Soft Sensor-Systems for Optimizing Plant Operation

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ABSTRACT

In recent years, an increasing number of companies have been promoting DX initiatives in industrial processes in order to improve productivity. Fuji Electric has been developing technology for soft sensors that can estimate quality in real time using temperature, pressure, and other process data. Our newly implemented soft sensor design tool enables efficient building and deployment of highly accurate mathematical models that were challenging in the past. The performance of the soft sensors was verified with a process simulator. The new soft sensor designed with our tool is able to estimate quality values that have been difficult to measure in real-time and improve plant control, resulting in reduced specific consumption and lower costs.

1. Introduction

In recent years, industry has been increasingly promoting digital transformation (DX) for automation and increased efficiency in manufacturing processes. As society and markets change, an increasing number of companies in steel, chemicals, and other process industries have also been advancing efforts toward digitalization to improve safety, reduce environmental impact, stabilize quality, and reduce costs and workload.

As on-site plant operation is crucial in process industries, operators must have an accurate understanding of the status of plants to appropriately implement intervention and control. Soft sensors, helping understand the status of plants, can further innovate plant operation and promote DX in the process industries.

2. Soft Sensors

2.1 What are soft sensors?

Soft sensors are attracting attention as sensors designed for the safe and stable operation of manufacturing plants, as well as for the maintenance and control of quality.

In the process industries, key quality values such as the concentration of components in a product are still measured via sampling-based laboratory analysis. The problem with this method is that it takes a long time to obtain results and is costly. On the other hand, since in-process temperature and pressure measurements can be taken in real time and at a low cost, if those measurements are correlated to quality values, quality can be estimated in real time. A soft sensor is a mathematical model that enables the estimation of quality values, which are response variables, from explanatory variables such as temperature and pressure, which are easy to measure. They are called soft sensors because their functions are implemented as software.

2.2 Roles and effects of soft sensors

A soft sensor will yield the following benefits:

(a) As in Fig. 1, operators used to operate plants without knowing the current quality and could not perform operations with confidence. If a soft sensor shows the estimated current quality in real time, operators can appropriately perform plant operation and intervention.

(b) Real-time estimated quality reduces the margins that were previously established under the assumption that quality was uncertain, thereby reducing waste, improving quality and saving energy.

(c) When a target quality value can be measured by equipment, soft sensors can detect equipment errors.

2.3 Challenges for soft sensors

Achieving the effects described in Section 2.2 requires the efficient design and implementation of accurate soft sensors.

To accurately estimate process quality values with a soft sensor, it is necessary to apply appropriate mathematical models and parameters using suitable combinations of explanatory variables. Users need to select optimal combinations from many candidates, which requires enormous efforts because it can only be enabled by manually searching the combinations by trial and error. A major challenge to achieve the practical implementation of soft sensors is to drastically

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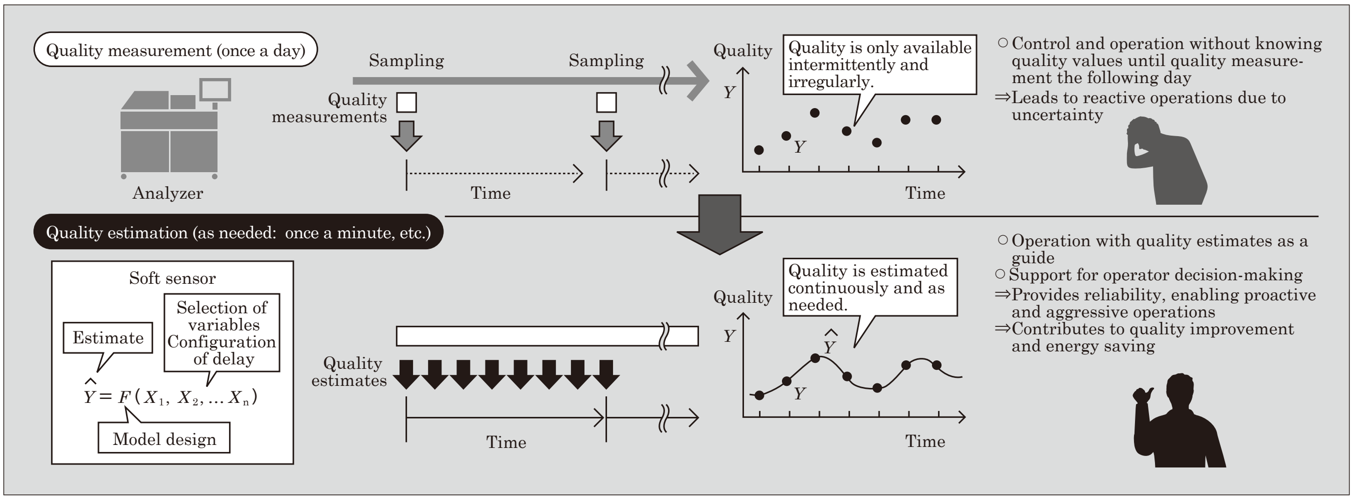

Fig.1 Effects of a soft sensor

improve the efficiency of the processes required for this soft sensor design.

In addition, in order to operate designed soft sensors in actual plants, users need to implement systems to input explanatory variables such as temperature and pressure measurements and perform calculations using mathematical models to output quality estimates (response variables). A mechanism is also necessary for updating the parameters of the estimation models of the soft sensor in response to changes in actual plants.

3. Soft Sensor Design Tool

3.1 Outline of the soft sensor design tool

We developed a tool to efficiently design highly accurate soft sensors without the manual trial and error process that was previously necessary. This soft sensor design tool was jointly developed by universities, quality control and production management departments of chemical companies, engineering companies and Fuji Electric at the Workshop No. 32 "Soft Sensor Implementation" (chaired by Kimito Funatsu) at the 143rd Committee on Process Systems Engineering organized by the Japan Society for the Promotion of Science. In this workshop, the series of procedures have been standardized and automated to determine combinations of explanatory variables, estimation model types and parameters, which had been a major challenge in soft sensor design in the past. Section 3.2 describes the series of processes that were automated.

3.2 Steps from soft sensor design to operation

The steps from soft sensor design to operation are shown in Fig. 2.

(1) Data collection

In this step, the data required for soft sensor design is collected. It is necessary to obtain both the response variables to be estimated, such as product quality, and explanatory variables that may affect the response variables, such as process data.

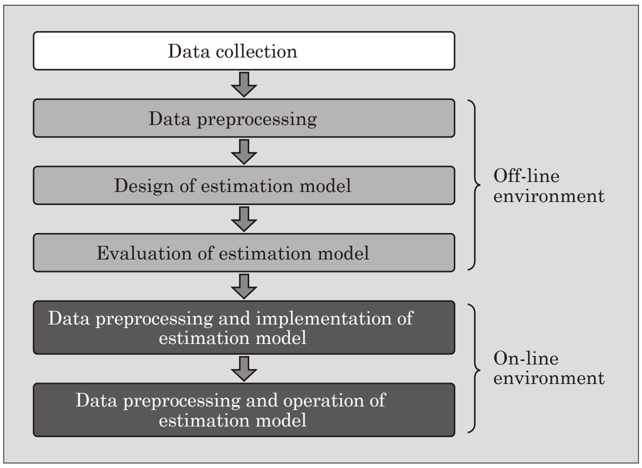

Fig.2 Steps from soft sensor design to operation

(2) Data preprocessing

Collected explanatory variables may contain outliers, irregular data or noise. Since these will interfere with the proper design of the soft sensor, data preprocessing is performed, such as removing outliers and irregular data and eliminating noise by moving average, in this step.

(3) Building and evaluation of the soft sensor

There are several candidate methodologies to estimate response variables from explanatory variables. Notable candidates are regression models such as partial least squares (PLS) and support vector regression (SVR), as well as just-in-time (JIT)-PLS, which sequentially and automatically update estimation models in response to changes in processes. Many candidate soft sensors are built with the combinations of these estimation models and explanatory variables to compare the accuracy of their estimates for evaluation.

(4) Implementation of the soft sensor

According to the evaluation results, users select a soft sensor that will achieve the target accuracy and implement it on the inferential PC provided in the online environment.

(5) Operation of the soft sensor

The process data to be used as explanatory variables is measured in real time and stored in the data server of the process control system. The inferential PC feeds the explanatory variables obtained from the data server of the control system into the soft sensor and writes the estimated outputs into the data server and pass it on to the control system.

(6) Redesign of the soft sensor

If the characteristics of the plant equipment changes over time due to the accumulation of scale (deposit) inside piping or other factors, it may cause a difference from the estimation model, and the estimation performance of the soft sensor may deteriorate. Redesign of the soft sensor is required before the deterioration of estimation performance exceeds the permissible level. Users can redesign the soft sensor by repeating the data collection, data preprocessing, and soft sensor design and evaluation processes.

3.3 Configuration of the soft sensor design tool

Figure 3 shows an example of a system configuration of the soft sensor design tool. This design tool is provided with a mechanism that standardizes and automates the series of designing steps described in Section 3.2. This tool consists of two software components, the off-line tool and on-line tool.

(1) Off-line tool

The off-line tool allows users to design a soft sensor.

The tool generates several condition-specific candidate estimation models using training data according to the conditions specified by users such as the data range (period) to be studied, the selection of candidate explanatory variables, the range of delay time, and the types and settings of candidate estimation models. By applying each candidate estimation model to the test data, the tool estimates response variables and calculates the root mean squared error (RMSE) and the determination coefficient R^2. The tool automatically performs these processes to compare values and select a estimation model (a soft sensor) that achieves the best performance. Text format files are generated to deploy to the on-line tool with response and explanatory variables, as well as for the selected model information.

Table 1 lists the functions of this off-line tool.

(2) On-line tool

The on-line tool allows users to operate a soft sensor in actual processes.

This tool estimates product quality values (response variables) from the explanatory variables sequentially loaded from the database of the plant's control system, using a estimation model based on the model information generated in the off-line tool. Thus, the tool can immediately operate the model selected by the off-line tool in an actual plant. The estimated

Table 1 List of functions of the off-line tool

No.	Description of function	Remarks
1	Loading of past data (explanatory variables, response variables)	–
2	Selection of samples (for training and testing)	–
3	Settings of fixed/selected variables, configuration of maximum delay	–
4	Variable selection, model building, and performance evaluation based on training data	–
5	Evaluation of estimation performance based on test data	RMSE*1, R^{2}*2
6	Calculation and enumeration of all selected variables and models as candidates for search	–
7	Output of model file	–

*1 RMSE: Root mean squared error
*2 R^2: Coefficient of determination

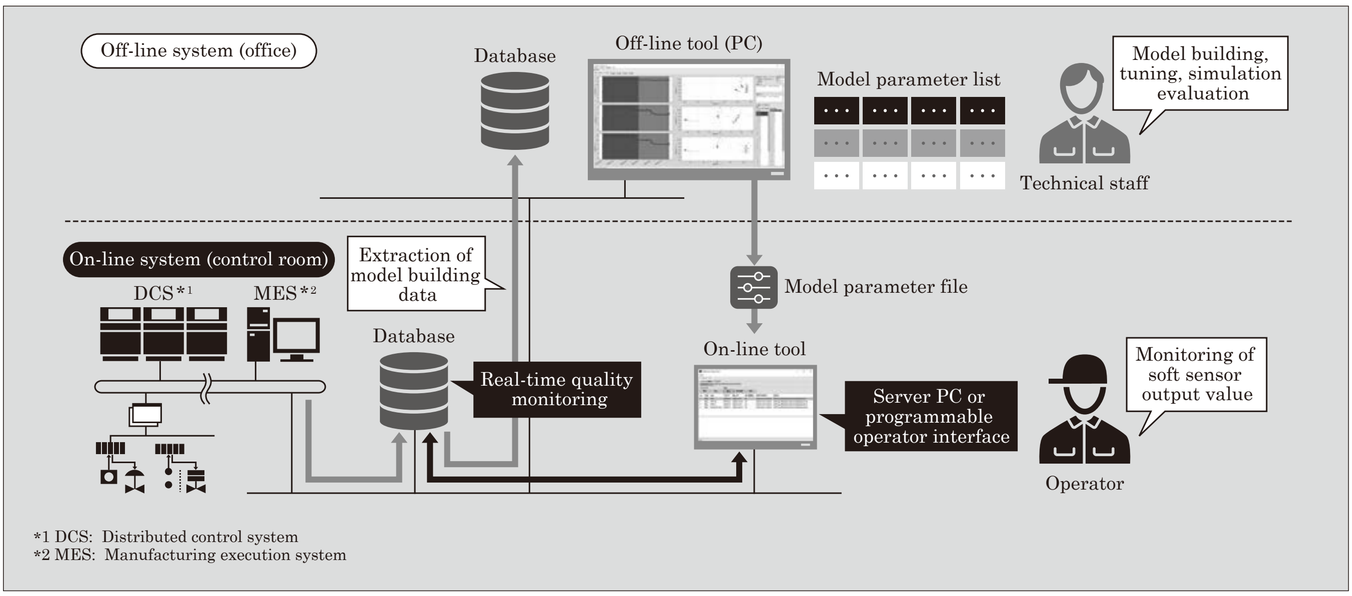

Fig.3 Example of a system configuration for the soft sensor design tool

Table 2 List of functions of the on-line tool

No.	Description of function	Remarks
1	Loading of model files	–
2	Starting and stopping estimation (by model)	Several models acceptable
3	Entry of historian data (instantaneous values)	Each cycle
4	Calculation and output of estimates according to historian data and model inference	Each cycle
5	Indication and storage of results	Each cycle

quality values are stored in the database of the plant's control system, allowing operators to check the values any time.

Table 2 lists the functions of the on-line tool.

Using these tools allows users to standardize a soft sensor development procedure without trial and error. Users can simply and quickly implement the steps from soft sensor development to operation, saving a significant number of engineering labor hours compared to manual implementation.

4. Application Example of the Soft Sensor Design Tool

4.1 Target process

To verify the effect of the soft sensor designed with the developed tool, we used the data generated with a vinyl acetate monomer (VAM) manufacturing process simulator[(1),(2)] developed at the Workshop No. 27 "Process Control Technology" at the 143rd Committee on Process Systems Engineering organized by the Japan Society for the Promotion of Science. Since this simulator has been developed to enable simulations in environments similar to those in actual plants, we can use it as a benchmark model for purposes such as quality estimation, as in this case, as well as control.

The VAM manufacturing process shown in Fig. 4 produces VAM as a product by subjecting ethylene (C_2H_4), acetic acid (CH_3COOH) and oxygen (O_2) that have been input as materials to processes such as reaction, gas-liquid separation and absorption, and then separating and refining them in a distillation column. Then, we estimate the response variable (in this case, the water concentration at the bottom of the distillation column) is estimated according to 49 explanatory variables for temperature, pressure and flow rate. If the water is returned to the reactor, stability will degrade. Since it is difficult to measure water concentration in real time, sampling measurement by means of manual analysis was common in the past.

4.2 Verification result

We carried out the steps from data preprocessing to evaluation of the estimation model using the data obtained from the VAM manufacturing process simulator described in Section 4.1. While explanatory variables are measured per minute in this data, response variables are measured once a day. As such, the data acquisition timing is differs. The newly developed tool can automatically identify and select explanatory variables that are acquired at the same time as response variables. To design an estimation model, we provided the estimation models of PLS, SVR and JIT-PLS with adjusted coefficients to obtain dozens of combinations of candidate estimation models. Figure 5 highlights how the soft sensor design tool reduces labor hours. By using this tool, we have reduced the time it takes to complete the processes up to evaluation of the estimation model to approximately a third of that of the manual trial-and-error method.

In this verification, the JIT-PLS was selected as best estimation model for the soft sensor. We compared its performance with that of the PLS-based soft sensor, which was the main model previously used based

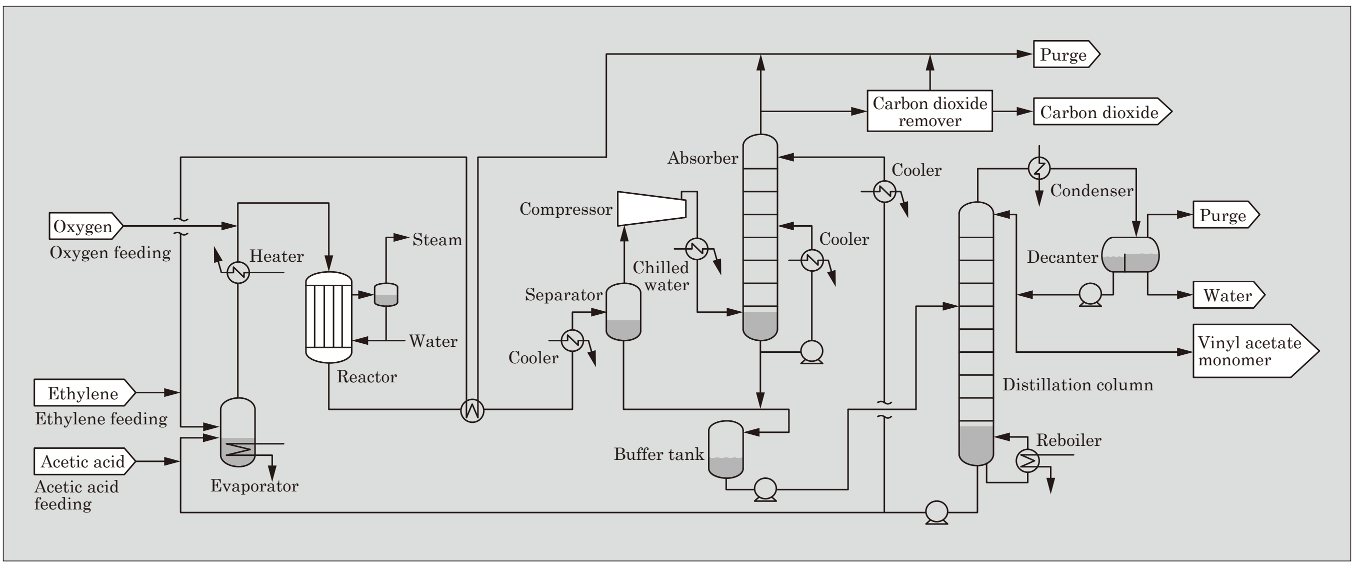

Fig.4 Vinyl acetate monomer (VAM) manufacturing process[(1)] (Translated by Fuji Electric)

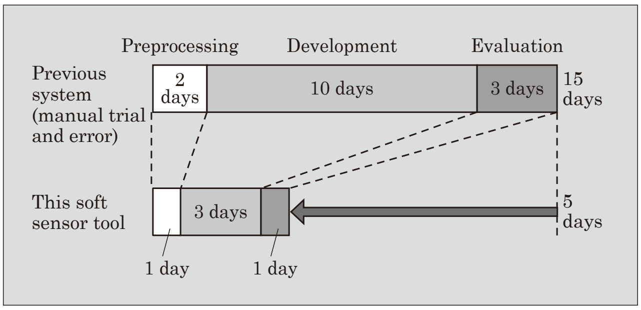

Fig.5 Breakdown of labor-hour reductions achieved by the soft sensor design tool

on manual construction. Figure 6 compares the optimization results from the use of the soft sensor design tool. The RMSE (estimated error) of the conventional method (PLS) was 0.46%, while that of the best result (JIT-PLS) was 0.26%; showing a higher accuracy for the soft sensor designed with this tool.

4.3 Cost reduction effect of the soft sensor

Using the VAM simulator described in Section 4.1, we estimated the improvement of the plant operation that would result when applying this soft sensor to

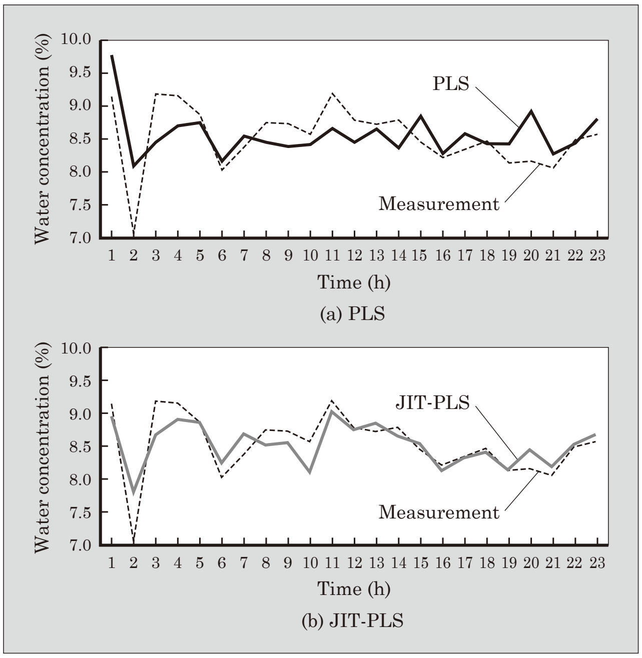

Fig.6 Example of optimization by the soft sensor design tool

the VAM manufacturing process. In the past, it was not possible to measure the water concentration at the bottom of the distillation column in real time. For this reason, the water concentration could not be controlled directly, and it took long time to stabilize the plant. Now, however, since the soft sensor enables its real time estimation, the water concentration in the reboiler at the bottom of the column can be directly controlled with the estimated value to achieve quick stabilization. As a result, the water concentration at the relevant area can be reduced in a stable manner, and in tandem, the amount of steam to be fed to the evaporator and reactor can also be reduced, along with the consumption rate of raw materials. With these improvements, a cost reduction equivalent to 8 million yen a year can be expected. In addition, there were no errors in the soft sensor estimates that would negatively affect the control of the abovementioned reboiler.

5. Postscript

In this paper, we have described soft sensors that contribute to the optimization of plant operation. This technology allows us to easily introduce soft sensors into existing control systems. The technology will contribute to increased productivity in plants by optimizing control using the estimated output by the soft sensor to achieve stabilization of product quality, improved energy saving and safety, reduction of operator workload and environmental impact, and more. By synchronizing this technology with the plant information management system (PIMS) implemented in the Fuji Electric monitoring and control system "MICREX-VieW FOCUS Evolution," seamless integration with the existing software of plant operation support can be achieved. Fuji Electric will contribute to the innovation of the plant operations of customers by expanding functions that support plant operation.

References

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