Technology Explanation

Development of an Equipment Predictive Maintenance System

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Abstract

In the manufacturing industry, maintenance activities for machines and equipment operating at production sites are essential for maintaining stable production of high-quality products. The concept of equipment maintenance can be broadly divided into three categories: breakdown maintenance, preventive maintenance and predictive maintenance. In recent years, predictive maintenance has been attracting attention due to the development of the Internet of Things (IoT) and Artificial Intelligence (AI).

On the other hand, KYB's equipment maintenance methods focus on breakdown maintenance and preventive maintenance. In the former case, equipment failure causes a drop in productivity and product defects, and in the latter case, excessive maintenance increases maintenance costs.

To solve these problems, we have developed an equipment predictive maintenance system. This system utilizes the latest technologies, including IoT, AI, and cloud computing, to build a system with functions such as data collection, storage, failure prediction, and visualization and the system is now in operation at a practical level. This paper describes the basic functions developed to realize predictive maintenance, and the operation management mechanisms and features that have been developed for global deployment.

1 Introduction

The Internet of Things (IoT) and Artificial Intelligence (AI) have advanced dramatically in recent years and attracted the attention of not only academia and the IT industry but also a variety of other fields including medical and manufacturing.

The manufacturing industry has made use of IoT and AI to "detect faulty parts," "predict equipment failure" and "optimize production plans," which has made it possible to achieve these activities with higher accuracy.

In terms of equipment failure prediction, we are now finally seeing the possibility of implementing "predictive maintenance," which refers to a maintenance system based on the automatic monitoring of equipment status to provide a prediction of failure occurrences, enabling maintenance personnel to carry out maintenance when a sign of failure is detected. Under predictive maintenance, maintenance can be carried out in a timely manner, preventing occurrences of failures as well as maximizing the usage of parts. Thus, predictive maintenance will hopefully minimize maintenance costs.

On the other hand, the equipment maintenance system in actual practice by KYB focuses on "breakdown maintenance," which only requires personnel to conduct maintenance after failure, and "preventive maintenance," which requires personnel to conduct maintenance periodically or after a certain period of operation. In the former case, equipment failure causes productivity losses and product defects. In the latter, excessive maintenance may increase maintenance costs.

To solve these problems, we have developed a predictive equipment maintenance system. This system utilizes the latest technologies, including IoT, AI, and cloud computing, to build a system with functions such as data collection, data storage, failure prediction, and visualization, and the system is now in operation at a practical level.

2 Requirements

The following lists the requirements for implementing a equipment predictive maintenance system and putting it into operation:

① An environment for continuously accumulating and analyzing data collected from equipment must be available.

② The system must be able to provide not only normal/abnormal judgement but also numerical assessment of failure risk.

③ The system must be able to predict a failure at least two weeks before its occurrence [Note 1)], rather than immediately before the occurrence.

④ The current status of equipment must be visualized and available even to personnel in an office.

⑤ The system must be designed for general purpose to be applied to different types of equipment, not to a specific one.

⑥ The system must be able to be deployed on a global basis.

Note 1) This period has been determined with consideration given to how long it generally takes to get ready for maintenance (part arrangement and personnel allocation) after prediction of a failure. In reality, the period depends on the equipment.

3 System Overview

3.1 System Architecture

To realize predictive maintenance, it is necessary to collect data for determining the status of equipment. Data items to be collected and the collection methods depend on the target equipment and/or the failures to be detected. One of the typical data items is "vibration." Vibration data is usually collected at a high sampling rate (for example, 10 kHz or more), resulting in large amounts of data. On the other hand, it may be sufficient for some types of equipment to collect data at a low sampling rate (for example, about 1 Hz), which generates small amounts of data. Therefore, in order to achieve global deployment of a general-purpose system applicable to many different types of equipment, the system must be designed to be able to handle small amounts of data at a lower cost while having sufficient capacity to deal with a surge of data, if any.

This means that the storage capacity and processing capability should be able to be scaled up/down according to the data volume to be handled and processed. However, the conventional on-premises Note 2) system was incapable of achieving such scaling, so in this development project, we established KYB's own platform on the Amazon Web Services (AWS) public cloud.

Fig. 1 shows a block diagram of the system we developed.

The platform can provide various serverless Note 3) services to deal with most tasks related to predictive maintenance except for a few tasks. The processing performance and its associated costs can be charged by a subscription system under which users only pay for "as much as they use." KYB can also cope with the service flexibly depending on the scale of equipment.

Note 2) "On-premises" means that the software system is installed on computers on the premises of the organization using the software.

Note 3) "Serverless" is an idea that the organization builds a software system by using managed services controlled by a public cloud service provider such as AWS and dynamically setting necessary resources for processing, instead of having its own server by itself.

3.2 Collection of Equipment Data

We built a data collection system that periodically captures data from sensors installed to determine the status of target equipment and stores the data in files in an FA computer. These files are periodically uploaded to AWS.

To illustrate this, the following introduces a case of data collection from an overhead trolley conveyor for product transfer. Photo 1 shows the drive motor for the conveyor and its peripheral components. An acceleration sensor is installed in the drive of the transport chain (bottom left corner of Photo 1). Photo 2 is an enlarged view of the area where the acceleration sensor is installed. This installation

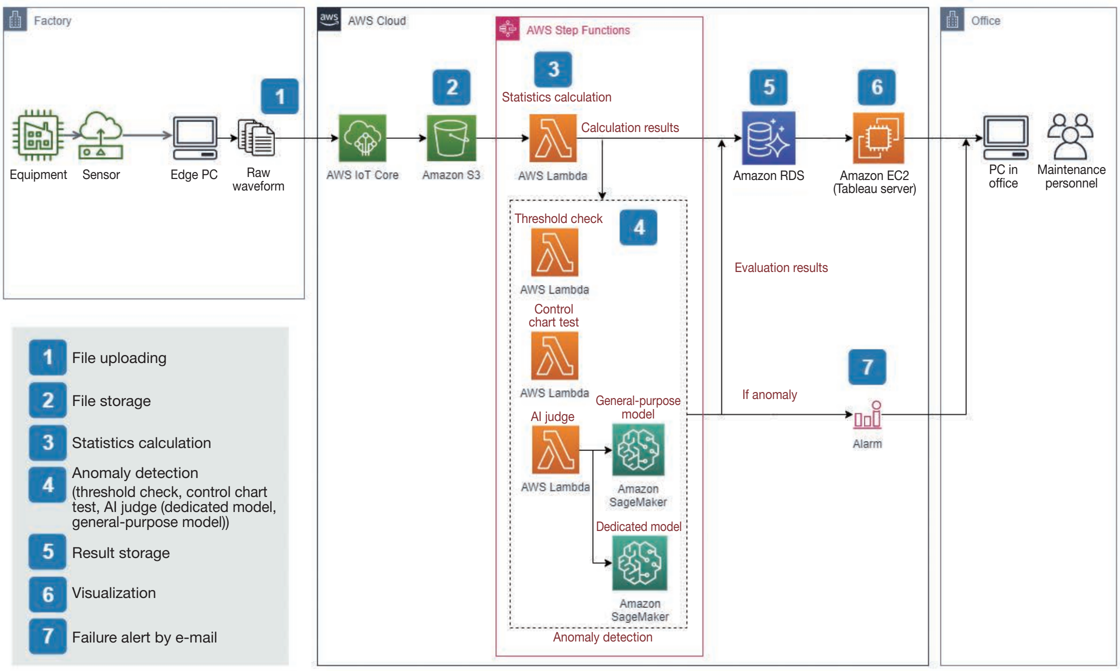


Fig. 1 System Architecture Diagram (overview)

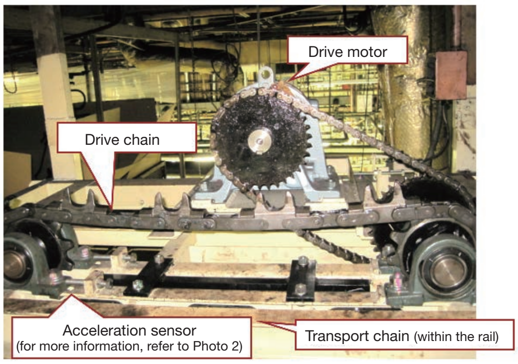


Photo 1 Conveyor equipment

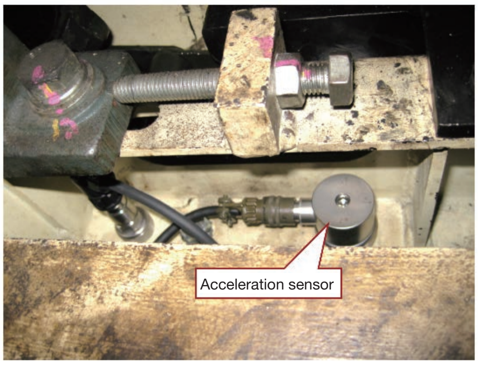


Photo 2 Area with acceleration sensor

is intended to predict conveyor failures during transport by measuring the vibration of the drive.

Predictive maintenance focuses on the detection of status changes caused by wear or other anomaly of equipment from a long-term point of view and does not cover sporadic failures. In other words, data should not necessarily be collected all the time. Periodic collection, for example, "collect data only for 10 seconds every hour" may be sufficient. We then developed an application program that collects data for a certain period of time at regular intervals and outputs files, as part of this development project. It should be noted that we designed the data collection system to output files of collected data before uploading so that the system can generally be applied to many different types of equipment including PLC [Note 4].

For data uploading, AWS IoT Core [Note 5] and AWS STS [Note 6] services are used to implement the uploading of files of collected data to AWS and the uploaded data is finally stored in Amazon S3, which is a storage service of AWS. By using these services, only devices registered on AWS are allowed to upload data securely using temporary authentication information.

Note 4) Programmable Logic Controller: a control device that was developed as an alternative to relay circuits

Note 5) A service that makes various AWS services available to IoT devices

Note 6) AWS Security Token Service: a service to provide temporary security authentication to permit access to AWS resources

3.3 Equipment Failure Prediction Function

3.3.1 Overview of Function

To implement a predictive maintenance system in this development project, we used machine learning to develop a failure prediction function. For judging the equipment status between normal and abnormal (failure) as in this case, "supervised learning" and "unsupervised learning" techniques are generally available. We selected the unsupervised learning technique because it was difficult to obtain large amounts of anomaly (failure) data as required by the supervised learning technique. We only used "normal" data for learning, according to the concept of anomaly detection that tries to detect deviations from the "normal" data set.

For machine learning, we created two types of models based on different concepts: "a dedicated model" and "a general-purpose model."

Table 1 shows a matrix of these two models:

Table 1 Comparison of models

	Dedicated model	General-purpose model
Available for	Several months	1 week
Accuracy	High	Middle [Note 7]
Algorithm	Any	Statistical machine learning
Feature	Any	Statistics-based
Learning	Manual	Automatic
Prediction	Automatic	Automatic

Note 7) The accuracy is lower than for the dedicated model, but higher than for the conventional threshold check.

The dedicated model is a machine learning model specifically designed for a specific equipment unit. In general, machine learning seldom produces ideal results only with data input. Fine tuning such as extraction of appropriate features, selection of learning techniques or parameter setting may contribute to more accurate results in many cases. For an equipment unit requiring high accuracy, a dedicated model specific to the unit is created. However, creating a dedicated model entails a problem in that it takes a longer time to be completed due to the fine tuning. In a case that a dedicated model was created for an equipment unit, it took several months to complete the model creation, including data collection.

On the other hand, the general-purpose model is designed to be able to be generally applied to any equipment unit, not a specific one. A general-purpose model is created by the statistical machine learning technique that uses features mainly for statistics, including the average of a set of normal data for around one week, [Note 8] and then detects deviations from the normal data set. That is, the general-purpose model enables simplified anomaly detection only with a simple method. The accuracy is certainly lower than for the dedicated model, but it may be sufficient depending on the equipment. It is also possible for us to operate the system based on a general-purpose model that can be quickly adapted in the early stage after its introduction, and to switch to a dedicated model as soon as it is completed. In this way, the failure prediction function we developed can offer both quick deployment and high accuracy with these two types of models.

Note 8) The period can be freely adjusted.

3.3.2 Cases of Development

As an example of the learning methods we devised for the development of dedicated models for given equipment, this section introduces Spec Masked Autoencoder. This method uses Autoencoder (hereinafter "AE"), which is one of the deep learning methods. AE was originally used for dimensionality reduction or feature extraction and is recently used for data creation, clustering or anomaly detection. The method we developed adopted the concept of anomaly detection. Fig. 2 shows the learning flow of these methods.

The general AE carries out encoding and decoding for machine learning so that the input data is identical to the output data. For Spec Masked AE, a mask is added to hide part of the input information and then removed to expose the output data. Machine learning is conducted so that the output data is identical to the original input data [1]. The mask addition and removal process is added in this way to intentionally make the issue more difficult to suppress overlearning [Note 9], with an aim at developing a flexible model.

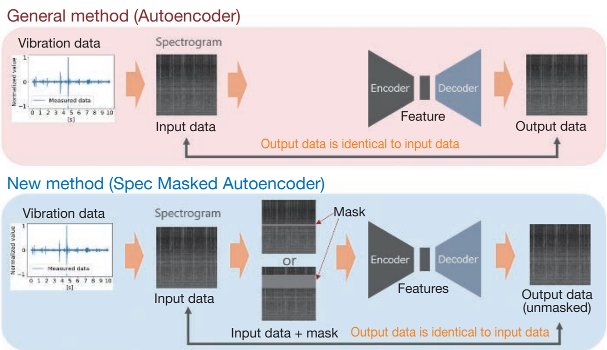


Fig. 2 Learning flow of AE and Spec Masked AE

Note 9) Overlearning refers to adapting to learning data too much to become unable to adapt to unknown data.

3.3.3 Operation and Management of Machine Learning Models

For a software system using machine learning, model development is just the beginning. It is needed to develop a scheme to properly manage the entire system to allow continual operation. For example, if the conventional trend of data collection changes due to seasonal variation or a change in the processing conditions of the equipment, the system may no longer yield proper judgement with the existing model. In this case, the model should be updated by relearning. During the updating, the model evaluation, version control and distribution method must be clear. An unexpected error may otherwise occur.

In this development project, we effectively used AmazonSageMaker [Note 10] and AWS Step Functions [Note 11], both of which are AWS services, to implement model management and develop a learning and prediction workflow. For model management, for instance, the model is tagged to indicate whether the model is for development or for actual use and just changing the tag of the model for development, for example, will switch the model over to actual use. For the general-purpose model, learning, distribution and prediction processes have been automated so that a model can be automatically created to allow prediction to be started as soon as a set of data has been collected for a specified period of time.

Note 10) A service to provide an environment where machine learning models can be quickly developed, learned and distributed.

Note 11) A service that allocates two or more AWS services to create a series of workflow.

3.4 Visualization of Equipment Status

To visualize the status of equipment, we developed a view using Tableau, which is one of the BI tools [Note 12].

Note 12) Business Intelligence tool: A tool to collect, analyze and visualize large amounts of data accumulated in an organization, thereby helping the organization to make decisions quickly.

3.4.1 Equipment Anomaly Information View

Fig. 3 shows the view displaying equipment units with anomalies, and the distribution and changes of their failure risks [Note 13) Note 14)]. This view is basically displayed as a main screen all the time. On this screen, the user can identify the equipment units with anomalies or high failure risks and then take actions as follows:

- Check equipment data (statistics).
- Go and see the actual equipment.
- Develop a maintenance plan for repair.

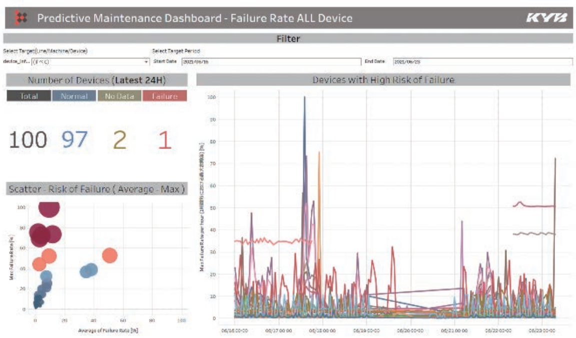


Fig. 3 Equipment anomaly information view

Note 13) Numerically indicates the extent to which the equipment is likely to have a failure.

Note 14) Data shown in the view is only sample data and different from the actual data.

3.4.2 Specific Equipment Statistics View

Fig. 4 shows the view displaying changes and variation of statistics (such as average and standard deviation) of data collected from a given equipment unit [Note 15]. If the equipment unit is found to have an anomaly or a high failure risk, the user can open this view to see how the actual statistics of the equipment unit have changed. It is expected that the user can specifically determine the anomaly.

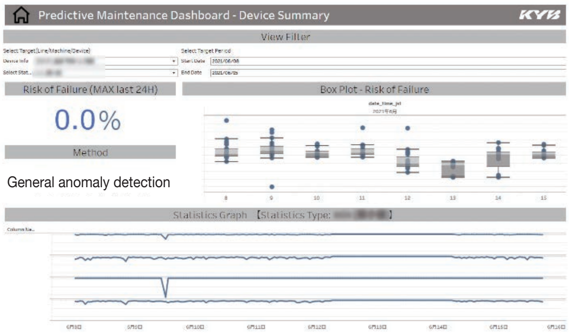


Fig. 4 Specific equipment statistics view

Note 15) The part with confidential information has been intentionally deleted or shaded.

3.4.3 Multiple Equipment Statistics Comparison View

Fig. 5 shows the view displaying changes in statistics of data collected from two or more equipment units[Note 16)]. If any one of the equipment units is found to have abnormal changes in statistics, the user can open this view to compare the unit with another under the same conditions or monitored with the same data items side by side. It is expected that the user can identify the location of the anomaly.

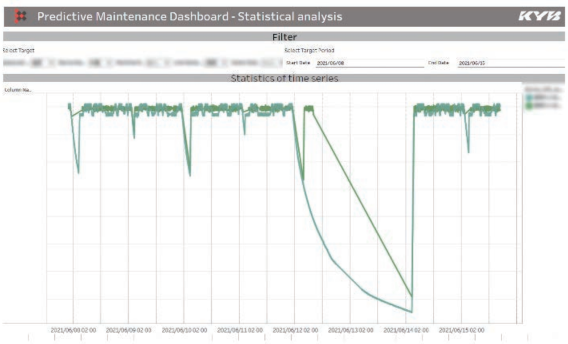


Fig. 5 Multiple equipment statistics comparison view

Note 16) The part with confidential information has been intentionally deleted or shaded.

4 Cases of Equipment Failure Prediction

This chapter introduces cases of equipment failure prediction using the dedicated or general-purpose model we have developed.

4.1 Equipment Failure Prediction with Dedicated Model

A case of equipment failure prediction using a dedicated model is shown in Fig. 6. In this case, a failure actually occurred before the system was put into operation (i.e., data collection was already started but no model had been created). A dedicated model was created thereafter and used to provide retrospective failure prediction against the past failure as shown in the figure[Note 17)]. In Fig. 6, the X-axis indicates time covering nearly five months while the Y-axis indicates the failure risk output by the machine learning model. The first red dotted line shows the date on which the failure occurred and when a temporary remedy was administered. The second red dotted line indicates the date on which the major affected parts were replaced. Consequently, if a threshold level according to the failure risk output by the machine learning model had been set as indicated by the horizontal dotted line in the figure, the failure could have been predicted about one month before the occurrence. In fact, the failure risk decreased after a temporary remedy was administered but remained at high levels to some extent and tended to dramatically drop after the replacement of major parts. Therefore, the prediction curve can be said to represent ideal results in accordance with the actual status of equipment.

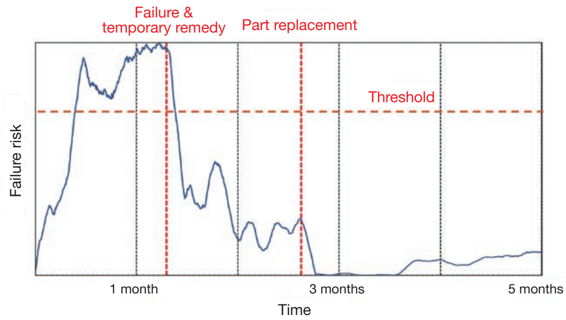


Fig. 6 Retrospective failure prediction for a past failure

Note 17) Specific numbers have been intentionally deleted or shaded as they are confidential information.

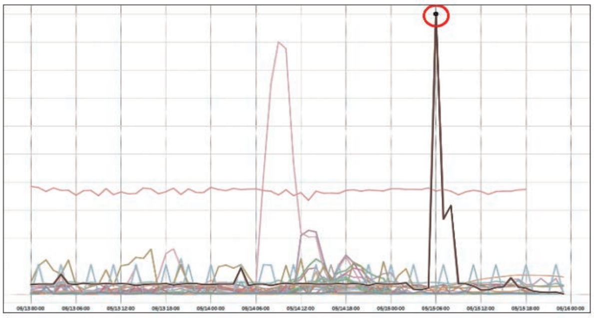
4.2 Equipment Failure Prediction with General-purpose Model

Cases of equipment failure prediction using a general-purpose model are shown in Figs. 7 and 8. These figures show the failure risk proposed by the system during anomaly detection and changes in actually collected data (temperature in these cases)[Note 18)]. In both the figures, the X-axis indicates time while the Y-axis indicates failure risk for diagram (a) and temperature for diagram (b). The area enclosed by a red circle indicates anomalies detected by the system.

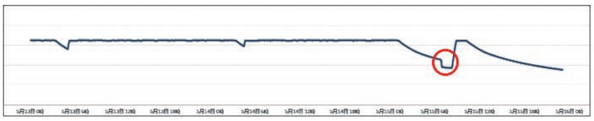
Fig. 7 shows a case of anomaly detection with a sudden fall of temperature. For the equipment, which normally experiences moderate decreases in temperature with natural cooling, the temperature suddenly dropped to raise the failure risk dramatically. In fact, the sudden drop in temperature was caused by equipment maintenance, not an equipment failure. Nevertheless, the system successfully detected a unusual point of change.

Fig. 8 shows a case of anomaly detection with fluctuations in temperature. For the equipment, which is normally exposed to almost constant temperature or moderate increases or decreases, the temperature repeatedly fluctuated in a short time to raise the failure risk dramatically. In fact, the fluctuations in temperature were caused by repeated start-ups and interruptions of the equipment for the purpose of tool changes and commissioning, not an equipment failure. Nevertheless, the system successfully detected a point of change different from the norm in this case as well.

The cases above indicate that it is possible to detect equipment anomalies by using a general-purpose model, even for changes that can hardly be detected with simple threshold evaluation.

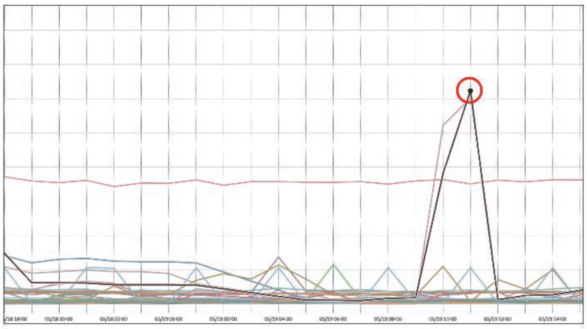


(a) Changes in failure risk

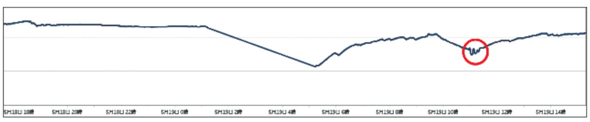


(b) Actual temperature changes

Fig. 7 Anomaly detection with sudden fall of temperature



(a) Changes in failure risk



(b) Actual temperature changes

Fig. 8 Anomaly detection with irregular changes in temperature

Note 18) Specific numbers have been intentionally deleted or shaded as they are confidential information.

5 Efforts Toward Global Deployment

As shown in Fig. 1, this new system relies on the cloud environment to provide a platform for a series of failure prediction from data analysis to visualization. Thus, the system can be expected to be deployed more swiftly than the conventional counterpart. To realize stable system operation while making use of the advantage, however, it is necessary to satisfy the following requirements:

① The operating status of the system must be able to be monitored.

② The operation rule of the system must be clarified.

This chapter describes how we have met these requirements:

5.1 Development of System Monitoring Function

To ensure that the operating status of the system can be determined anywhere, we implemented system status visualization and notification functions in the system by putting the Datadog server monitoring tool to full use. Fig. 9 shows a block diagram of some of the system monitoring functions. The function is designed to transfer all security and system log data to Datadog for batch control and to notify any anomaly to a chat tool (Microsoft Teams), thereby enabling an administrator to promptly initiate remediation.

What is to be monitored by the system can be roughly divided into:

① security

② system.

The following sections specifically describe each of these.

5.1.1 Security Monitoring

The security monitoring here refers to the monitoring of whether the secure environment is maintained. For example, is there any room for the system to allow outsiders to invade? Is there any risk of data leakage? Can the system detect any attack? Although it is a precondition to establish secure security in the design stage, it is not unreasonable to assume that the system may be attacked by an external entity as long as it is connected to the Internet. Therefore, we built an environment to provide continual security monitoring. The following introduces some of these established security monitoring functions.

In this new system, Amazon GuardDuty (hereinafter "GuardDuty") is enabled to detect any illegal login, activ-

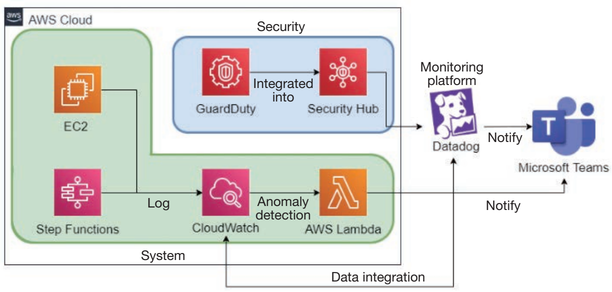


Fig. 9 Block diagram of system monitoring function

ity or communication to AWS. GuardDuty is a fully managed thread detection service that continuously monitors AWS accounts for malicious activity or illegal operation. It collects and monitors logs of accounts used to operate AWS and of IP addresses connected to AWS all the time, thereby enabling detection of illegal accesses and activities.

The system also uses AWS Security Hub (hereinafter "Security Hub") to generally verify total security. Security Hub is a service that collects and manages all security-related information on AWS. Information about GuardDuty stated above is also collected by Security Hub. In the case of an anomaly, the anomaly information, including the time of occurrence, description of the anomaly, and location of the anomaly, is notified as shown in Fig. 10 [Note 19)] so that the user can promptly cope with security vulnerability.

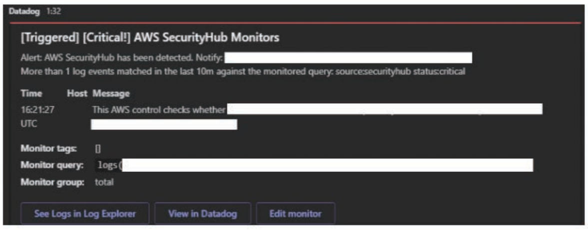


Fig. 10 Notification

Note 19) Values and logs related to the system are not disclosed.

5.1.2 System Monitoring

The system monitoring function monitors the system operation for stability, for example, whether the system is operating properly or whether the system can easily cope with an anomaly, if any. This new system uses Amazon CloudWatch [Note 20)] (hereinafter "CloudWatch") for total system monitoring to collect metrics and logs. The collected metrics and logs are visualized by Datadog.

Part of the Datadog dashboard is shown in Fig. 11 [Note 21)].

Fig. 11 shows a dashboard that centrally controls metrics and logs of services implemented. The user can grasp the situation by identifying, for example, which process has failed and what caused the failure.

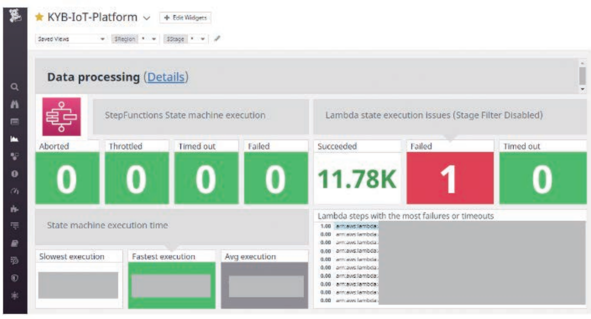


Fig. 11 Datadog dashboard

Note 20) A service that collects metrics and logs of AWS resources and applications

Note 21) Values and logs related to the system are not disclosed.

5.2 Clarification of Operation Rules with IaC

When building this system, we adopted the concept of Infrastructure as Code (hereinafter "IaC") to secure superior deployment and improved maintainability.

IaC is the process of managing infrastructure configuration with code. The server environment and application settings, which have conventionally been configured manually, are all coded. This means that there is no procedure for manual configuration. Instead, the user creates configuration management files that describe environments to be built with code. Fig. 12 shows the difference between IaC and conventional operation. Major benefits of IaC include fewer human errors due to reduced manual operation, easier version control thanks to coded files, and automated operation from test to implementation with CI/CD [Note 22)].

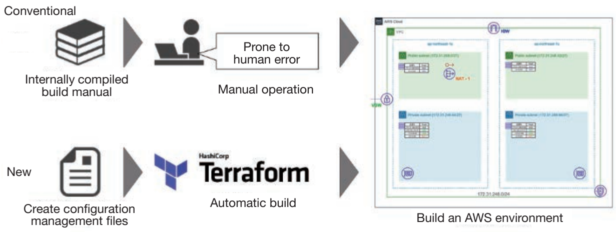


Fig. 12 Difference between IaC and conventional build

In this new system, infrastructure creation has been automated by linking the existing GitLab version control tool with HashiCorp's Terraform, which is one of the IaCs, providing an environment that enables control of differences. If another site is to introduce the equipment prediction system, it is possible to build another same environment instantly for the site. Fig. 13 shows this automated flow of infrastructure creation. In Fig. 13, the steps ① and ② correspond to existing processes of preparation of instruction manuals, discussion of specifications, and version control. The introduction of IaC eliminates the need for controlling instruction manuals and only requires the appropriate site to discuss specifications. The next step ③ shows automated testing of configuration management files. Individual test jobs are carried out before their files are merged [Note 23)] into GitLab. Should a job not be cleared, the system issues an error and does not allow the files to be merged into GitLab.

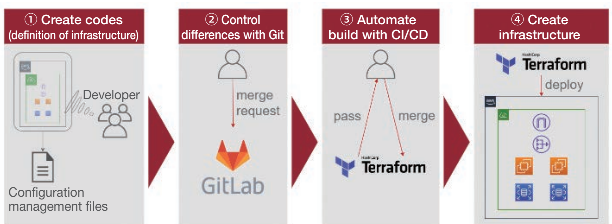


Fig. 13 Flow of infrastructure creation with IaC

Note 22) A system that automates the build, test and development processes. Stands for Continuous Integration and Continuous Delivery.

Note 23) Refers to the process of integrating edited contents into their original files.

6 Future Prospects

This new system makes it possible to predict equipment failures and to also provide an environment that allows us to become aware of something new when we access the visualized status information of our equipment.

To efficiently promote lateral deployment of this system, it is indispensable for us to cooperate with other sites. While discussing the issues on the target equipment with the related sites, we will steadily promote the introduction of the new system, providing an environment where we can identify the status of all equipment units wherever we are, whether home or abroad.

For even more meaningful analysis, we have worked on this system for potential linkage with various other systems. The most recent example is that we have discussed possible linkage between data of remedies actually administered during equipment maintenance and the equipment's vibration/temperature measurement data collected for the system. If this is achieved, it can be expected to widen the data utilization, including verification of the effects of the remedies and analysis of similar cases. However, data linkage poses a challenge that the data is available in text format, not numerical. To tackle this challenge, we are considering applying AI to text analysis to achieve a more advanced analysis.

Our final goal is to build an expanded company-wide, cross-functional IoT-Platform based on information linkage with Production and Quality Management, contributing to higher productivity and improved quality.

7 Concluding Remarks

This new system has realized predictive maintenance and real-time equipment monitoring that were difficult to be achieved before. With predictive maintenance, maintenance cost reductions are expected. We would like to not only apply the system to equipment maintenance alone but also establish linkage between the system and various other systems to implement even higher analysis functions and add greater value.

Finally, we would like to take this opportunity to sincerely thank those concerned from related functions who gave us their great support and cooperation for this development.

References

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