliability are obtained, so that the equipment can be diagnosed as soon as possible. Generally speaking, there is a contradictory relationship between reducing the number of training sessions for AI diagnosis and the reliability of diagnosis, but if an appropriate number

of training sessions is secured, it is possible to ensure sufficient reliability of diagnosis for practical use. As another means of acquiring AI training data, we believe that it will be useful in the future to acquire the necessary AI training data for each device by using idle devices owned by users or when replacing older devices.

2) Evaluation and use of diagnosis results
The results of AI diagnosis are output as the degree of abnormality of the diagnostic waveform relative to the training waveform but it is generally considered difficult to set a uniform threshold for the degree of abnormality to be determined as an equipment abnormality because it is thought that there will be differences among different models. AI diagnosis can detect signs of abnormality before the actual failure occurs as changes in the abnormality level at a very early stage, so it is considered useful to evaluate the trend of increase or decrease in the abnormality score each time a piece of equipment operates. In addition, the AI diagnosis that is being applied is capable of identifying the parts of the diagnostic waveform that are increasing the degree of abnormality, and it is considered useful to be able to link this to the presumed causes of abnormality and recommended inspection items based on FMEA for equipment operation. In the future, it is necessary to study the evaluation and usage of the diagnostic results while considering the convenience of the user.

4. Conclusions

The digitalization of equipment for CBM of substation equipment is expected to expand rapidly in the future. The following points can be mentioned as key points for more effective and reliable equipment diagnosis:
-In equipment condition diagnosis by equipment monitoring, it is necessary to diagnose the equipment condition comprehensively by monitoring results from multiple sensors with different sensing items.
-The results of equipment condition monitoring and diagnosis need to have HMI functions to communicate information to maintenance personnel in a user-friendly and effective manner, and need to be scalable for use of the acquired data.
-The application of AI technology to equipment condition diagnosis has the potential to detect signs of abnormality at an early stage, which cannot be detected by parameter-based characteristic value management diagnosis and is expected to contribute to the further advancement of equipment diagnosis technology.

BIBLIOGRAPHY

[1] K. Uchida et al: “GIS On-line monitoring solution using real-time data collected form GIS mounted sensors”, CIGRE 2020 AORC Web-library event, No.C000072, 2020
[2] Y. Matsushita et al: “Practical use of monitoring / diagnostic systems to realize more efficient maintenance, stable electric power supply and optimized refurbishment”, CIGRE 2014, B3_114_2014, 2014
[3] Grabocka J et al., “Learning Time-Series Shapelets”, ACM SIGKDD, 2014/4
[4] Yamaguchi A et al., OCLTS: One-Class Learning Time-Series Shapelets, International Journal of Data Mining Science (IJDAT), 2019/5.
[5] Yamaguchi A et al., One-Class Learning Time-Series Shapelets, IEEE International Conference on Big Data (Big Data 2018), 2018/12.