Featured Articles

Using Operation Information in Reliability Design and Maintenance: Analytics for the IoT Era

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OVERVIEW: An analytics platform was developed that analyzes the operation information of mechanical systems collected using the IoT and utilizes the results in reliability design, operation, and maintenance. The product use environment, applied load, and structural reliability are clarified from the operation information and used to advance reliability design. If the failure risk obtained by multiplying the failure probability by the cost of failure is used as an indicator of reliability, then reliability can be compared in units of cost, which makes it possible to increase the reliability of entire mechanical systems throughout the entire product lifecycle from design to operations and maintenance. To demonstrate the impact of this research, operation of an analytics platform was started that collects operation information from a wind power generation system online using the IoT and analyzes the failure risk. Reliability is expected to improve continuously through the developed analytics platform.

INTRODUCTION

WHEN designing the structure of a product, the loads that will act on it are predicted and a structure is chosen that can withstand the expected load. As a result, predicting the load is extremely important for designing highly reliable products. Because use environments and use methods have become more diverse in recent years with the increasing globalization of markets, predicting the loads needed for a design has also become more complicated. However, the spread of information infrastructure has also been progressing extremely rapidly, and collection of operation information using the Internet of Things (IoT) has become widespread. If the collected information also contains information related to the loads that act on the product, then that information will be extremely useful for load prediction during design and for the design of highly reliable structures. Furthermore, stable product operation can be realized by clarifying the loads obtained from operation information and the residual life of the product when it is used continuously under those loads and then increasing the appropriateness of the maintenance and operation methods.

This article describes the technology and analytics platform developed in order to measure and collect operation information and utilize it for product structural design, maintenance, and operation.

RELIABILITY ANALYTICS

Fig. 1 shows an overview of reliability analytics in which operation information and analytics results are communicated by connecting the real environment of the sites and data analysis rooms where products operate with virtual environments and this information is utilized for reliability design, maintenance, and operation. Product reliability can be continuously improved by repeating the following four-step process.

(1) Perform measurements of products both on and off site

(2) Collect and analyze data

(3) Use data assimilation analysis, total integration analysis, virtual reality, and augmented reality

(4) Apply the analysis results to reliability design and operations and maintenance services

Reliability Design Using Measurement Data

Within reliability analytics, reliability design using measurement data is the approach of analyzing the reliability of products from operation data and applying the analysis results to design.

Product structural reliability can be evaluated based on the stress (= load/cross-sectional area) that occurs when a load acts on a product. For example, when evaluating the reliability with respect to metal fatigue, the damage, failure probability, and residual life due to

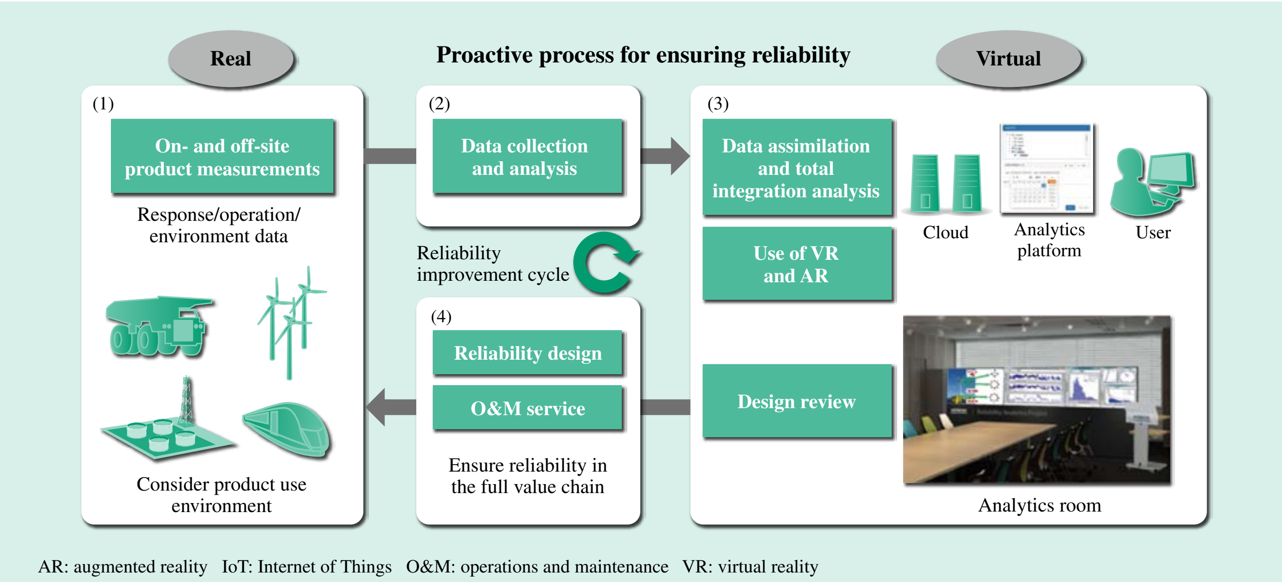

Fig. 1—Reliability Analytics.
Operation data collected using the IoT is analyzed in an analytics room, and reliability is improved continuously by applying the results to reliability design and O&M services.

metal fatigue can be found as indicators of reliability by counting the amplitudes and cycles of the stress waveforms that occur in the product and then applying the damage accumulation. If the strain is measured by attaching a strain sensor to a product, then the stress can be easily calculated from the strain, and the damage, failure probability, and residual life under operation can be found from the measured stress. These reliability indicators can be found by predicting the load during design, so comparison of the evaluation results from measurements during operation with the evaluation results from design makes it possible to give design feedback for (1) verifying the validity of the predicted loads, (2) increasing the precision of the analysis models used in design, and (3) increasing the appropriateness of reliability design standards.

Fig. 2 shows the results of evaluating reliability with respect to metal fatigue in tower welds from the operation information of wind turbines. Strain sensors were attached near two tower welds at

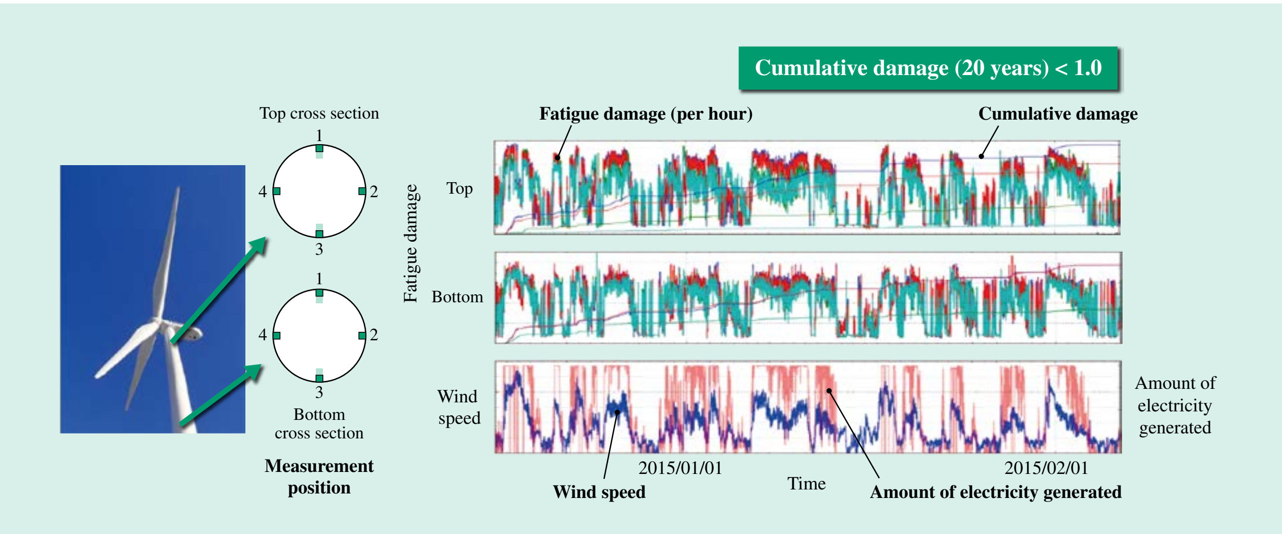

Fig. 2—Reliability Analysis Based on Operation Information of a Wind Turbine.
Damage, failure probability, and residual life were analyzed based on the metal fatigue in tower welds from their strain data, and the safety margin was found to be sufficient.

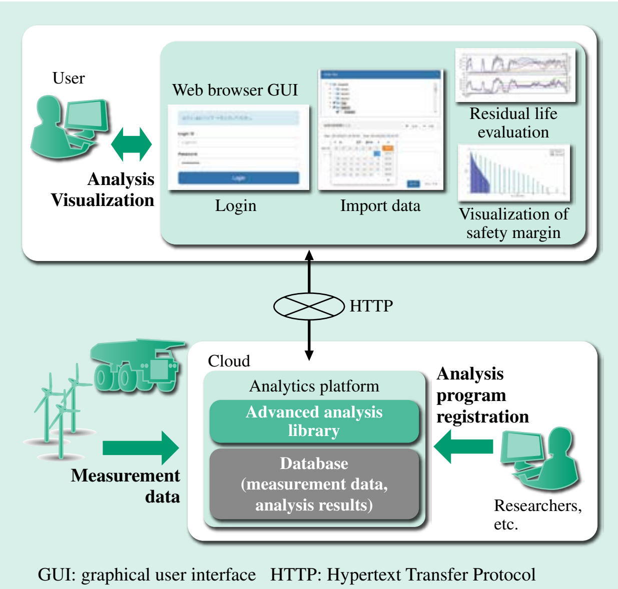

Fig. 3—Analytics Platform for Sharing Data, Analysis Results, and Libraries.
Users access the cloud where the operation data are stored by using a web browser and perform analysis work using pre-registered analysis libraries.

different locations in the vertical direction and the strain during operation was measured. The stress was then calculated from the measured strain, and the damage and residual life were calculated from the stress. Because the estimate of the cumulative damage over 20 years was less than the permissible value of 1, it was confirmed that the tower welds were sufficiently safe with respect to metal fatigue and that the residual life was in excess of the service life. Furthermore, feedback on items (1) to (3) mentioned above was performed by considering the difference between the predicted design values and the measured damage values.

To promote the spread of this kind of reliability design using operation information, an analysis platform was developed that allows users to share and use operation information and reliability analysis results (see Fig. 3). The operation information collected by the IoT is accumulated in a cloud database. Users can access the cloud using a web browser and analyze the collected data using a sophisticated analysis library.

Risk-based Reliability Management

Mechanical products are generally made up of multiple elements (subsystems and components). As a result, reliability is often evaluated on a per-component basis during design and maintenance. There are cases where the failure probabilities of two elements are almost the same according to reliability evaluation results, and in such a situation, the priority order of elements for ensuring reliability should be decided by taking into account the magnitude of the effect of the failures of those elements. A technique for evaluating the reliability of an entire mechanical product was therefore developed by taking the value of failure risk, which is found by multiplying the failure probability of a particular element by the effect of that failure, as a reliability evaluation metric.

In conventional structural reliability evaluation, the safety factor and allowable values are set appropriately depending on the mode and other characteristics of the load that acts on the product from the material strength distribution, and it is checked that the stress that occurs remains less than the allowable value (see Fig. 4). With the development of the IoT, the failure probability can now be determined as a quantitative metric of reliability by collecting operation data, clarifying the stress distribution, and determining the overlapping areas of the stress distribution and material strength distribution. Furthermore, by investigating the effect of failures in units of cost and applying the failure risk obtained by multiplying the effect by the failure probability as a reliability evaluation metric, an economic perspective can be introduced into the reliability evaluation. Taking this failure risk as a metric makes it possible to decide whether a design should be improved or whether an issue should be

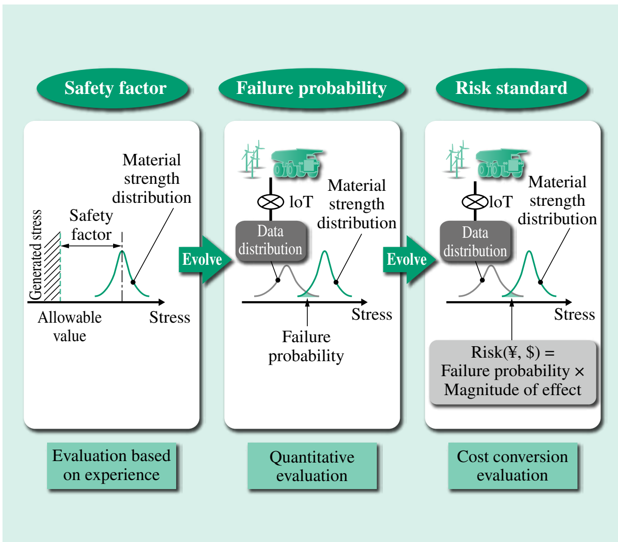

Fig. 4—Advanced Method for Evaluating Structural Reliability.
The method for evaluating structural reliability by deploying the IoT evolves into a method for quantitative evaluation based on failure probability, which then further evolves into an evaluation method that includes an economic perspective.

handled by maintenance and operation in order to ensure the reliability of a particular element. In other words, a measure can be established for improving reliability over the entire product lifecycle by using failure risk as a metric.

ONLINE ANALYTICS PLATFORM

An analytics platform was developed for performing online analysis of failure risk from collected data for wind power generation systems. The present state including the wind speed and amount of electricity generated is displayed from the measurement data used for control, and the current and future failure probability and failure risk are calculated by performing structural reliability analysis using strain sensor data. The online analytics platform consists of a time-series data store that accumulates the collected data, a workflow-based analysis platform for analysts to register and execute analysis logic, and an analysis platform for operators to view the current state and state of trends (see Fig. 5).

Because wind power generation systems consist of many elements, including the tower, blades, and gear reducer, the reliability analysis logic was developed with duties divided among multiple analysts. To integrate the analysis logic developed by multiple analysts and perform analysis of the entire system, an analysis environment that makes it easy to integrate analysis logic is required (DevOps environment). A workflow-based analysis platform was adopted for analysis logic management in the online analytics platform in order to provide this DevOps environment. With the workflow-based analysis platform an analysis logic is modularized as multiple blocks (nodes), and the entire analysis flow is built by arranging these nodes into a graph (see Fig. 6).

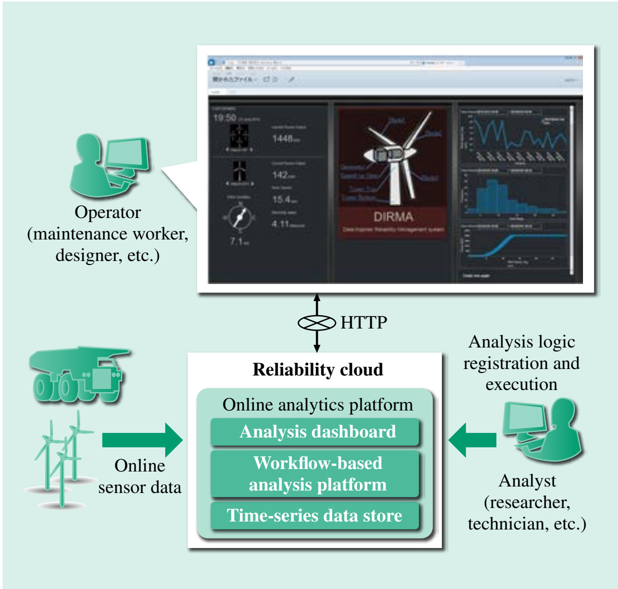

Fig. 5—Structure and Overview of the Online Analytics Platform.
Sensor data are accumulated in the online analytics platform in a reliability cloud. Analysts build their analysis on this platform. Operators access the reliability cloud via a web browser to view analysis screens showing the current state.

Data Processing in the Developed Platform

The online analytics platform requires both easy support for analysis logic that evolves on a daily basis and high availability to allow operation with stable sensor data collection and analysis processing for 24 h a day. The following three characteristic processes were therefore introduced into the online analytics platform.

(1) Data registration processing

Sensor data collected from the wind power generation system are temporarily stored on a file server and are then registered in the time-series data store after performing pre-processing such as format conversion. The registration interval was set to 10 min to match the minimum control interval of the wind power generation system. Pentaho data integration, which has interfaces for connecting with a large number of data sources and offers excellent extract, transform, load (ETL) processing, was adopted for pre-processing such as format conversion.

(2) Data analysis processing

The damage, failure probability, and failure risk are calculated by obtaining the strain sensor data and other data from the time-series data store. This processing is performed together with the data registration processing and is executed at 10-min intervals. The analysis processing employs many calculations on the time-series data, such as calculating the damage from the 10-min interval strain data. Because of this, the damage evaluation, failure probability estimation, and failure risk calculation logic are created as nodes based on the KNIME[*1] open-source analysis software developed at the University of Konstanz (see Fig. 6).

(3) Data visualization processing

The current state (e.g., the current wind state and electricity generation state) and the data analysis results (e.g., damage, failure probability, and failure risk) are presented on a dashboard on the web so that

*1 KNIME is an open source workflow platform developed at the University of Konstanz in Germany. The KNIME trademark is used by KNIME.com AG under license from KNIME GmbH.

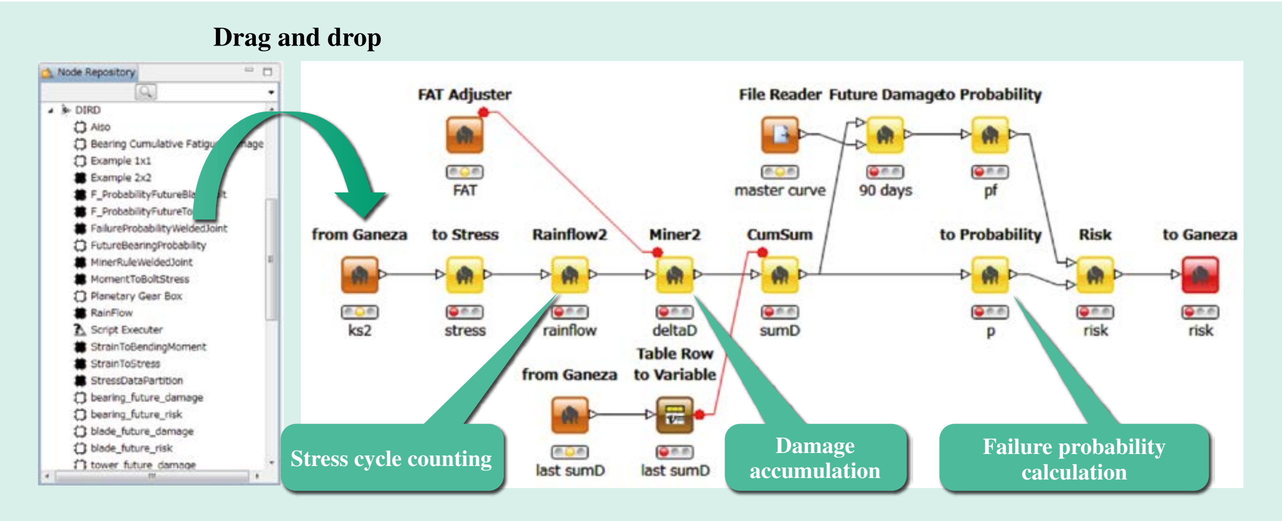

Fig. 6—Building an Analysis Flow in KNIME.
Nodes are connected to each other and used by dragging and dropping them onto a canvas. In the figure, data are read from the data store and then registered in the data store again after analysis of stress cycle counting, damage accumulation, and failure probability calculation.

operators can understand the current state and identify problems. This function was built based on the Pentaho Business Analytics dashboard management tool by using JavaScript[*2] to extend the rendering library for line graphs, scatter plots, frequency distributions, and so forth.

Enhanced Fault Tolerance for Development of an Online Platform

The processing executed during data analysis includes analysis logic that has dependency relationships, including analysis using past analysis results, such as calculation of damage, and integration of the analysis results from multiple analysis flows such as failure risk evaluation. Normally, each data analysis process is performed at 10-min intervals, and pre-determined analysis flows are executed by using the latest sensor data. However, delays in data collection or missing data are possible due to unexpected malfunction of the communication lines from the site ready and the input data needed for analysis might not be when analysis starts due to analysis logic being switched out by the analyst. A task management function was therefore built for the analysis logic. For all of the analysis logic, the timestamp of the measurement data that arrived when the analysis started and the timestamp of the already analyzed data are compared, and the amount of time subject to the analysis processing is calculated from the time difference (see Fig. 7). If the data collection and time difference are normal, analysis of a single data block is performed as planned. However, if the time difference is large due to data collection

*2 JavaScript is a registered trademark of Oracle Corporation and its affiliates.

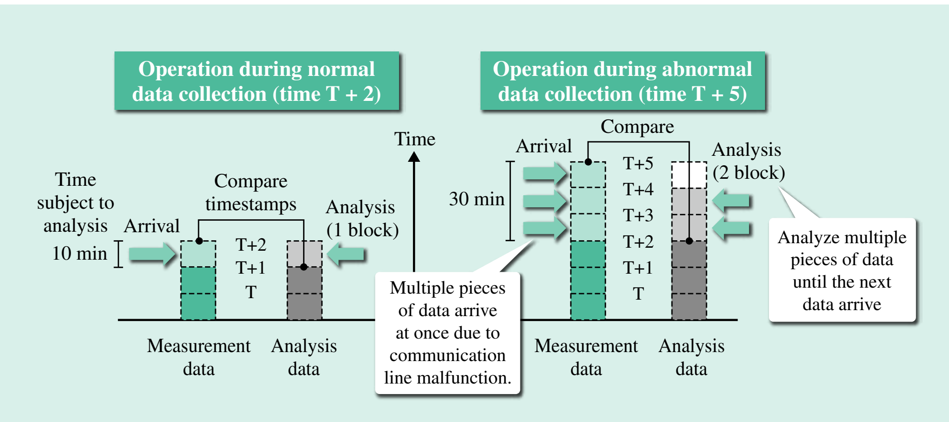

Fig. 7—Overview of Task Management Function.
The timestamp of the measurement data that arrived when the analysis started and the timestamp of the analyzed data are compared to determine the time subject to analysis. If an unexpected delay in data arrival occurs, several pieces of data are analyzed until the next data arrive according to the amount of time subject to analysis.

delays, multiple data blocks are analyzed until the subsequent data arrives. In this way, processing is implemented that can perform continuous analysis under delayed or missing data while independently executing each analysis block.

CONCLUSIONS

An analytics platform that measures and collects operation information and utilizes it for product structural design and maintenance and operation was developed. Now, with product use environments and methods becoming more diverse, structural reliability design and maintenance and operation based on operation information is an extremely effective method for high-efficiency operation of products. The development of the IoT has made it possible to collect a relatively large amount of data and made it easier than before to perform quantitative reliability evaluation such as failure probability calculation. Increased reliability of mechanical systems can be implemented across the entire system and entire lifecycle by introducing the failure risk calculated from the failure probability as an evaluation metric. Hitachi intends to expand the reliability analysis demonstrated using the wind generation system to other products, and hopes to contribute to building safe and secure social infrastructure through highly reliable mechanical systems.

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