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Technology

Integrated Platform for Facility Monitoring for Anomaly Detection

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Abstract

In this paper, we describe the integrated platform for facility monitoring for anomaly detection that will make our DX strategy. When applying the predictive detection of equipment failure signs, we use the properly know-how utilization, algorithmic and AI types according to the scale and complexity of the application target. The characteristics of each and applied examples are presented.

1. Introduction

Nippon Steel Corporation established an integrated platform for facility monitoring. We use it to consolidate and organically link various data assets output from various devices and systems and allow the consolidated data to be freely used within the company. Examples of such data assets are control data that is output from multiple control systems in the production processes, wireless IoT sensor data that is collected by NS-IoT, and image data that is collected by location-free ITV systems. This paper describes the integrated platform for facility monitoring for anomaly detection that utilizes various types of data pieces to promptly detect anomalies in various types of facilities.

2. Issue with the Conventional Facility Diagnostic Functions and Task to Resolve It

Nippon Steel has established various types of facility diagnostic systems including vibration diagnostic systems targeting rotary machines. Meanwhile, for conventional facility diagnostic systems, sensors and wires are installed in target facilities, data collection mechanisms are formulated, and experts in machinery and electricity develop an individual anomaly detection logic pattern for each facility and apply it to each facility. Accordingly, to expand facilities to which such systems are applied, enormous amounts of labor and costs are necessary. Therefore, it is difficult to formulate a facility diagnostic function that covers entire steelmaking lines consisting of various types of facilities and thereby facility diagnostic systems have been introduced only to important facilities. Under such circumstances, when establishing the integrated platform for facility monitoring, we aimed to establish a facility diagnostic system that would be able to execute various processes from the design of facility anomaly detection logic to the application of it to actual worksites in a seamless way without taking the time and effort required to collect and integrate data. Then we worked, using this developed system, to develop facility anomaly detection logic patterns and expand their application without using a substantial amount of labor and costs.

3. Elements of the Integrated Platform for Facility Monitoring

3.1 Virtual database that can utilize data in an integrated manner

Although we collect various types of data pieces, such as production process control data and wireless IoT sensor data, they are asynchronous data assets in different forms and different cycles separately stored in individual systems. To establish facility anomaly detection logic, data pieces in different sampling cycles are sometimes combinedly analyzed, for example, a combination of data in minutes collected by wireless IoT sensors and control data collected in seconds. Therefore, a mechanism that can handle such various types of data pieces in an integrated manner is required. One resolution is to establish a large-capacity storage to collate data. However, this method has disadvantages, such as double management of data and an enormous investment amount. Accordingly, we have developed and introduced Smart Database as a mechanism to virtually consolidate data assets and manage the consolidated data in an integrated manner without storing data in a common storage (**Fig. 1**). Smart Database has a function for managing specifications, such as data names and units, and locations of the systems where the actual data is stored (IP addresses), etc. Smart Database also has an interface function that enables referring to the data in the systems and an application interface (API) that responds to requests from the functions of facility monitoring for anomaly detection. Without investment in a large-capacity storage, Smart Database has made it possi-

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ble for users to utilize various types of data pieces in an integrated manner without caring about where such data is stored. We are now promoting development such that the data that Smart Database can utilize is linked with the integrated data management platform NS-Lib™ (another paper numbered 18 in this special issue) to allow the data to be used for other purposes, in addition to the integrated platform for facility monitoring.

3.2 Functions of facility monitoring for anomaly detection

To apply facility monitoring for anomaly detection, functions need to be appropriately used based on the scales of target facilities and the complexity of problems. Consequently, we have developed three functions listed in **Fig. 2** for problems for which: 1) the logic is simple and clear based on the expertise acquired from past operational and maintenance problems at actual sites, 2) the logic can be described based on statistical and physical model algorithms because the anomaly occurrence mechanisms are known although the problems are complicated, and 3) because the anomaly occurrence mechanisms are not known, establishing algorithms is difficult, and thereby machine learning is required. Function 1 named the Trend Observation and Management System (TOMAS) was developed for operation and maintenance staff at the front line of manufacturing sites. For function 2, the real-time observation and operation controlled system that had been developed by Nippon Steel for engineering staff and was in practical use was adopted. For function 3, invariant analysis of NEC Corporation and our Polygon AI (to be described in another paper 10 in this special issue) were introduced for engineering staff. Each function will be described below.

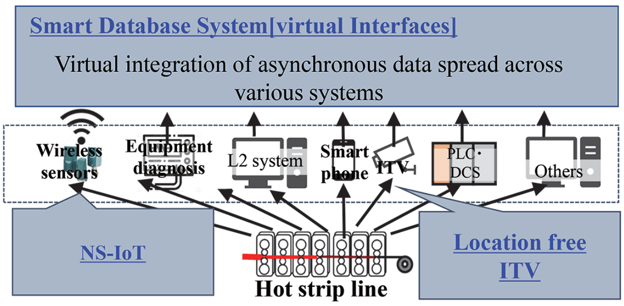

Fig. 1 Smart database system

3.2.1 Trend Observation and Management System (TOMAS)

Our detailed analysis of facility failures in the past found that even when facilities differ, most anomaly detection logic patterns can be expressed by combinations of standardized and generalized components. Therefore, we carefully selected and combined simple and general-purpose feature value extraction logic patterns that would be able to be applied to various cases and that could be intuitively understood; then we developed the Trend Observation and Management System (TOMAS) that would be able to detect facility anomalies by managing the trends of the feature values. TOMAS makes it easy for operators and maintenance staff to describe expertise utilized at actual sites, which makes it possible to establish mechanisms that monitor the trends of facility anomalies on their own.[1)]

As a case where TOMAS is effectively applied, the failure of a solenoid valve of a finishing mill is introduced below. In the past, the solenoid valve coil of a hydraulic roll positioning device of a finishing mill partially broke, which suspended the rolling for several hours. This case shows that the application of TOMAS to this facility failure in the past enables early detection of anomalies. As shown in **Fig. 3**, our interviews and investigation revealed that as signs of the break of the solenoid valve, phenomena where when materials were jammed, the solenoid valve connector momentarily broke due to the shocks, which dropped the current of the solenoid valve abnormally had been observed from one month before the failure. Considering this fact, logic to cut out data in periods for which designated conditions were satisfied was combined with another logic pattern to calculate the change rates of the data so as to extract the change rates of the current for one second before and af-

	Know-how utilization	Algorithm type	AI type
	TOMAS (Trend Observation and MAnagement System)	Real-time observe and operation controlled system	- Invariant analysis - Polygon AI
Method	Combination of logic patterns	Statistical Analysis and Physical model	Machine learning
User	Facility operators	Technical staff	Technical staff
Model building	Prepared modules	Graphical programming	Specialized Analysis engine
Object	Equipment component	Equipment component or Equipment	Equipment / Facility

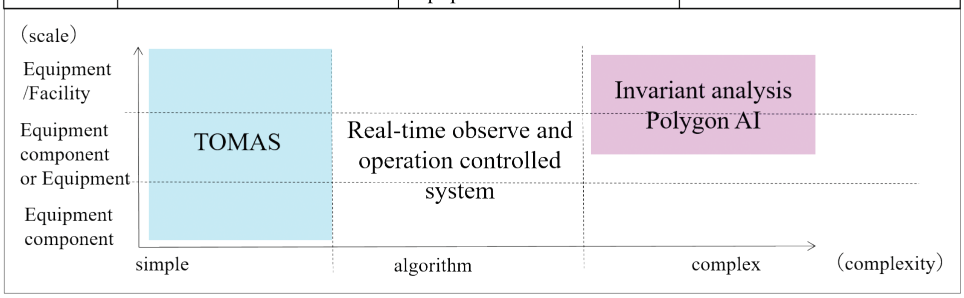

Fig. 2 Functions of the integrated platform for facility monitoring

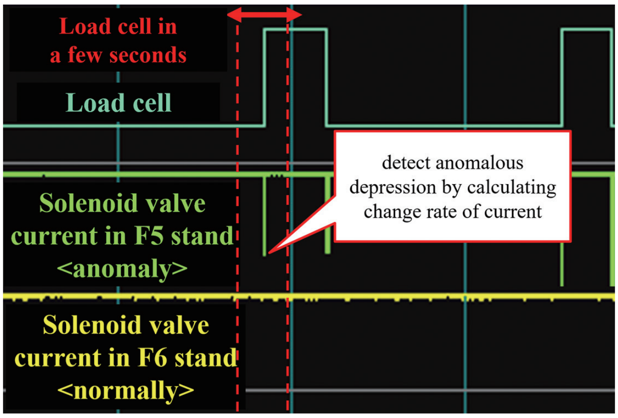

Fig. 3 Failure mechanism of solenoid valves of finishing mill

Fig. 4 Failure mechanism of cylinders of coiler

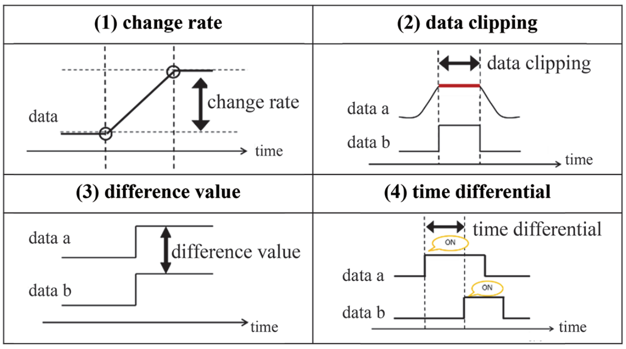

Fig. 5 Example of extract feature value

ter jamming of materials. The application of the aforementioned logic patterns to the past failure data has confirmed that the abnormal drop in current of solenoid valves can be appropriately detected and thereby anomalies can be detected at an early stage.

As the second application case, this paper introduces the failure in a coiler hydraulic cylinder. For this failure, a deteriorated cylinder caused the coiler to malfunction, resulting in the coiling failure of a hot-rolled coil. Our interviews and investigation revealed that, in the facility in question, delay in cylinder operations was seen as a sign of deterioration of the cylinder as shown in **Fig. 4**. Accordingly, logic to calculate the differences in the time values when two signals rose was applied to extract the time from when a cylinder operation command signal came on to when a cylinder operation limit switch signal came on. By applying the aforementioned logic to the past failure data and managing the trend, it has been confirmed that the deterioration trends of cylinders can be appropriately detected and thereby anomalies can be detected.

As described above, it has been confirmed based on the actual facility data that many facilities can be generally diagnosed by carefully selecting and establishing simple and general-purpose feature value extraction logic patterns that quantify facility operations. **Figure 5** shows part of the feature value extraction logic patterns implemented with TOMAS. We are planning to design necessary feature value extraction logic patterns based on requests from actual sites and analysis of past facility failures as required and expand them also in the future.

For TOMAS, programming-less registration screens have been developed so that operators and maintenance staff at the front line of manufacturing sites can easily establish anomaly detection logic patterns that are combinations of feature value extraction logic patterns. In addition, considering the trend where more operations will be performed from anywhere, the registration, trend view, and alarm list screens have been made accessible (thereby operable and viewable) from any place in addition to actual sites, as long as the internal network is available.

Furthermore, to make it possible to easily verify whether established anomaly detection logic patterns will function as intended, TOMAS is equipped with a logic verification tool that uses past operation data (playback simulation function). This function is provided to allow maintenance staff to easily try out their ideas in daily operations by making it possible to seamlessly check on one screen whether anomalies can be detected without fail and whether errors are not wrongly issued when the state is normal before implementing the devised logic patterns into the production environment; this function works to turn their ideas into great assets quickly.

At factories to which TOMAS was introduced, the number of target facilities was expanded within one year and approximately 200 logic patterns that were registered by operators and maintenance staff at the front line are in use to detect facility anomalies (**Fig. 6**).

3.2.2 Real-time observation and operation controlled system

The application of TOMAS has enabled detecting anomalies in many facilities via simple feature value extraction logic patterns. Meanwhile, for complicated anomaly mechanisms, using data analysis algorithms based on statistical and physical models is desired. In such complicated cases, logic patterns to be applied vary from target to target, such as process, facility, and device, and thereby it is sometimes difficult to just apply combinations of simple feature value extraction logic patterns.

To resolve the problem, the real-time observation and operation controlled system[2)] that had been developed by Nippon Steel and was in practical use was adopted. In the system, general-purpose PCs can be directly connected to the Level 1 network (programmable logic controllers (PLCs) and distributed control systems (DCSs)) and the system provides flexible software development environments, high reliability, and high-periodicity. For the real-time observation and operation controlled system, to allow users to freely establish logic patterns and reduce development loads, National In-

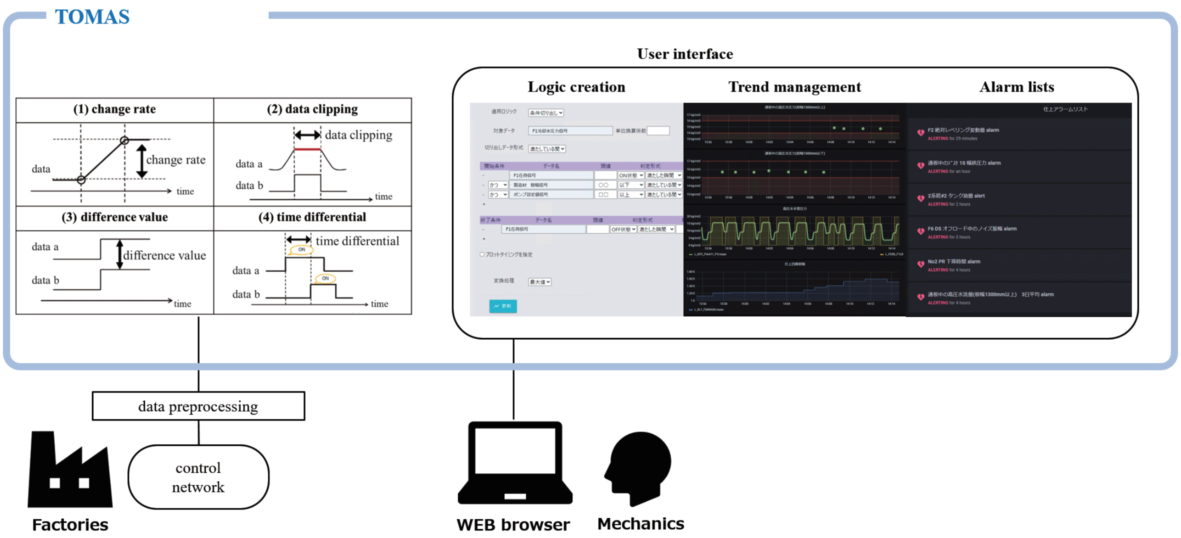

Fig. 6 Example of TOMAS application

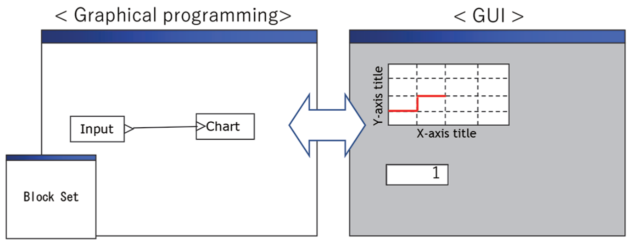

Fig. 7 Programming with block diagrams

struments Corporation's LabVIEW™ was adopted; LabVIEW™ can create programs using block diagrams without creating scripts (**Fig. 7**). In addition, Nippon Steel's proprietary facility anomaly detection functions were turned into components for LabVIEW™, which enabled the quick application of such facility anomaly detection functions to other similar facilities. This mechanism enables engineering staff who do not have much experience with programming to create anomaly detection logic patterns involving complicated algorithms based on statistical and physical models.

When data is input and output via Smart Database, real-time processing becomes difficult due to the limitation of the fast-response performance. To resolve the problem, for facilities that are controlled at high speed (at intervals of several milliseconds), for example, hot-rolling lines, we have developed a mechanism that can process high-speed data (at intervals of milliseconds) in real-time by directly connecting Level 1 (PLCs and DCSs) and general-purpose PCs to directly process data as shown in **Fig. 8**.

As described above, the real-time observation and operation controlled system has been incorporated into manufacturing lines in various scales throughout the company and more than 400 facility anomaly detection logic patterns have been developed and applied.

3.2.3 Invariant analysis

For TOMAS and the real-time observation and operation controlled system, humans devise and create anomaly detection logic and algorithms for target facilities. However, there are some facility failures for which the mechanisms and anomaly monitoring methods are not clearly understood. Nippon Steel determined to use ma-

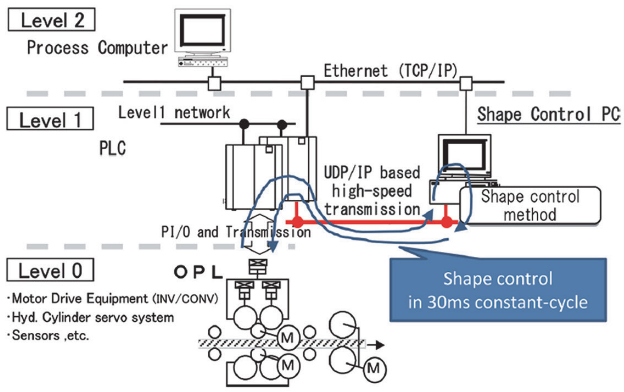

Fig. 8 Example of the application of new real-time control system in plate leveler

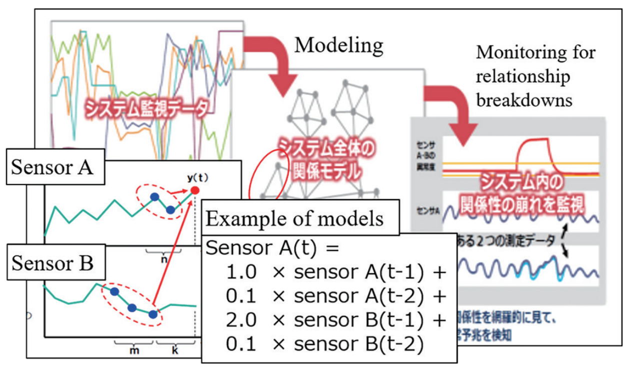

Fig. 9 Invariant analysis

chine learning for such cases to make anomaly detection logic creation and monitoring more efficient and adopted NEC's AI analysis software "NEC Advanced Analytics – Invariant Analysis" (**Fig. 9**).

The major characteristics of invariant analysis are as follows: 1) Steady linear relationship existing between data pieces in normal operation states can be defined as invariability and automatically extracted and relationship models for the entire systems can be cre-

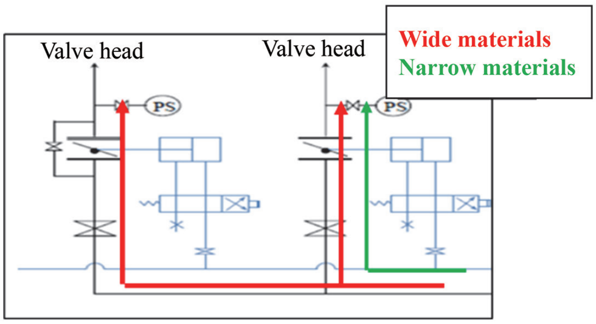

Fig. 10 Example of operation cases

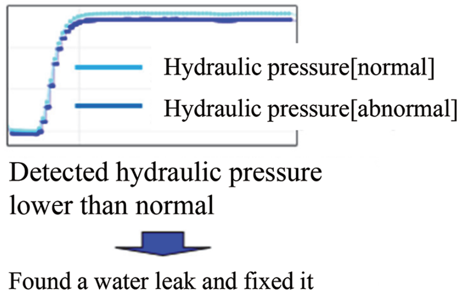

Fig. 11 Example of fault detection (water leakage)

ated and 2) because models describing the linear relationship between various variables are given as statistical models (Auto-Regressive (AR) or Auto-Regressive with eXogenous (ARX) models), abnormal sections can be estimated and the results can be easily interpreted.

Nippon Steel, based on operation and facility data in normal operation states collected mainly from hot-rolling mills at intervals of 100 milliseconds, established and evaluated monitoring models for main facilities.

Data in normal operation states includes operation patterns that vary from material to material as shown in **Fig. 10**. Accordingly, regarding data on patterns that are not included in the established anomaly detection models, overdetection frequently occurs. Meanwhile, some materials are not much used for production. From these facts, we understood it would be difficult to collect data for all patterns and establish an individual anomaly detection model for each of the patterns to switch models. To resolve this issue, we separated data pieces by main operation patterns based on our knowledge on processes, which allowed us to adjust models such that they would be able to practically detect anomalies while suppressing overdetection.

As of 2023, 18 models have been created and they have been functioning well to detect anomalies, for example, detection of water leakage at an early stage as shown in **Fig. 11**.

4. Conclusion

This paper outlined Smart Database that can handle various pieces of data in an integrated manner in the integrated platform for facility monitoring and the facility anomaly detection functions that utilize such data and also described their utilization. We will promptly incorporate the integrated platform for facility monitoring throughout the company to contribute to stabilizing the facilities of the entire company.

References

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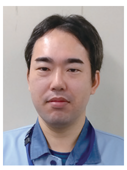

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