Cooperation between Control Technology and AI Technology to Improve Plant Operation

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As the manufacturing industry is shifting its production model from mass production to the production of multiple products in small or variable quantities, more sophisticated operation of production equipment is required. Yokogawa has a unique approach to this problem, which was adopted by the New Energy and Industrial Technology Development Organization (NEDO). This paper describes details of this NEDO project and its achievements, as well as a study on the effective use of AI technology, which is another theme of this project.

INTRODUCTION

In the manufacturing industry, the production model is shifting from mass production to the production of multiple products in small or variable quantities. This requires more sophisticated operation of production equipment, as well as guidance and automatic control that can respond to brand changes and fluctuations in production load, thus helping operators perform precise control and operations.

In response to this trend, Yokogawa developed a cooperative optimization solution, which was adopted by the New Energy and Industrial Technology Development Organization (NEDO) and implemented as a NEDO project in fiscal 2017 and 2018[(i)]. This paper describes the details of this project and its achievements.

As part of this project, we worked jointly with NTT Communications Corporation ("NTT Com")[(ii)] to study the effective use of AI technology. This paper also introduces its results.

In addition, we propose combining conventional control technologies and AI to improve operations at the manufacturing site, and describe herein its details and action plan.

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KEY POINTS OF THE COOPERATIVE OPTIMIZATION SOLUTION

Through activities to improve operations at manufacturing sites, we identified the following three points, which formed the basis of developing the cooperative optimization solution (Figure 1).

- Cooperative control between production processes and power sources
- Cooperative control between production processes
- Use of plant big data

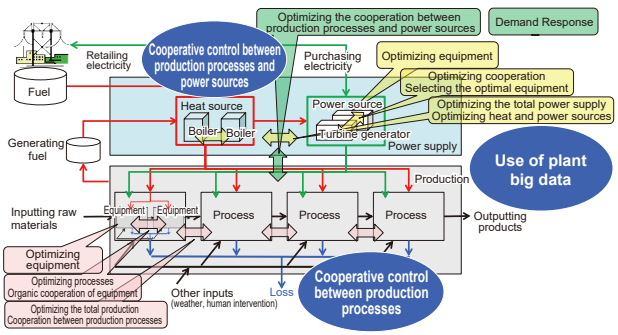

Figure 1 Key points of the cooperative optimization solution

Conventionally, the production process determines the necessary quantities of electricity, steam, and other energy forms, and power is often kept fed even while production equipment is temporarily idle. If the production side and the power supply side could exchange detailed data, it would improve efficiency and save energy. This is the meaning of cooperative control between production processes and power sources.

When a product is manufactured through multiple processes, it is often difficult to improve the controllability by optimizing the upstream process alone. This problem can be solved by considering multiple processes; data from the downstream process may be useful to improve the controllability of the upstream process. This is the meaning of cooperative control between production processes.

Plant big data play an important role in quantitative analysis for improving the controllability. This is the third key point. The data reflect various conditions that the plant has experienced in the past and contain various process measurement data, control parameters and output data, data on events during manipulation by operators, and so on. Specifically, they are:

- DCS data on the production process
- DCS data on the power source
- Data on the production process
- History data of DCS operation

OVERVIEW OF THE NEDO PROJECT

Information Flow in the Manufacturing Site

The lower part of Figure 2 shows the flow of operations (A: detection → monitoring and control). The control system ensures safe operations by using various data in the manufacturing site. The upper part shows the flow of information (B: detection → accumulation → analysis, wisdom, learning → optimization). With various data in the manufacturing site, new measures are designed to improve the operation and introduced to the site.

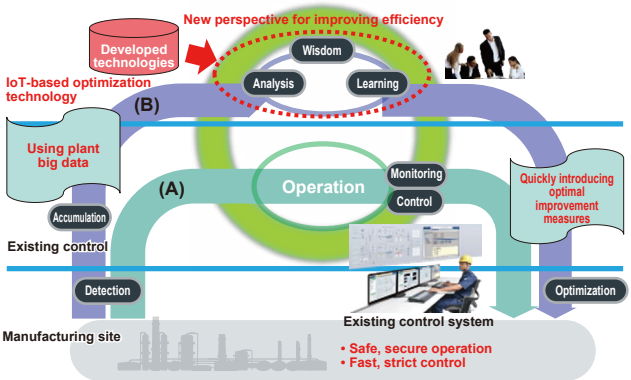

Figure 2 Information flow in the manufacturing site

The information flow contains huge amounts of plant big data that have been accumulated, which indicate how the plant was run, how much operations fluctuated, how the processes influenced each other, and so on. To determine specific measures for improving operations, various data analysis methods such as time-series correlation analysis, frequency analysis, and the fictitious reference iterative tuning (FRIT) theory that calculates the optimal control parameters [(1)] were applied to this information. Necessary tools were developed in this project.

Creating an operation improvement plan should not take too much time. Therefore, we studied how to apply AI technology to analyze plant big data quickly and intelligently.

Overview of the NEDO Project and its System

Figure 3 shows an outline of the NEDO project and its joint development system.

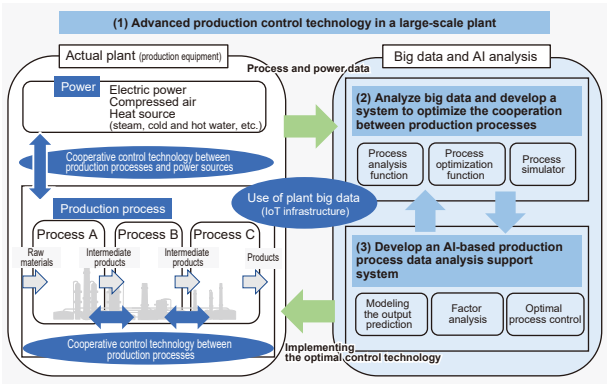

Figure 3 Outline of NEDO project

As described earlier, this project was based on the three points in the cooperative optimization solution and its themes were: (1) apply advanced production control technology in a large-scale plant (effective use of the development system, development of business models, and application to the manufacturing site) (organization in charge: Yokogawa Solution Service), (2) analyze big data and develop a system to optimize the cooperative control between production processes (organization in charge: Yokogawa Electric Corporation), and (3) develop an AI-based production process data analysis support system (organization in charge: NTT Com).

To develop an AI-based production process data analysis support system, the following two targets were set.

- Shorten the analysis time and improve the model accuracy
  Reduce the analysis time and improve the accuracy of the control model by using machine learning to automatically extract effective data for analysis and create time-series models.
- Improve the accuracy of the control parameters
  Solve the optimization problem to automatically calculate the optimal control parameters and improve the accuracy.

The three companies tackled their respective themes and jointly attained the achievements described below.

ACHIEVEMENTS OF THE COOPERATIVE CONTROL SOLUTION

Cooperative Control between Production Processes and Power Sources

The first model plant in this project was a paper mill. Specifically, we focused on the pulp manufacturing process. Based on information about the cutting position of the paper machine, we optimized the consumption of steam and investigated how effectively this cooperative optimization measure improved efficiency.

We found that the power source could be optimally controlled based on the process information and that the energy for supplying steam could be reduced accordingly. The potential steam reduction was about 100 kL/year of crude oil equivalent. Similar cooperative control can be achieved by exchanging additional information between the production process and the power source.

Cooperative Control between Production Processes (Pulp and Paper)

Among the continuous processes in pulp and paper manufacturing, we examined how to cooperatively control and optimize the preparation process and the papermaking process (Figure 4). Through process data analyses and trials based on the results, we successfully shortened the time required for the brand change. The potential energy reduction was about 400 kL/year of crude oil equivalent.

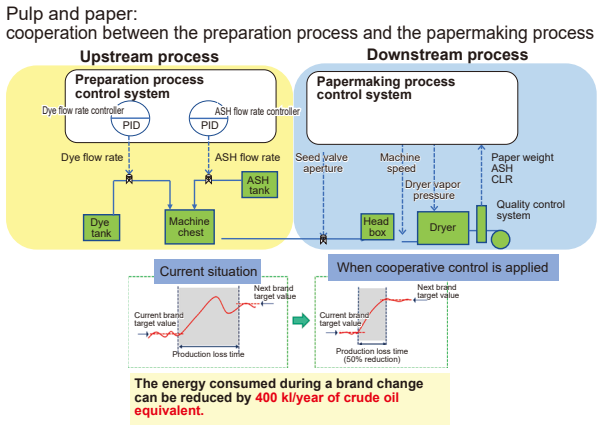

Figure 4 Cooperative control between production processes (pulp and paper)

Cooperative Control between Production Processes (Chemical)

The second model factory was a chemical plant and we targeted the cooling control of the gas-liquid separator, which was located before the distillation column (Figure 5). Based on the analysis of process data in both facilities, we calculated the optimal parameters for the cooling control and the related control loop and then applied them to the actual plant. Since the operation of the gas-liquid separator was stabilized and excessive cooling was avoided, the steam consumption was reduced in the downstream distillation column. In addition, the flow rate of the intermediate products delivered from the distillation column was stabilized (Figure 5), eliminating the need for the buffering device before the subsequent process. As a result, total energy reduction was 350 kL/year of heavy oil equivalent.

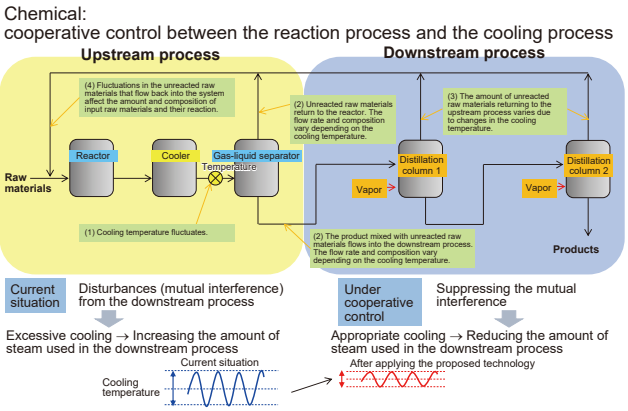

Figure 5 Cooperative control between production processes (chemical)

ACHIEVEMENTS IN APPLYING AI TECHNOLOGY

Application of AI Technology in Three Stages

When developing an AI-based process data analysis support system, we believe it is necessary to go through the following technological stages. In the first stage, data are analyzed and control models are created mainly by human operators. To go to the second stage, it is necessary to develop a means to automatically extract effective data for analysis by machine training and other methods, and to reduce the analysis time and improve the accuracy of the control model. Once established, this technology will greatly improve the conventional data analysis task. In the second stage, a highly accurate time-series model for the target process is created from the past data of a real plant. In the NEDO project, to create this time-series model, we used effective nonlinear methods: multilayer perceptron (MLP), BiLSTM, and QRNN. As a result, we obtained correlation coefficients greater than 0.7 in the model. To verify whether this time-series model can reproduce the behavior of the target process, we evaluated its accuracy index. In addition, we used the model to solve the optimization problem and automatically calculate the optimal control parameters (PID values). The details are described later along with the results of a field test.

The third stage is to be tackled in the future. Some processes are difficult to control with conventional approaches and require manual intervention by operators. Therefore, AI control guidance and an AI controller are needed. These can be created by applying reinforcement learning to the time-series model created in the second stage, which obviates the need for response tests in actual plants.

Field Test and Results

Figure 6 outlines a field test for applying AI technology and its results. The target process was the distillation column in a chemical plant.

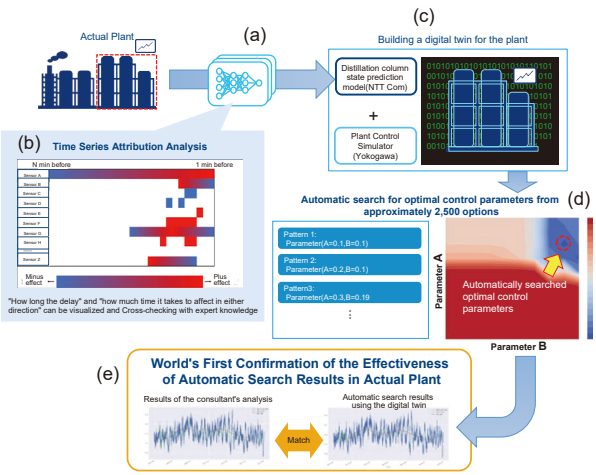

Figure 6 Field test for applying AI technology and its results (source: NTT Com)

In Figure 6, section (a) is a model for predicting the time-series state of a distillation column, which is created by applying deep learning to the process data of the distillation column in a real plant.

Section (b) is time-series attribution analysis technology of NTT Com for visualizing the certainty of the model. It clearly shows how the objective variable and explanatory variable are correlated in terms of the time-series, whether the correlation is positive or negative, and how strong it is. In other words, this technology removes the model from its black box and provides certainty.

The system in section (c), which is achieved by combining the model created in section (a) and Yokogawa's plant control simulator for the target process, reproduces the behavior of a virtual chemical plant. In this system, there are several variable parameters including PID values of the main control loop. The behavior of the target variable can be calculated by using the optimization problem method while varying the parameters.

Section (d) uses the system of section (c) to display the results of automatic search for P, I, and D values (the optimal control parameters of the main feedback control loop) from among approximately 2,500 options. The optimal control parameters obtained here were almost the same as those calculated based on the FRIT theory.

Section (e) shows that when the target variable was simulated while varying control parameters, its behavior closely matched that obtained by human analysis.

As described earlier, prior to applying AI technology, we calculated optimal control parameters based on the FRIT theory, carried out trials, and confirmed that control was improved in an actual plant. We believe that the results of this field test are practical for improving the control of actual chemical plants.

CONCLUSION

By integrating plant control optimization technology with AI, we successfully reduced the time for data analysis, created a time-series model based on process data, and confirmed the practicality of the created model while securing the logic of plant control.

Leveraging these achievements, we are developing a new method for improving the operation of the process, which is difficult to control with the conventional method and requires manual intervention by human operators.

Specifically, we are planning to optimize the conventional control and then apply AI control based on a neural network to part of the process that shows nonlinear behavior. We are also trying to combine new control methods with conventional plant control. One example is applying machine learning to operators' manual interventions and automating them. We intend to reduce the complex manual operations by operators in the field, thus stabilizing operations, using materials more effectively, and saving energy.

We will continue tackling these challenges and achieve a new plant control.

(i) This project "Development of Production Optimization Technology with Advanced EMS" was adopted by the New Energy and Industrial Technology Development Organization (NEDO) for its project, "2017 Strategic Innovation Program for Energy Conservation Technologies."

(ii) In this NEDO project, "Development of AI-based Process Data Analysis Support System" was commissioned to NTT Communications Corporation.

REFERENCES

(1) Ken-ichiro Wada, Hiroyuki Miyamoto, et al., "Cooperative Process Optimization Using Plant Big Data," Yokogawa Technical Report English Edition, Vol. 62, No. 1, 2019, pp. 23-26