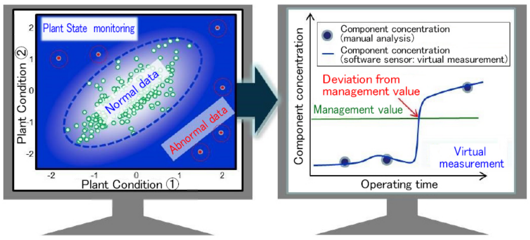
Virtual Measurement and Monitoring Technologies for Plant Water Quality using Software Sensors



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Mitsubishi Heavy Industries, Ltd. (MHI) examined the feasibility of the virtual measurement of power plant water quality using software sensors developed in collaboration with the University of Tokyo. MHI developed a software sensor model that follows changes in plant operation that combines genetic algorithm-based variable selection, a nonlinear regression model and an adaptive model, and verified that the chloride ion concentration, which had been difficult to continuously measure, could be virtually measured through analysis using actual plant data.

The Mitsubishi Heavy Industries Group has been expanding its digital solution business that provides maintenance and operation supports using AI and IoT. Going forward, MHI will develop applications that incorporate software sensors to build a power plant water quality diagnosis system that can monitor state quantities regardless of operator skill.

1. Introduction

Due to an increase in independent power producer (IPP) projects and a shortage of skilled operators, there has been increasing need for water quality management support for the stable operation of power plants(1). Plant water quality is managed using sensor measurement values and composition analysis values. However, problems such as bursting, corrosion and scaling of evaporator tubes may occur. To prevent these problems, continuous monitoring of important composition and concentration values is effective, but there is no specified monitoring device that achieves such monitoring at reasonable installation and maintenance costs. In addition, if human and material resources are insufficient, there is a limit to manual management.

Recently, the technological progress of AI and IoT has been remarkable. Virtual measurement technologies using so-called software sensors, which simultaneously analyze various types of data, have been actively developed, and their practical use in the chemical and petroleum industries, semiconductor industry, steel industry and pharmaceutical industry has been progressing(2).

As such, we use these software sensors to continuously virtual monitor the important composition and concentration values of the plant water based on the existing plant data, and are developing virtual measurement technologies with the aim of optimizing operation in terms of the performance and running cost. **Figure 1** schematically represents the situation before and after the application of the software sensors.

This paper introduces an example of examining the concentration prediction of chloride ions (Cl), which affects the corrosion, etc., of equipment.

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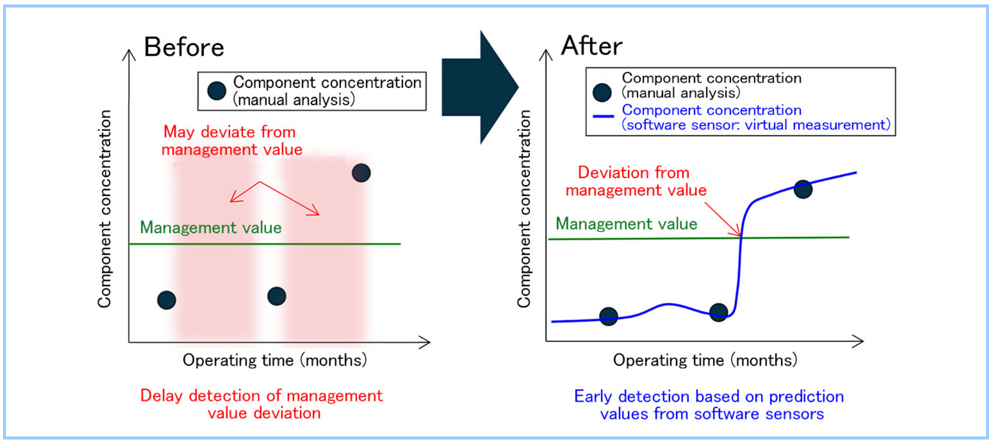

Figure 1 Water quality monitoring before and after application of software sensors

2. Software sensors

2.1 Software sensors

Software sensors[(3),(4)] construct in advance a numerical model based on the correlation between explanatory variables such as temperature and pressure that can be easily measured directly by online sensors and objective variables that can be obtained only irregularly by manual analysis. These software sensors then use the numerical model to estimate the value of the objective variable to be monitored from the explanatory variables to be continuously measured. **Figure 2** illustrates a conceptual diagram thereof[(5)]. By using the software sensors, it is possible to utilize objective variables as if it were virtually being continuously measured using existing sensor values.

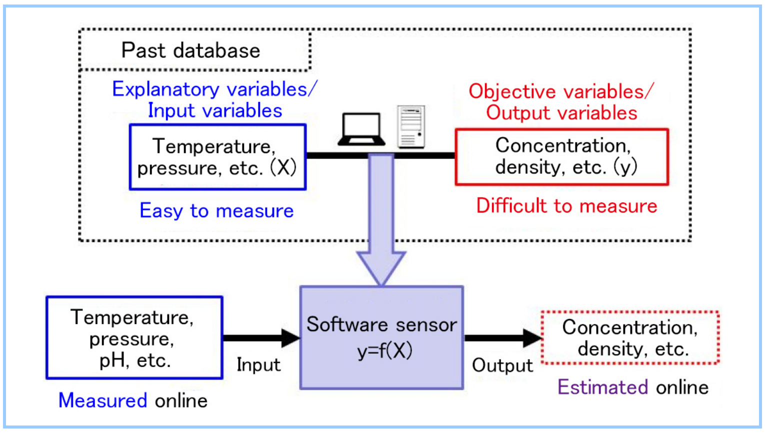

Figure 2 Conceptual diagram of software sensor

2.2 Means for selecting explanatory variables in consideration of time delay

When constructing a numerical model using software sensors, it is important to select explanatory variables that have a high correlation with the objective variable to improve the prediction accuracy. When measuring a fluid, however, a given sensor value can change due to the time delay accompanying the movement of the fluid. The delay depends on the position of the sensor in the system and the response delay of the sensor, so when an analysis is performed using multiple sensor indication values at the same time, problems such as significant errors or failure to find a correlation occur. If the relationship between the objective variable and the explanatory variable is known from the physical model or experience, a good model can be constructed by adjusting the time to maximize the correlation. However, when multiple data samples are used or when the correlation is unclear, it is difficult to consider the time delay.

As such, this time we adopted a method that considers dynamic characteristics using a genetic algorithm and selects variables simultaneously (Genetic Algorithm-based Process Variables and Dynamics Selection, or GAVDS[(6)]). **Figure 3** presents the concept of the time delay in the plant. When predicting variables downstream of the plant (y in Figure 3) from multiple upstream variables (x_1 and x_2 in Figure 3), a model with higher prediction accuracy can be constructed by predicting y(t) at time t from $x_1(t-t_1)$ or $x_2(t-t_2)$ obtained at the same time or a combination of the two, rather than from $x_1(t)$ or $x_2(t)$. However, when a numerical model is constructed including the measured values of past explanatory variables, the number of explanatory variables becomes enormous, and the processing time becomes huge. Accordingly, by using a genetic algorithm, which is one of the optimization methods, a combination of an explanatory variable and a time delay suitable for predicting objective variables was extracted.

In this way, it was made possible to select variables in consideration of the delay of each sensor reading by using GAVDS.

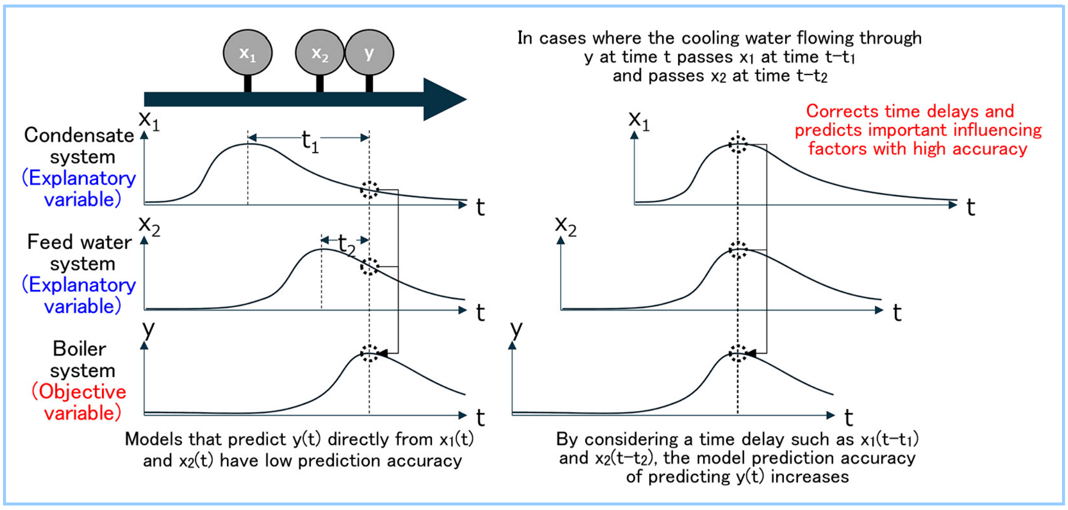

Figure 3 Example of variable selection by GAVDS
(Method to automatically select variables necessary and their time domain for predicting y with high accuracy)

2.3 Prediction model

A prediction model was constructed using the selected model construction sample (combination of sensor values). In this analysis, we compared three methods: partial least squares regression (PLS[7]), which is a linear regression method, support vector regression (SVR[8]) and random forest (RF[9]) which are a nonlinear regression method.

2.4 Sample selection of data for model creation

In a plant, the relationship between the objective variable to be predicted and the explanatory variable used for prediction changes over time due to the deterioration of the equipment, the adhesion of scale to the pipes, etc. For this reason, the accuracy of the prediction model created from the initial model construction sample may decrease over time.

To address this problem, software sensors that follow changes in plant operation (hereinafter referred to as adaptive software sensors) were applied. When using adaptive software sensors, prediction is performed while selecting and updating the sample used for creating the prediction model using a predetermined method. As methods for this, the MW (Moving Window) method[10] and the JIT (Just in Time) method[11] have been studied. **Figure 4** gives the concept of the MW method and the JIT method. The MW method selects several highly-correlated samples close to the required time, constructs a prediction model, and changes the samples one after another over time. This method has a feature that can easily cope with model deterioration. On the other hand, the JIT method selects several samples close to the current plant state from the accumulated past samples and constructs a prediction model. In this analysis, we adopted the MW method, which easily follows changes over time during operation, as a method for selecting the samples used to construct the prediction model.

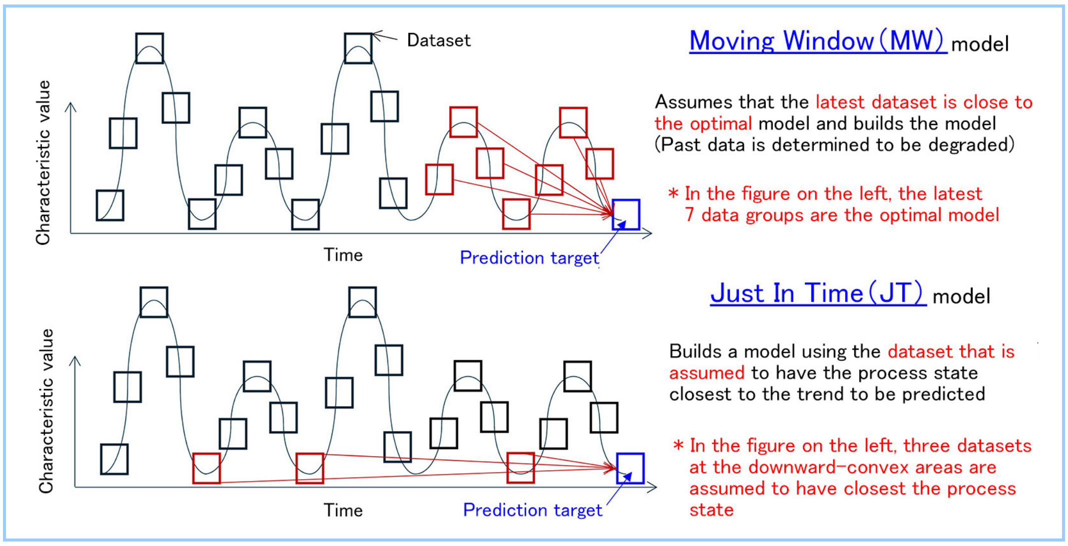

Figure 4　Comparison of adactive models

3. Examination of impurity concentration prediction

3.1 System diagram of examination target and prediction data location

If seawater enters the system for some reason and Cl ions contained in the seawater enter the circulating water system, Cl ions get mixed in with the steam via the condensing system, feed water system, boiler system, steam system, etc., and in the worst case, they are deposited on the steam turbine. For this reason, the Cl concentration of high-pressure drum water was selected as a sampling point for detecting seawater leakage from the condenser. **Figure 5** indicates the contamination range at the time when a seawater leak occurs and the prediction target point. Generally, when the Cl concentration at the outlet of the condensate pump near the condenser can be detected, a seawater leak can be detected early. However, since the target of this examination is a trace seawater leak with a concentration level that cannot be detected through the electrical conductivity or acid conductivity of the condensate pump outlet water, the Cl concentration in the high-pressure drum water, which is concentrated by the evaporation of water in the drum, is used as the prediction target. By estimating the Cl concentration in the high-pressure drum water, it is possible to make an early decision on whether to continue plant operation based on the state of impurity contamination in order to minimize the risk of steam turbine corrosion due to trace seawater leaks.

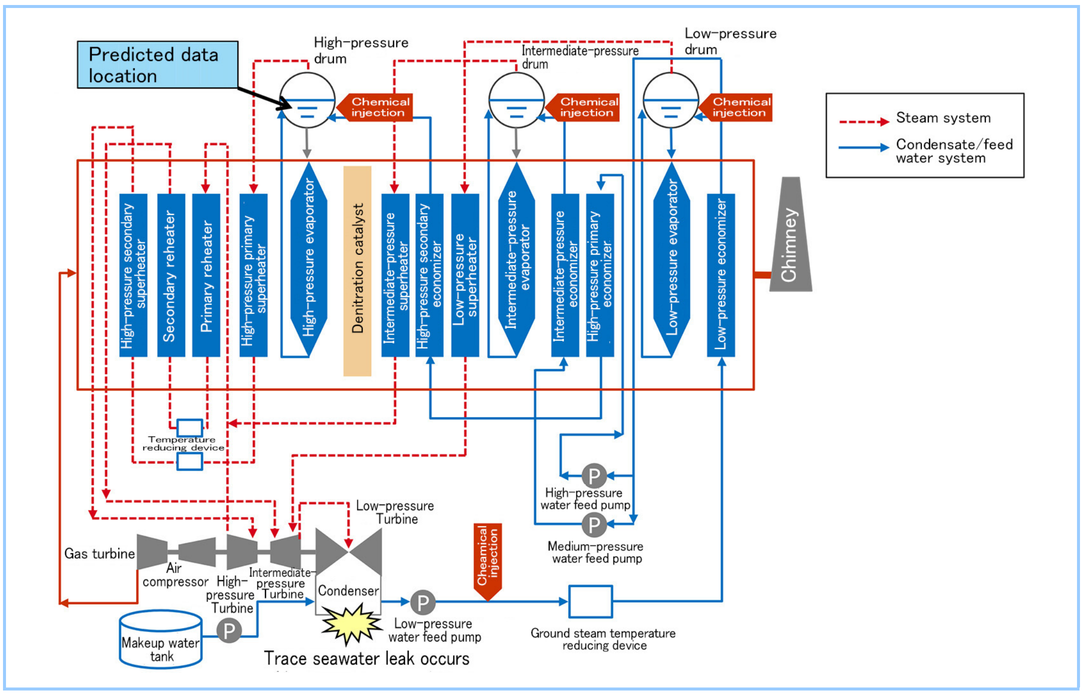

Figure 5　Prediction data locations of Cl concentration at the time when seawater leak occurs

3.2 Examination target data

This examination used the water quality data of the condensate and feed water systems of a natural gas-fired gas turbine combined cycle thermal power plant. **Table 1** lists the data used as explanatory variables and objective variables. The explanatory variables are electrical conductivity, pH, etc., the measured values of which can be continuously obtained online from sensors installed in the plant. The objective variable is the Cl concentration of the high-pressure drum water, which is an optimal variable for understanding the mixing of Cl ions into the circulating water system as described above.

Table 1 Variables of examination target

Explanatory variables	Objective variables
Continuous data (2344 points)	Manual analysis data (134 points)
① Condensate pump outlet CC, EC	⑤ High-pressure drum water Cl
② Low-pressure economizer inlet CC, EC, DO, pH, N_2H_4	
③ Low-pressure drum water EC, pH, Si	
④ Intermediate-pressure drum water EC, pH, Si	
⑤ High-pressure drum water EC, pH, Si	
⑥ Low-pressure superheater outlet steam CC	
⑦ Gas turbine combustor inlet steam CC	
⑧ Reheater outlet steam CC	
⑨ High-pressure superheater outlet steam CC	

CC: acid conductivity, EC: electric conductivity, DO: dissolved oxygen, pH: Potential of hydrogen, N_2H_4: hydrazine, Si: silica, Cl: Chloride ion

3.3 Examination results and considerations

(1) Selection of main parameters using GAVDS

Figure 6 gives the results of GAVDS analysis. On the horizontal axis of this heat map, zero is the current time, and a negative value on the left corresponds to a past time. The vertical axis indicates explanatory variables. The portions shown in yellow on this map indicate the explanatory variables with a high correlation with the Cl concentration of the high-pressure drum water, which is the objective variable, and their time delays. From the results of this analysis, it was found that the electrical conductivity (EC) of the high-pressure drum water at the time 0 to 10 minutes before and after has the highest correlation with the Cl concentration of the high-pressure drum water at the current time, and that it is an important explanatory variable and time delay for predicting the objective variable.

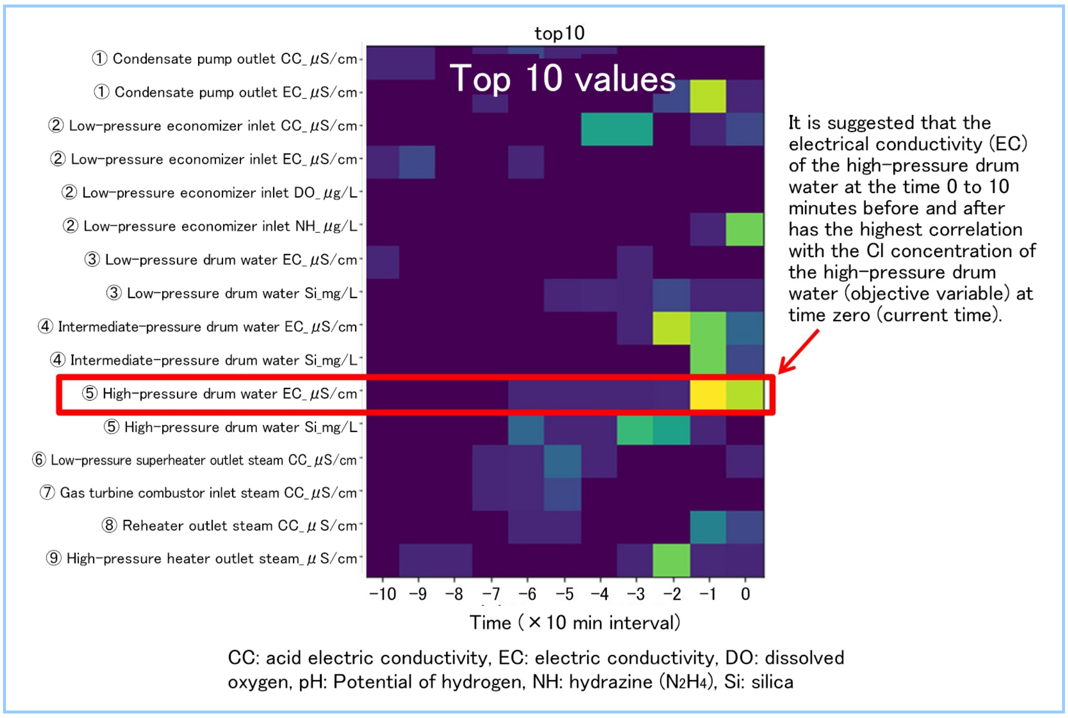

Figure 6 Example of GAVDS analysis results

(2) Prediction of Cl concentration in high-pressure drum water

Mainly using the explanatory variables selected in the GAVDS analysis, as shown in **Figure 7**, the first half of the dataset was used as the learning data and the second half as the verification data, and the Cl concentration in the second half was predicted.

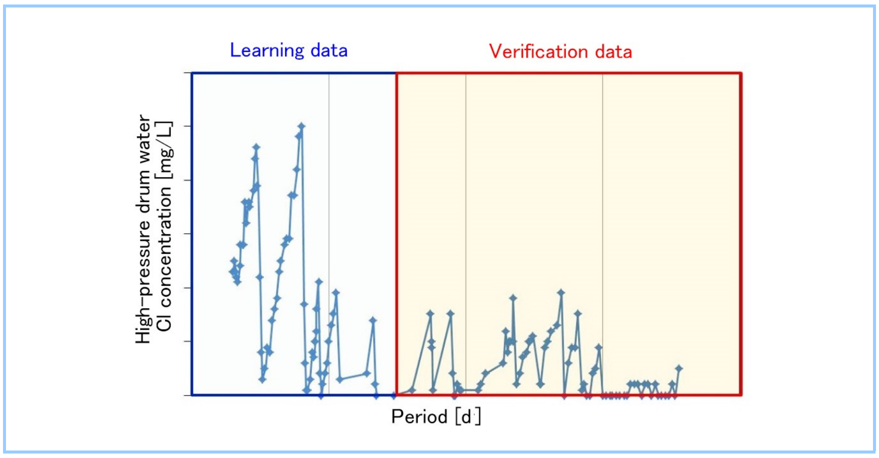

Figure 7 Learning period and verification period of data to be examined

MW, which is a method that can deal with plant data drift, was used as an applicable model, and PLS, SVR, and RF were used as regression models. **Table 2** presents the analysis results. Within the verified range, it was confirmed that the prediction accuracy became highest when RF was used as the regression model, and that the Cl concentration could be predicted with a coefficient of determination of R^2 = 0.68. **Figure 8** shows the trend of Cl concentration in which the predicted value and the actually measured value are displayed in a superimposed manner.

Table 2 CI concentration prediction results

Sample	Regression model	R^2	RMSE
MW	SVR	0.62	0.03
MW	RF	0.68	0.03
MW	PLS	0.63	0.03

R^2: Coefficient of determination
RMSE: Root mean square error
MW: Moving Window
PLS: Partial Least Squares Regression
SVR: Support Vector Regression
RF: Random Forest

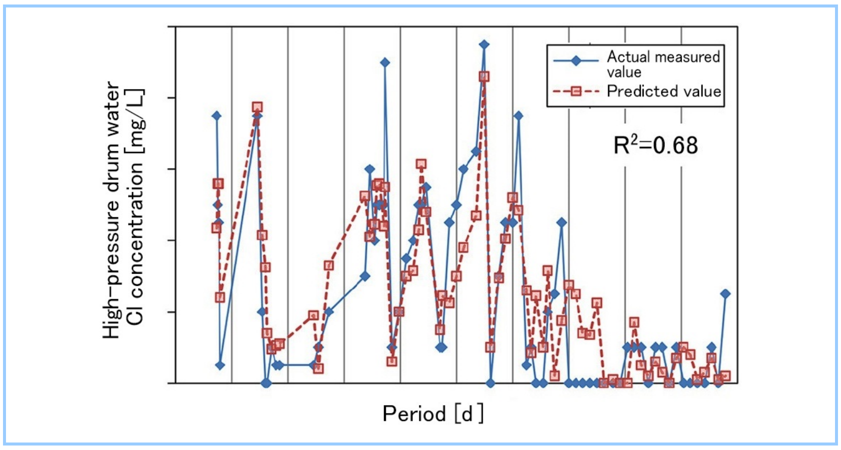

Figure 8 Trend comparison between measured and predicted Cl concentration values (analysis method: MW-RF)

Generally, the electric conductivity of high-pressure drum water is used to control the concentration of chemicals injected, so it was thought that the electric conductivity meter could detect salt contamination only in the case of a relatively large leak of seawater and that a change in electrical conductivity due to a trace seawater leak could not be distinguished from that due to chemical injection. As a result of this analysis, it was made possible to predict the Cl concentration in high-pressure drum water without being affected by disturbances due to chemical injection by properly extracting and modeling explanatory variables using GAVDS. We are currently accumulating data and verifying models with other plant water qualities to further improve the accuracy of the models.

3.4 System development for monitoring and diagnosing state quantity of plant water quality

The Mitsubishi Heavy Industries Group is expanding its digital solution business that provides plant maintenance and operation supports, and is developing various applications and promoting their implementation in plants. **Figure 9** provides an example of a water quality diagnosis flowchart combining software sensors. We are developing a hybrid water quality diagnosis system that uses a state monitoring system and software sensors that is equipped with a water quality monitoring and abnormality diagnosis model that does not depend on operator skill. By combining conventional water quality monitoring based on empirical rules and physical models with virtual measurement and water quality diagnosis using software sensors, we will build a system that contributes to plant operation control.

With a view to future power plant operation using AI and IoT, we will support the continuous operation of power plants by contributing to reducing the risk of unplanned plant shutdowns and ensuring product reliability by utilizing and applying technologies such as software sensors.

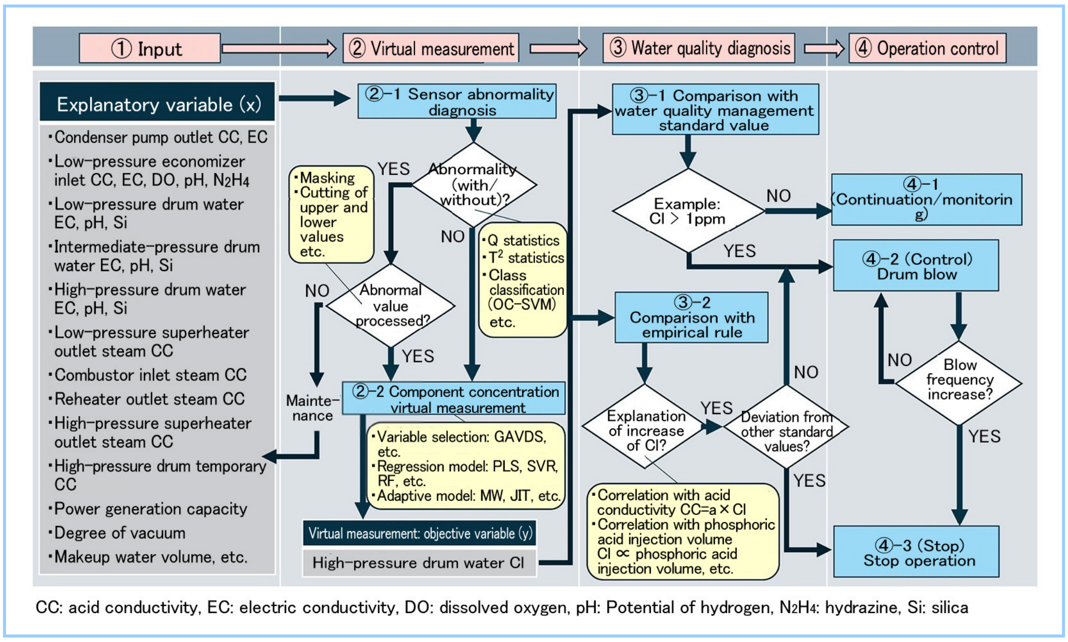

Figure 9 Example of water quality diagnosis flowchart combining software sensors

4. Conclusion

In recent years, digital solution businesses have been developed to provide maintenance and operation supports utilizing AI and IoT for thermal power plants, chemical plants, the steel industry and environmental equipment. Under this situation, the Mitsubishi Heavy Industries Group is developing various applications and promoting their implementation in plants.

This paper summarized the concept and research results of a virtual measurement technology for plant water quality using software sensors developed in collaboration with the University of Tokyo. At present, we are examining model improvement and combination with abnormality detection by accumulating data and verification using other plant water qualities, and working on the implementation of this technology in a plant water quality diagnosis system. We plan to apply this technology to thermal and nuclear power plants, which will lead to safe operation and maintenance activities of the equipment.

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