Cooperative Process Optimization Using Plant Big Data

Ken-ichiro Wada [*1] *Hiroyuki Miyamoto* [*1] *Takashi Sasaki* [*1]

Customers wish to improve control efficiency to increase the operating efficiency of their plants. However, such efforts typically do not extend beyond optimizing individual processes. This paper introduces our approach to improving the control efficiency of a plant composed of multiple processes by optimizing the entire process, and outlines our technologies for analyzing huge amounts of data and computing optimal control parameters, which cannot be obtained from the expertise of field operators. The paper also introduces some examples of applying the approach to paper mills and chemical plants.

INTRODUCTION

Manufacturing processes in the chemical, pulp and paper, and other material industries consist of multiple continuous processes, and the controllability of each process is usually optimized by different departments in charge. Since these departments believe that their own process is fully optimized, it is often difficult to take additional measures for improvement beyond the scope of their responsibility. To improve controllability across a plant with multiple processes, it is necessary to examine the situation of a huge number of control loops across multiple sections, identify the problems of each process, and perform optimization while considering possible interference among the processes. This cannot be accomplished simply by monitoring the information from measurement instruments and improving the controllability of individual processes.

To improve the controllability of multiple continuous manufacturing processes, we propose cooperative process optimization. This is an integrated method of (1) using plant big data and identifying causal relationships including possible interference among processes, (2) proposing reasonable improvements based on control theories and process simulation technologies, and (3) evaluating the results.

*1 P&W Solution Management Department, Analyzer Center,
IA Products & Service Business Headquarters

COOPERATIVE PROCESS OPTIMIZATION

Basic Procedure

Figure 1 shows the basic procedure of the cooperative process optimization. To resolve customers' problems effectively, we first collect real-time data, analyze these data based on a clear-cut theory, and determine improvement measures. To allow customers to understand our improvement proposal, we simulate and visualize expected improvements before applying it to the field. By repeating this cycle over a long time, we can offer continuous improvements. Each step in Figure 1 is explained below.

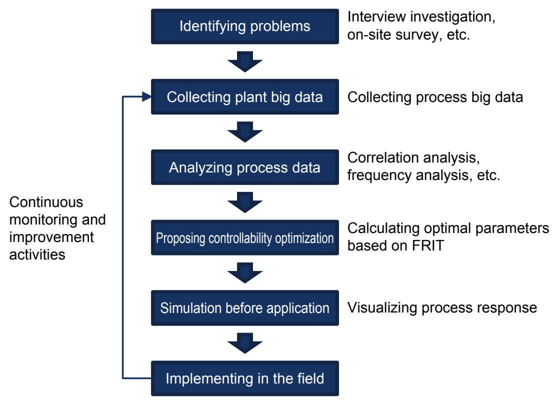

Figure 1 Basic procedure

Collecting Plant Big Data

Through general-purpose OPC communication, we collect DCS tag data (mainly PV, SV, and MV of each control loop) from more than 1000 points for each process every second. This is because DCS control is generally performed in cycles of 1 second and it is essential to collect these real-time data to analyze and improve controllability, and also because there is a need to cover all areas in which the process is likely to be affected.

The data gathering time varies with the type of industry, process, problems, and so on. In many papermills, the manufacturing cycle of all paper brands typically takes one month, so data are usually collected for longer than one month. If factors need to be analyzed over a much longer time such as seasonal variations and time-dependent changes, a longer period should be set accordingly.

Analyzing Process Data

After collecting data, we first examine the relationship between the target tag and others. For example, to stabilize an output of a process (flow rate, concentration, etc.), we analyze the correlation between the target tag data and others and sort the latter in order of high correlation.

Then, we examine the tags having a close correlation in detail to identify the primary cause. In this step, we clarify the causal relationship through trend checking, frequency analysis, cross correlation analysis, etc. This helps identify which control loop should be improved to stabilize the target output.

Proposing Controllability Optimization

The next step is to optimize the control parameters of the target control loop by using the collected plant big data.

First, we perform the process identification, which is needed for the subsequent calculations. For this purpose, we use a closed-loop identification technique based on the data obtained following disturbances or setpoint changes during operation.

To calculate the optimal control parameters, Yokogawa's original algorithm (patent applied)[2] based on the fictitious reference iterative tuning (FRIT) theory[1] is used. First, we input the current control parameters to determine the current sensitivity function of the control loop; this function shows how much an output is attenuated when the control loop is disturbed, with a lower sensitivity function meaning a higher tolerance to disturbance. Then, supposing highly possible disturbances and setpoint changes, we set a new sensitivity function (target sensitivity function) that lowers the gain at a specific frequency. After all these procedures, we can determine the optimal control parameters that reduce the gain to the target level.

Figure 2 shows the relationship among the current sensitivity function, target sensitivity function, and optimized sensitivity function. As can be clearly seen, the gain of the optimized sensitivity function has fallen around the target frequency. This means that the tolerance to disturbance has been improved. Note that the attenuation target is determined based on the results of frequency analysis on collected data.

The FRIT method allows the optimal control parameters to be obtained quickly by analyzing collected real-time data, without having to use a trial-and-error method.

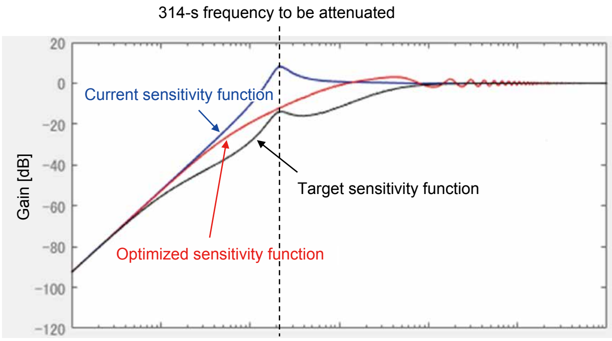

Figure 2 Optimization of control parameters with a tool

Simulation before Application

The control parameters determined by the process control parameter optimization tool often differ greatly from the previous parameters in the field, and field operators usually hesitate to apply new ones with 10 times higher gain in the field. Therefore, we run simulations to confirm the improvements that can be expected (see the two cases in the following section). System responses can be simulated by specifying a controller, process model, and disturbance model. The results are visualized in a graph, which can be used for confirmation and for explanation to the customer.

CASE 1: PAPER-MANUFACTURING PROCESS

Problem to Be Solved (Cyclic Fluctuation of Product Quality)

Case 1 is a papermill in which we successfully eliminated the cyclic fluctuation of product quality and shortened the time for grade change[3][4]. Papermills usually manufacture many kinds of paper with different thicknesses, colors, and other properties. Changing one product to another during continuous manufacturing is called a grade change. There are two processes in paper manufacturing: the stock preparation process for preparing materials and dyes, and the paper-making process for forming and drying the materials. Each process is managed by different departments as if independent processes. Operations required to change paper grades are performed independently by the departments.

In the plant, basis weight (g/m^2), which is an important product quality in the paper-making process, fluctuated in a 50-minute cycle, and this fluctuation prolonged the time from the start of change until the quality reached a product level (until the quality stabilized within the allowable range from a target value). Regardless of the efforts of the field staff, this problem had not been resolved for years.

Data Analysis (Identifying Interference among Processes)

In accordance with Yokogawa's cooperative process optimization procedure, we collected plant big data and then analyzed process data. The results showed the underlying causal relationship: controlling the basis weight in the paper-making process caused fluctuations in the level of the stock box in the stock preparation process (the stock box is a tank for water-diluted pulp, located after the stock preparation step), which in turn caused the level of the mixing chest to fluctuate. When this fluctuation was controlled, the material concentration was changed, and this change again affected the basis weight in the paper-making process (Figure 3). A more detailed data analysis revealed that this fluctuation cycle was about 3000 s (50 minutes). This finding was in accordance with the fluctuation cycle that had been confirmed in the field.

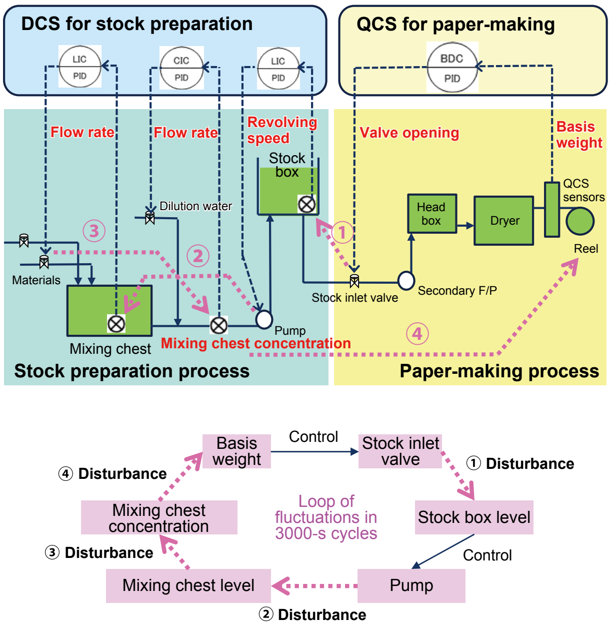

Figure 3 Interference among processes in a papermill

Examination and Simulation of Improvement

Based on the analysis results, we decided to improve the controllability of the level of the stock box and the concentration of the mixing chest. Since the fluctuation cycle of each control loop was known from the frequency analysis of collected data, we used the optimization tool to calculate control parameters that reduced a sensitivity function in respective frequency domains. The graph in Figure 2 is the result of control optimization of the stock box level in this case.

The tables in Figures 4 and 5 show the calculated PID parameters and simulated fluctuation graph based on actual data. The proportional gain and integral time of the PID parameters for controlling the stock box level have become 10 or more times higher, and the proportional gain for controlling the mixing chest concentration has become 6 times higher. Figure 4 shows that fluctuations are reduced around the 300-s frequency, which is the target of attenuating the sensitivity function.

Before applying the new parameters to the field, we presented these simulations to the customer and gained their understanding of the expected improvements. The upper panels in Figures 4 and 5 compare the predicted improvement trend (red) with past actual data (green), and the lower panels show the predicted improvement regarding frequency characteristics.

PID parameter

	Proportional gain	Integral time	Derivative time
Conventional	0.2	25	0
After optimization	2.1	290	0

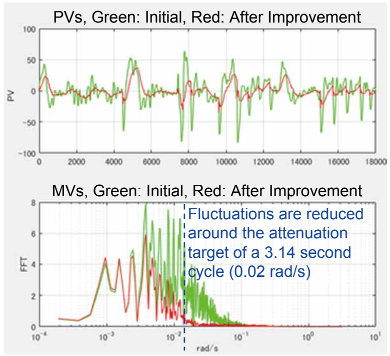

Figure 4 Simulated improvement in controlling the stock box level

PID parameter

	Proportional gain	Integral time	Derivative time
Conventional	0.5	60	0
After optimization	3.0	60	0

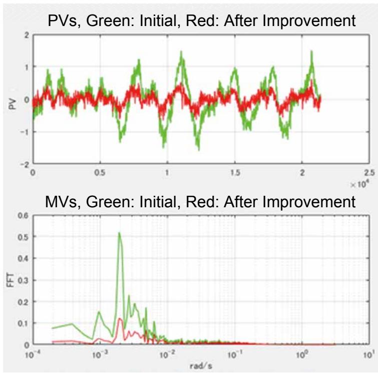

Figure 5 Simulated improvement in controlling the mixing chest concentration

Improvements

In this case, applying new control parameters stabilized the control of the stock preparation process. This in turn stabilized the basis weight in the paper-making process, shortening its stabilization time after a grade change by 50% or more, from 43 minutes to 18 minutes (Figure 6). Since this solution helps save materials and power, the annual economic benefits are estimated to be tens of millions of yen.

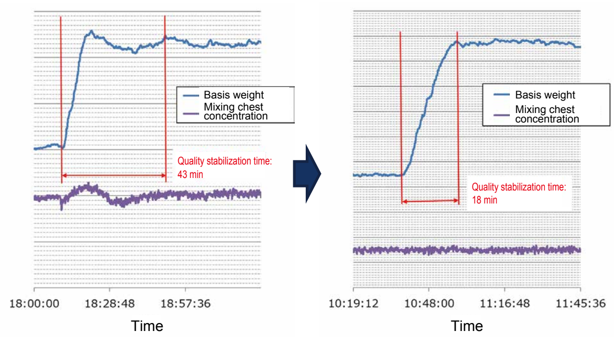

Figure 6 Improvement in a papermill (shortened grade change time)

CASE 2: CHEMICAL PROCESS

Problem to Be Solved (Temperature and Flow Rate Fluctuations of Intermediate Product)

Case 2 is a chemical plant in which we successfully reduced the temperature and flow rate fluctuations of an intermediate product and saved energy[5].

Figure 7 shows the target process. Unreacted materials are returned to the previous process from the gas-liquid separator and the distillation column, both of which are located after the reactor. When any disturbance affects the reactor or the gas-liquid separator, this spreads all other elements in the process through the returned flow. As a result, it is difficult to stabilize the flow rate and temperature of the intermediate products after the distillation step.

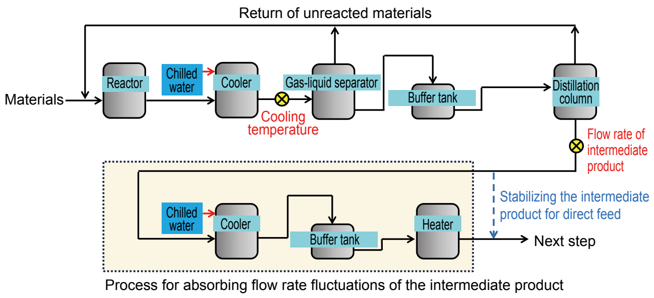

Figure 7 Chemical process

Analyzing Data and Determining Improvement Targets

In this case, we examined how disturbances in the reactor and gas-liquid separator affected other elements in the process. By using the data analysis tool, we determined that the disturbance spreads throughout the process within 15 to 50 minutes and selected about ten control loops (for temperature and level) in the process after the reactor as controllability improvement targets.

We performed system identification and calculated PID parameters for these control loops by using the parameter optimization tool. Like Case 1, it was necessary to make such large changes to parameters that even veteran operators could not easily accept them. We presented the results of our simulation to win the understanding of the customer, and then applied the new parameters to the field.

The results are shown in Figure 8. We were able to reduce the temperature fluctuation of the intermediate product after cooling and the flow rate fluctuation after distillation, both by more than 80%. Previously, the flow rate fluctuation was too large to feed the intermediate product directly to the next step, and so additional facilities and energy were required: the intermediate product was cooled, stored in a buffer tank, and then re-heated before use. After the improvement, it could be fed directly to the next step, reducing energy cost by more than 10 million yen annually. In addition, the stabilized process consumes fewer materials. Considering these benefits, the total effect is expected to amount to tens of millions of yen each year.

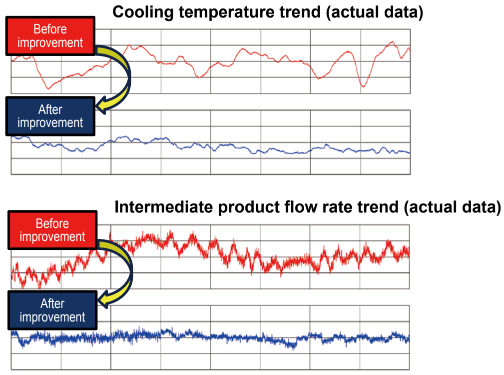

Figure 8 Improvement result of a chemical plant

CONCLUSION

This paper introduced a general procedure of Yokogawa's cooperative process optimization solution and two examples of its application. With this solution and Yokogawa's proprietary technology, customers can examine the details of interference among processes, identify problems, and obtain optimal parameters for multiple control loops quickly. This task is difficult to perform for operators who focus on independent processes.

By applying this solution to a sequence of processes that are operated and managed separately, customers can improve the operation of multiple processes, which has been difficult to achieve. This solution aims not to optimize an entire plant in a single session but to repeat small successes and gradually expand the scope and effects. This solution is superior to a short-sighted strategy of pursuing partial optimization. Yokogawa will work on saving resources and energy at manufacturing sites and help achieve the sustainable development goals (SDGs).

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