Development of Predictive Technology by Digital Twin Simulation

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In recent years, the IoT of plants and industrial equipment has attracted much attention. In particular, to use products for a long time, it is important to properly ascertain and predict the state of products from accumulated operation data and carry out more effective operation and appropriate maintenance. Digital Twin Simulation combines operation data with physical modeling that we have built based on physical and chemical knowledge through design, manufacturing, and testing. With this technology, it is possible to ascertain product characteristics that are difficult to capture with data alone and improve simulation accuracy. We applied this technology to actual product data. As a result, we have confirmed its effectiveness.

1. Introduction

In order to ensure that our customers can use our products safely and securely over a long period of time, it is important to accurately monitor and predict the condition of the equipment and provide adequate maintenance. We have developed preventive maintenance techniques based on data analysis such as the Mahalanobis Taguchi (MT) method[1]. Besides, in order to monitor and predict plant condition more accurately and more consistently with the laws of physics, we are now developing Digital Twin Simulation technology.

In this paper, Digital Twin Simulation technology denotes a simulation technology that combines sensor data collected each day from plants with physical modeling developed based on physical and chemical knowledge that we have accumulated through design, manufacturing, and testing. This technology allows more accurate prediction than conventional technologies, and enables operation optimization. This paper gives an overview of this technology and its effectiveness, with some application examples for verification, and describes future prospects.

2. Estimation and prediction with Digital Twin Simulation

2.1 Conventional estimation and prediction techniques and their problems

Chemical and power plants are required to operate with stability and high efficiency. It is important for large plants to have means of developing appropriate maintenance plans because a high economic load is required to shut down and restart them. Achieving this requires a technology for accurately estimating the condition of the plant, including abnormalities and deterioration, and predicting its future condition.

In recent years, Internet of Things (IoT) has been adopted for industrial equipment, and technologies for efficient use of operation data are attracting attention. In particular, research on statistical techniques, including machine learning, is being actively pursued as a technique for performing modeling of the relevant process based on plant operation data. These statistical techniques are superior in terms of versatility and simplicity because they can be widely applied as long as plant operation data is available. In addition, they have the advantage that they can be used to quantitatively evaluate connections between different items of data. However, statistical modeling techniques have the following problems.

(1) Generally, when a change is made to the operational conditions of the process, the prediction accuracy of the modeling decreases, resulting in physically incomprehensible predicted values. With some statistical techniques, it is difficult to develop an accurate modeling over a wide range of operational conditions, especially for operational conditions under which the plant has never operated.

(2) Because statistical techniques are used for modeling, calculations in the modeling do not have a physical meaning, and it is not possible to monitor the condition of the entire process. For example, even though it is possible to predict a specific variable (objective variable) for equipment, such as pressure, it is unclear how the entire process behaves.

Modeling with statistical techniques is called black box modeling because the physical phenomena of the process are not taken into consideration. In contrast, modeling based on physical and chemical knowledge of the process is called white box modeling, and modeling created with such modeling techniques are often called physical modeling. **Table 1** shows a comparison between statistical and physical modeling. With physical modeling, it is possible to predict the behavior of the plant based on the principles of the process, and the behavior of non-steady operation is often simulated. In addition, if physical modeling is performed for

Table 1　Comparison between statistical and physical modeling

Item	Statistical modeling	Physical modeling
Features	Created based on operation data using machine learning, etc.	Created based on physical and chemical knowledge.
Required conditions for each modeling	Appropriate plant operation data is required.	The engineer is required to be familiar with events that occur in the relevant process.
Prediction accuracy	- Prediction accuracy is high for steady operation. - Prediction accuracy is likely to be low for operational conditions in which sufficient data is unavailable.	- A certain level of prediction accuracy can be expected even with unknown operational conditions. - It is not possible to address time-dependent changes caused by maintenance, etc., and prediction accuracy decreases with time.

the entire plant, the behavior of the entire process can be understood based on the calculation results. Therefore, physical modeling is often used in designing a plant and its instrumentation and control before plant construction. However, once the plant has begun operation, the process itself changes little by little as the filters and other components deteriorate over time and maintenance is performed on them. As a result, deviations from the physical modeling become larger and larger. For this reason, physical modeling is used less frequently as time elapses after the start of plant operation.

2.2 Digital Twin Simulation

We are developing technology such that the physical modeling which we have developed through laboratory-level research and design and trial operation of pilot plants can be used not only in designing commercial plants but also throughout their life cycles, including operation and maintenance after they have begun operation. This paper describes Digital Twin Simulation technology, which combines physical modeling with daily operation data collected from the actual plant. **Figure 1** shows a conceptual schematic of Digital Twin Simulation.

The following describes how the physical modeling and operation data are combined in three steps.

Step 1: Data assimilation

To perform calculations, the same operational conditions are used for the simulator and actual process. At this time, there is always an error between the measured data obtained from the actual process and the simulation result. To correct this error, the physical parameters of the simulator (e.g., catalyst activity coefficient, heat conduction coefficient of the heat exchanger, and compression efficiency of the gas turbine) are adjusted sequentially. This operation is generally called “data assimilation.” **Figure 2** shows a conceptual schematic of data assimilation for a plant. Through data assimilation, it is possible to monitor process characteristics that cannot be measured directly in a real-time manner, and, through the simulator, to visualize the internal condition of all of the equipment, including areas where no sensors are installed.

Step 2: Analysis of equipment characteristics

By analyzing the physical parameters updated in step 1, it is possible to monitor equipment deterioration. In particular, by analyzing the physical parameters over time, it is possible to determine how much the equipment has deteriorated and how much equipment performance will be restored by maintenance, such as catalyst replacement. **Figure 3** shows a conceptual schematic of catalyst monitoring. By quantitively controlling not only raw sensor data but also the deterioration conditions specific to the plant, it is possible to monitor and control the condition of the plant based on the principles of each process phenomenon.

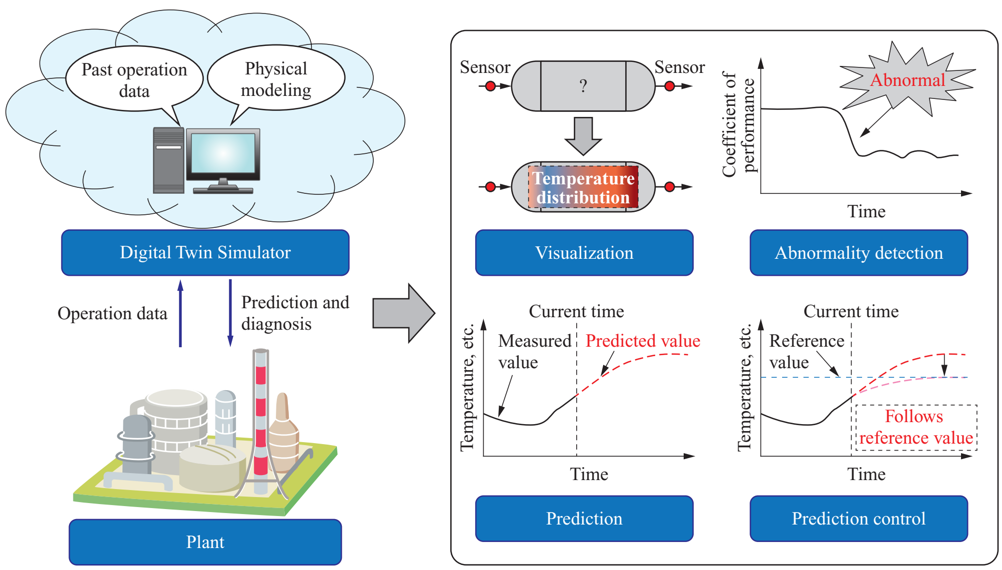
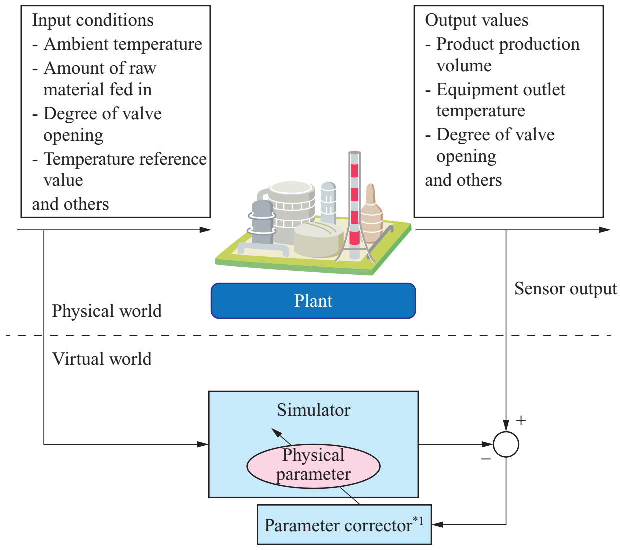


Fig. 1　Conceptual schematic of Digital Twin Simulation



(Note) *1 : The physical parameters in the simulator are adjusted sequentially so that the input and output values are consistent with the actual sensor values.

Fig. 2 Conceptual schematic of data assimilation for a plant

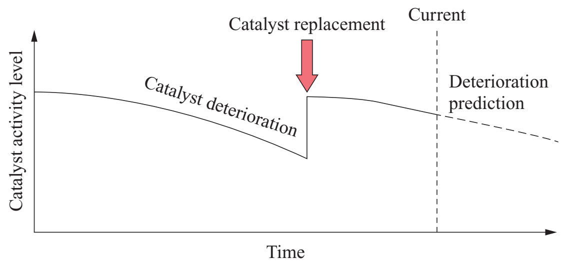


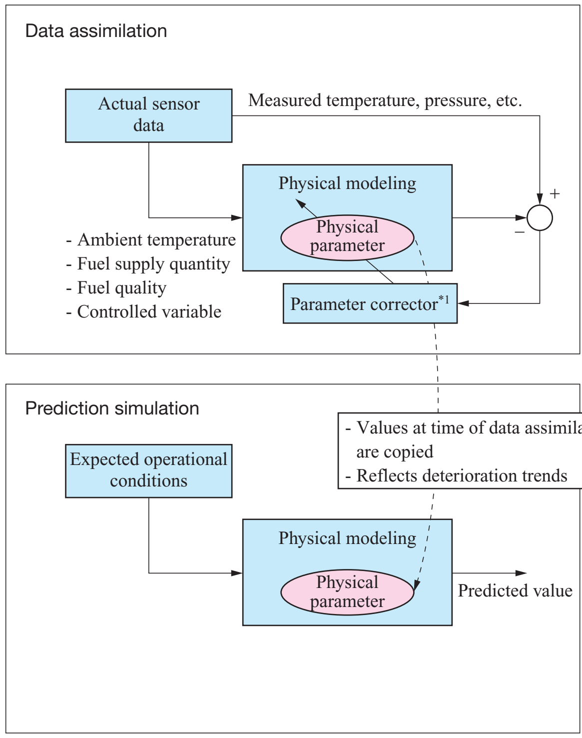
Fig. 3 Conceptual schematic of catalyst monitoring

Step 3: Prediction by simulation

By reflecting the physical parameters analyzed in step 2 in the simulation, it is possible to predict future plant condition for different operational conditions and time scales. For example, it is possible to dynamically simulate how the entire process will change over a time scale of a few minutes to a few hours if the amount of fuel supplied to a boiler is changed, or to simulate how the production efficiency of a product will change over a few months if a catalyst in a chemical plant continues to deteriorate at the current rate. Considering decreases in production efficiency due to aging deterioration of a catalyst and equipment and restoration of production efficiency through maintenance enables to develop a maintenance plan that takes economic performance into consideration. **Figure 4** shows prediction simulation, including the data assimilation in step 1.

3. Verification

For verification, we applied Digital Twin Simulation technology to a gas turbine engine for power generation. Using the measured data previously collected during steady



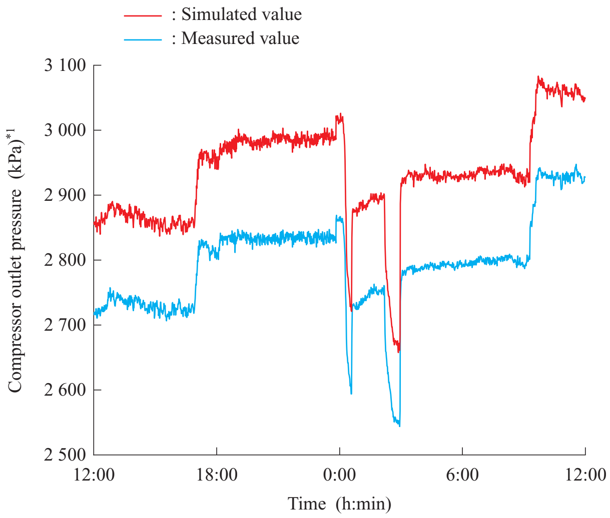
(Note) *1 : The physical parameters in the simulator are adjusted sequentially so that the input and output values are consistent with the actual sensor values.

Fig. 4 Prediction simulation

operation, we performed a simulation for the gas turbine engine, and evaluated the calculation accuracy of the compressor outlet pressure and error between the simulated and measured values.

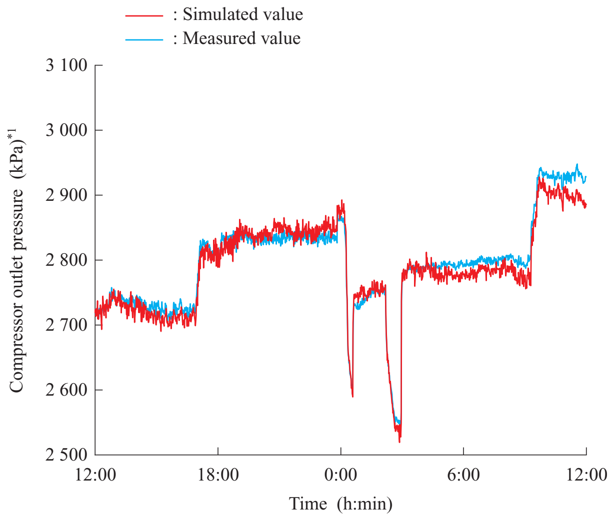
For the gas turbine engine used in this verification, we set the intake air temperature, pressure, fuel supply quantity and fuel quality, degree of valve opening, and other parameters in the simulator as operational conditions (input values). **Figure 5** shows the simulated and measured values obtained when the simulation was performed for 24 hours with the operational conditions of the actual plant. The simulated and measured values fluctuated in much the same trend, but the error between these values was 139.8 kPa RMSE (Root Mean Square Error), which means that prediction accuracy was low.

For this simulator, we performed data assimilation as described in **Section 2.2**. Using the 24 hours of measured data — for seven variables, including the temperature, pressure, and rotational speed of each part — collected starting 24 hours earlier than that in **Fig. 5**, we adjusted the compression efficiency in the engine and other physical parameters so that the output values of the physical modeling were consistent with the measured values. In this verification, we adopted a non-linear Kalman filter for the data assimilation algorithm because gas turbines exhibit strong non-linearity(2). **Figure 6** shows the simulated and measured values for compressor outlet pressure during data assimilation. The lines overlap almost entirely with each other, indicating that the simulated value (output of the



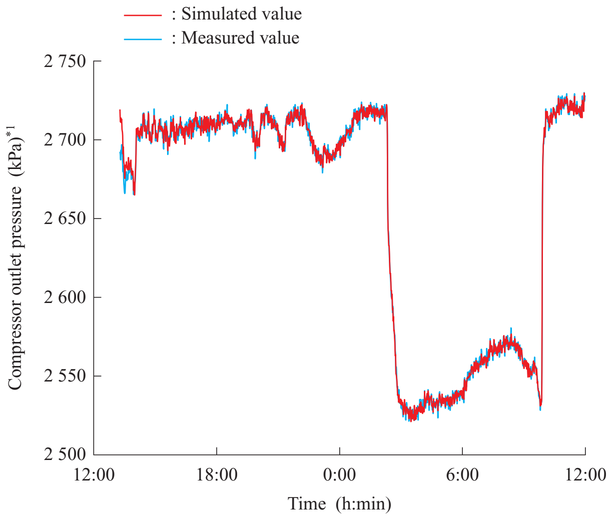
(Notes) RMSE = 139.8 kPa
*1 : abs

Fig. 5 Simulated and measured values



(Notes) RMSE = 16.1 kPa
*1 : abs

Fig. 7 Results of Digital Twin Simulation



(Notes) RMSE = 2.9 kPa
*1 : abs

Fig. 6 Simulated and measured values during data assimilation

physical modeling) is consistent with the measured value.

In this verification, the data assimilation period was only one day, and so no phenomena such as compressor deterioration could be identified from the data assimilation results. However, data assimilation can be expected to provide improved simulation accuracy.

Using the physical parameters obtained in the data assimilation, we performed a simulation with the same time and operational conditions as in **Fig. 5**. **Figure 7** shows the results of this Digital Twin Simulation. The prediction error was 16.1 kPa RMSE, so that the error decreased to approximately one tenth of that of the simulation in **Fig. 5**.

4. Conclusion

This paper has given an overview of Digital Twin Simulation technology, and demonstrated that simulation accuracy can be improved significantly by performing a prediction simulation with data assimilation that combines physical modeling and measured values for an actual gas turbine engine.

This technology combines plant operation data with physical modeling, thereby making it possible to monitor deterioration and other characteristics that can hardly be monitored with data alone, and to enhance simulation accuracy. In this verification, we performed a prediction simulation only. Combining this technology with optimization technology, we are aiming to optimize plant operation after the plant has begun operation and to develop more sophisticated maintenance plans and control logic.

With this technology, which combines plant operation data obtained through IoT with physical modeling that we have accumulated as well as with conventional data-based statistical approaches, we will offer customers services that run throughout the life cycles of our products. More specifically, we hope this technology can help customers arrange an optimal maintenance plan, operate our products optimally and efficiently with the fault diagnosis and prediction, and estimate the internal condition and remaining service life accurately.

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