Modeling and Control Technologies for Improving Product on Efficiency and Quality

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ABSTRACT

Requests for quality and safety in automation systems have recently intensified more than ever. Using advanced modeling and control technologies, these are actively worked to overcome the challenges in Fuji Electric. A multivariate statistical process control and quality simulation package which is able to diagnose anomalies in a manufacturing process and estimate product quality, and a proprietary disturbance observer are being developed and installed in general-purpose PLCs used for model-based predictive control. These modeling technologies and products will contribute to the realization of more advanced manufacturing and process automation.

1. Introduction

The control technology for more advanced automation is not limited to the field of industrial applications, and is increasingly being used in consumer applications such as automobiles and household appliances. There are many various types of advanced control technology, including two-degree-of-freedom PID control, non-interference PID control, *H* infinity control, fuzzy control, neural network control (neuro control), chaos technology, etc. Fuji Electric has previously utilized advanced control technology and modeling technology for load forecasting and river flow rate forecasting using neuro control, water purification chemical dose control using fuzzy control, fuzzy crane control and so on, in many products. Particularly in recent years, requests for product quality and safety have intensified. In response to such needs, multivariate statistical process control (MSPC) technology, which enables quality management that takes into account the correlation among multiple input variables, and model predictive control (MPC), which enables multivariable control that takes into account the constraints with a decoupling control system and provides excellent control stability, have been used in actual plants. Fuji Electric is actively engaged in MSPC technology and MPC technology on which modeling is based. To improve the efficiency of thin-film solar cells, MSPC has been applied to quality simulation technology and the results show an improved in efficiency. Also, to advance the application of MPC to the process control sector, which includes water treatments, iron and steel treatments and chemical processes, a disturbance observer function has been developed and incorporated into MPC. MPC has also been implemented with programmable logic controllers (PLCs) so that it can be used in control applications for medium and small-scale plants and equipment.

This paper describes Fuji Electric's efforts involving MSPC and MPC, as modeling control technology for advanced automation.

2. Efforts With Multivariate Statistical Process Control (MSPC)

2.1 Quality management that applies MSPC

In the manufacturing industry, as a higher level of quality control is sought, manufactured components and products are inspected to detect products that do not satisfy the required level of quality. However, by only judging whether the results of manufacturing are good or bad, the particular manufacturing process that causes the defect cannot be identified and consequently, product yield cannot be improved.

Therefore, in the manufacturing process, efforts to remove the cause of failure by detecting abnormalities early in the manufacturing process and then feeding back such information to the manufacturing site, and efforts to improve quality by the early detection of changes in product quality are being implemented. There are two main approaches.

(a) Fault diagnosis of the manufacturing process
(b) Product quality estimation using manufacturing process information

2.2 Fault diagnosis of the manufacturing process

The statistical process control (SPC) method is used for performing fault diagnoses of the manufacturing process. When performing a diagnosis, upper and lower limits that prescribe the range of normal operation for each process variable measured by the sensor

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are set, and if a process value exceeds these limits, an alarm is issued to notify the user of the fault.

With prior implementations of SPC, univariate SPC (USPC) was used to perform fault diagnoses based on whether the process value being monitored was within the upper and lower limits for each variable. However, if two variables are uncorrelated, for example, then even if each value is within the upper and lower limits, a fault would still possible, such as when the two variables deviate from a correlation relationship. In such cases, faults cannot be detected with USPC, and as shown in Fig. 1, a method for performing fault diagnosis that takes into account the multivariate correlation is needed. For this purpose, multivariate statistical process control (MSPC) is used.

Principal component analysis (PCA), one type of MSPC, summarizes information into an orthogonal principal component based on the correlation among multiple variables, and can be represented with a small number of variables. When PCA is applied to fault analysis, the two indices of Q and T^2 statistics are used.

Q statistics are computed as follows.

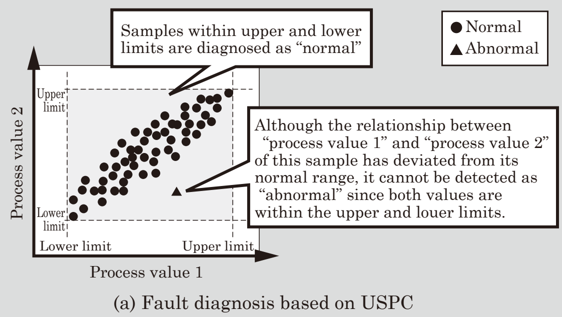
$$Q=\|x-\hat{x}\|^2=\sum_{n=1}^{N}(x_n-\hat{x}_n)^2 \quad \cdots\cdots (1)$$

Where, $\hat{x}$ is the estimated vector based on the PCA model of input variable x.

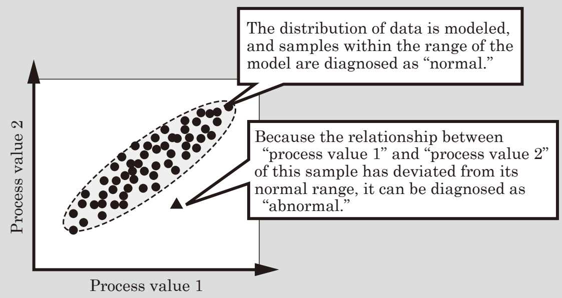
The Q statistic is an index for evaluating violations based on the correlation among variables for which model creation data existed, and faults can be detected by monitoring this index.

Also, each element of the Q statistics expresses the contribution of each input variable to the Q statistics,

Fig.1 Comparison of USPC and MSPC



(a) Fault diagnosis based on USPC



(b) Fault diagnosis base on MSPC

and the function that caused the detected fault can be identified from a contribution plot.

Next, T^2 statistics are computed below using principal component scores t_m.

$$T^2=\sum_{m=1}^{M}\frac{t_m{}^2}{\sigma_{t_m}{}^2} \quad \cdots\cdots (2)$$

Here, σ_m represents the standard deviation of the m^{th} principal component score.

In the principal component space obtained by compressing the original variables, the T^2 statistics correspond to the distance from the mean to each sample and express the degree of divergence from the mean within the range of the model (correlation). As a result, the correlation among variables is maintained. Since the divergence from the mean (amplitude) is large, "faults" can be detected.

2.3 Product quality estimation using manufacturing process information

In product quality estimation using manufacturing process information, a technique known as multivariate analysis, typified by multiple linear regression analysis, is used and based on the operating status of a manufacturing process, the manufacturing condition set points and the like, the correlation between the process status and the product quality is modeled, and the final product quality is estimated from the process status.

(1) Quality estimation based on a multilinear regression model

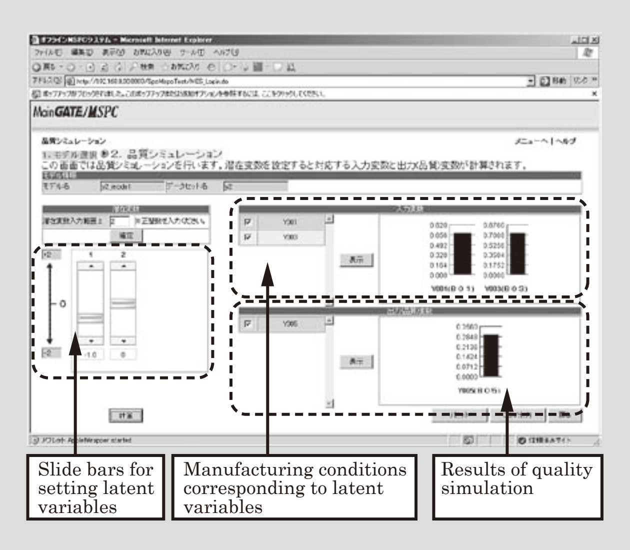
A multilinear regression model approximates an output variable (target variable) with the linear sum of input variables (explanatory variables), and is applicable not only for product quality estimation, but also for various types of predictions and diagnoses in many industrial fields, and has the advantage that the model formula is easy to understand intuitively.

With a multilinear regression model, if the data has multi-colinearity and the explanatory variables are correlated, the model will become numerically unstable and a stable model will be difficult to obtain. In order to create an appropriate model in such a case, correlated variables must be removed from the input variables. Previously, the typical procedure was to perform a preliminary analysis such as a correlation analysis and then choose the variables to be used in the multilinear regression model. Especially when there are many input variables, there is a strong tendency for the input variables to be correlated among themselves. But the increase of combinations of mutually correlated input variables which could be removed, are significant. This process is an extremely labor-intensive when performed manually.

(2) Quality estimation based on partial least squares

PLS (Partial Least Squares) is a modeling method developed in 1983 by Herman Wold and Svante Wold in the field of economics. In the case where correlation exists among the input variables, because these input

Fig.2 Example screenshot of quality simulation



variables are summarized into intermediate variables known as latent variables and are then used to express the output variables, this method has an advantage in that a stable model can be obtained even if there is multi-colinearity.

Moreover, with a PLS model, even in the case of many input variables, there is no need to choose input variables with a preliminary analysis as in the case of the multilinear regression model, and a model can be created simply using all variables directly. Consequently, the necessary effort to create a model can be reduced dramatically.

As shown below, the PLS model can express, as a regression equation, an output variable from an input variable via a latent variable.

$$t=(W^T P_C)^{-1} W^T x \quad (3)$$

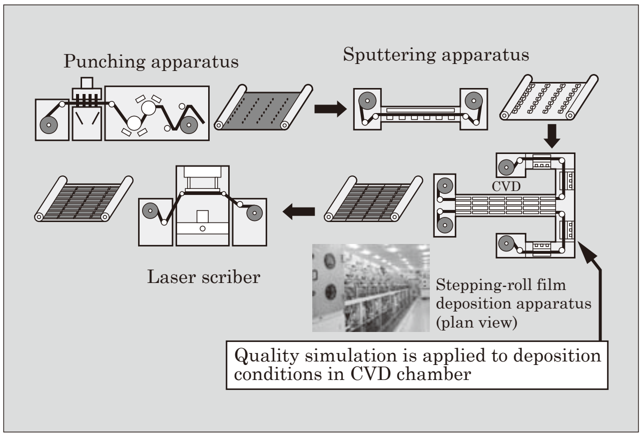
$$\hat{y}=Q_C t=Q_C (W^T P_C)^{-1} W^T x \quad (4)$$

Where, x is an input variable, t is a latent variable and $\hat{y}$ is the estimated value of the output variable, all of which are column vectors for one sample, and W is a weight matrix. P_C and Q_C are coefficient matrices relating to input variables and output variables. The dimension of vector t corresponds to the number of latent variables. Equation (4) directly expresses the output variable from the input variable x, and is equivalent to the multilinear regression model. By converting the PLS model into the form of a multilinear regression model, regression coefficients can be obtained. Accordingly, even in cases where there are many input variables and the construction of a direct multilinear regression model would be difficult, once the PLS model has been constructed, multiple regression coefficients can be obtained as described above.

(3) Quality simulation using the PLS model

A function has been developed for simulating with the PLS model how the output (quality) variable y changes in response to changes in the input (process) variable x. With a conventional multilinear regression model, in the case where mutual correlation exists among the input variables, the implementation of settings without consideration of the correlation among input variables would result in unrealistic combinations of input variables.

Fig.3 Manufacturing processes of thin-film solar cells



Therefore, the user sets the latent variable t, which is a variable that has summarized correlated input variables, and the estimated value of the input variable $\hat{x}$ and the estimated value of the output variable $\hat{y}$ are computed from the corresponding PLS model so that simulations can be carried out with the correlation among input variables maintained. Figure 2 shows an example screenshot of a quality simulation which has been developed as a package that runs on Windows*1. The user is able to freely and easily run simulations to determine how quality will change when manufacturing conditions are changed while comparing the results with their physical knowledge of manufacturing processes.

2.4 Quality simulation example of solar cell deposition process

An example quality simulation of the deposition process for Fuji Electric's thin-film solar cells shown in Fig. 3 is described below, wherein the relationship between manufacturing condition parameters and product quality is modeled with the PLS method and the manufacturing conditions are changed in order to improve product quality.

As manufacturing conditions in the deposition process, there are approximately 10 types of parameters, such as temperature, pressure, deposition time, deposition rate, thickness and doping rate, and the entire process has about 100 parameters. These parameters are mutually correlated, and changes in the manufacturing conditions must be carried out while maintaining the correlations. Product quality is evaluated according to the conversion efficiency of the cell.

A manufacturing experiment was conducted by

*1: Windows is a registered trademark of Microsoft Corporation in the United States and/or other countries.

changing the condition values gradually in consideration of the correlation for 30 parameters that have a strong effect on quality, among the approximately 100 parameters. Using data of 115 samples, a PLS model was created with the 30 condition parameters as input parameters and the efficiency value as the output parameter.

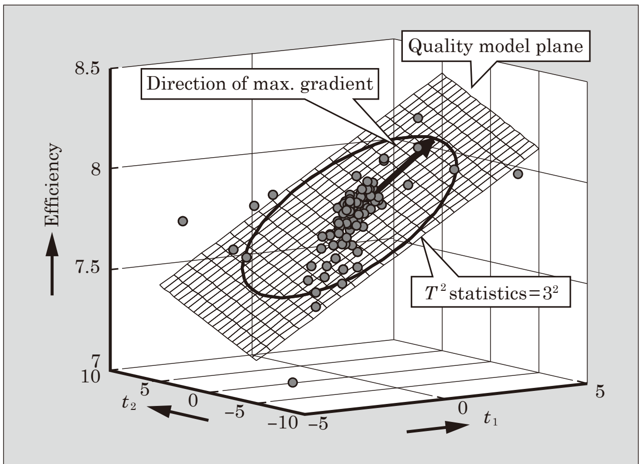
Figure 4 shows the distribution of efficiency values for two main latent variables. In the figure, the flat plane (quality model plane) represents the PLS model, and the distribution of actual data shown by points is approximated with this model.

Here, it is desirable for the efficiency to be as high as possible, and the efficiency can be increased by changing the parameters in the direction in which the slope of the plane is steepest (highest gradient direction). This is the "recommended direction" for change in the latent variable space.

In this case, the recommended direction is expressed as the direction of change of two latent variables (t_1, t_2), and as the range determined to be "normal" in the latent variable space (the t_1–t_2 plane), the T^2 statistic is constrained inside a 3^2 (corresponding to 3 times the standard deviation) circle so that conditions can be determined realistically within an appropriate range. Also, this can be converted to the direction of change of the original condition parameters. At this time, because the change maintains the correlation among the original parameters, the direction of change will be realistic and reasonable.

To obtain the best manufacturing conditions, in cases where a PLS model is not used, the changing of even 30 parameters by 3 levels each, for example, would require 3^{30} experiments which is impractical. Experimental points are determined by trial and error or empirically. In cases where a PLS model is used, optimal conditions are obtained by conducting searches on the quality model plane. Therefore experimental points can be determined efficiently.

Fig.4 The example of quality simulation using PLS model



3. Efforts with Model Predictive Control (MPC)

MPC is a control algorithm that is effective for multivariable systems having interference, for which sufficient control performance would be difficult to realize with PID control, and for control that involves long dead times. MPC has been utilized frequently in applications for the process control field, such as petrochemical plants, iron and steel processes, air conditioning and so on. Fuji Electric has used MPC in such applications as flocculation process control, rubber polymerization plants, energy plants and the like. So that MPC may be used in even more fields in the future, a disturbance observer is used to enhance the disturbance suppression performance and enable better control performance. Also, to improve the system performance, Fuji Electric has pioneered a real-time MPC computing unit (MPC execution engine) with a general-purpose PLC.

3.1 New method of MPC with disturbance observer

MPC enables much greater control precision than PID or the like since constraints and the convergence to a target trajectory can be taken into account when making long-term predictions. However, in cases of modeling error, occurring due to an unknown disturbance or nonlinearity not contained in a measured value, the actual performance will deviate from the prediction and the control performance will deteriorate as a result. Especially with MPC based on a step response model, a significant deterioration in performance is noted when a ramp-like disturbance occurs(1). The particular weakness to ramp-like disturbances is attributable to the MPC method of correcting prediction errors and is a fundamental problem.

To address this problem, three main approaches have been adopted in the past, namely, a method for modifying the model itself into a nonlinear model or state-space model (Method A)(1)(2), a method for including disturbance response characteristics in the model (Method B)(2), and a method for incorporating principles of robust control (Method C)(2). The advantages and disadvantages of these approaches are listed in Table 1. In all these methods, the difficulty in simultaneously addressing a modeling error and an unknown disturbance, and the increase in computational cost

Table 1 Comparison of methods to improve the disturbance characteristic

	Method A	Method B	Method C	How to evaluate
Modeling error	Fair	Poor	Good	Robustness with respect to modeling error
Unknown disturbance	Poor	Fair	Fair	Stability when unknown disturbance occurs
Computational time	Fair	Good	Poor	Computational time for implementation

are disadvantages.

In order to improve disturbance rejection performance, Fuji Electric developed a method that incorporates the concept of a disturbance observer, which has been used successfully in motor control applications and the like. Figure 5 shows a block diagram of the MPC with disturbance observer and an explanation of its operation.

Based on the computations of the block diagram, the reduction in prediction error due to an unknown disturbance d, when compared before and after introduction of the disturbance observer is as follows[(3)].

$$\|(I+P_n(j\omega)L)^{-1}P_n(j\omega)\| \leq \gamma \|P_n(j\omega)\| \quad (5)$$

I : identity matrix

$P_n(s)$: nominal plane model

L : observer gain

γ : performance index of disturbance rejection

The transfer function of a ramp-like disturbance ($1/s^2$) has infinite gain at zero frequency and converges to zero at high frequencies. To suppress this type of disturbance, conditions can be devised and established in the vicinity of zero frequency.

$$\|(I+P_n(0)L)^{-1}P_n(0)\| \leq \gamma \|P_n(0)\| \quad (6)$$

The solution L of inequality (6) can be obtained via a singular value decomposition of $P_n(0)$ as an explicit function of γ[(3)].

Meanwhile, according to the final value theorem,

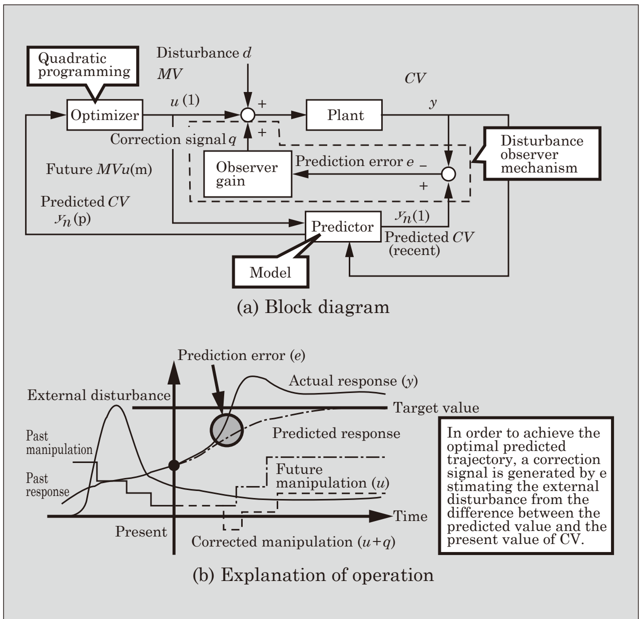
$$\begin{aligned}\lim_{t\to\infty}(P_n * U_i)(t) &= \lim_{s\to 0} s\,(P_n(s)U_i(s)) \\ &= \lim_{s\to 0} s\left(P_n(s)\frac{1}{s}e_i\right) = P_n(0)e_i\end{aligned} \quad (7)$$

holds.

e_i : i^{th} unit vector

$U_i(s)$: unit step function comprised of only the i^{th} element

Fig.5 MPC with disturbance observer



$P_n(0)$: matrix of collected convergence values of each element from step responses in a plant

Thus, based on the step response model, this method can be applied to MPC.

Figure 6 shows simulation results comparing the ability to maintain steady-state levels with MPC when a ramp-like disturbance is imposed on a Wood-Berry model[(4)], which is a benchmark problem in the process control field. The application of a disturbance observer enables a 75% reduction in the fluctuation of the value of internal variable CV.

The fluctuation of gain at manipulation inputs is considered to be equivalent to an input disturbance. For example, imposing a disturbance that is the same as that of the manipulated variable has the same result as doubling the gain. In order to reduce the sensitivity of prediction error to an input disturbance, model error for this type of manipulation input gain can be absorbed with this method. Moreover, this method can be realized with the observer computation only, and therefore the computational load is small. Accordingly, in the comparison of the three methods shown in Table 1, this method is superior in three aspects: modeling error, unknown disturbance and computational time.

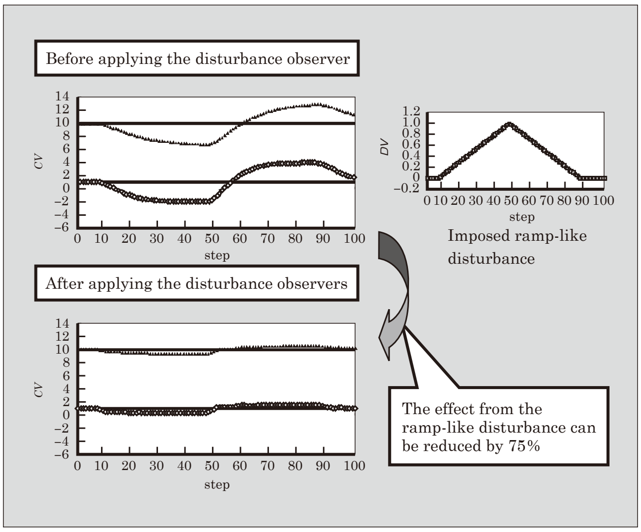
Also, methods for adjusting gain to ensure MV constraints of model predictive control have been investigated[(3)].

By applying this technology, an MPC function strongly resistant to disturbances can be provided to plants where high-level reliability is required for long-term continuous operation.

3.2 MPC system implementation using a general-purpose PLCs

MPC has been successfully utilized for many relatively large-scale processes involving more than 100 control variables, such as petrochemical plants and iron/steel processes. On the other hand, in small-scale

Fig.6 Simulation of the effect of the disturbance observer



processes and equipment having fewer control variables, controlling the variables simultaneously with MPC is also expected to achieve successful results such as stable operation and improved control performance. However, due to such constraints as reliability, installation cost and the like, MPC has only been utilized in certain processes. Consequently, Fuji Electric has realized an MPC system that uses a general-purpose PLC so that users can easily implement MPC for control objects having a modest number of inputs and outputs.

The system configuration is shown in Fig. 7. This system is configured with the MPC execution engine located in a PLC, and support tools such as for MPC tuning and internal modeling located in a PC. Features of the developed system are described below.

(1) Realization of high reliability with PLC

An MPC module contains the MPC execution engine and is constructed as an embedded application on Fuji Electric's PLC, the MICREX-SX. Consequently, the reliability of a device having PLC can be enjoyed. For control applications requiring high reliability, MPC modules can be mounted on a duplex system and an environmentally-resistant CPU may be used.

Usually, the MPC module and another module that executes a different control program are both mounted (in a multi-CPU configuration) on the same baseboard. However, the system may be configured with only the MPC module by itself, and for example, a MPC module may be installed as an add-on system to existing equipment.

(2) Realization of high-speed with MPC with constraints

MPC control rules implement the same functions as those implemented with PC software, and for example, constraints for controlled variables and manipulated variables are embedded directly. Also, as described above, the MPC execution engine operates with a single CPU, and therefore does not affect the execution of other applications. With an MPC having 4 inputs (manipulated variables) and 6 outputs (controlled variables), execution can be implemented with a minimum control period of 5 seconds.

(3) Improved convenience and ease of maintenance

When embedding MPC into a system, the MPC operating conditions, transfer conditions, stabilization processing when transferring, I/O processing such as filtering of controlled variables, and MPC peripheral functions such as fault processing must also be embedded. Previously, this engineering work had to be performed separately for the MPC tools running on a PC and for the control system on PLC or others. With this system, the MPC execution engine is provided as a function block (FB) of the "D300Win" design support tool for the MICREX-SX. The user can centrally configure and manage an MPC application, including the abovementioned peripheral processes, as the same software program and with the same tools as a PLC plant control program. A user familiar with MPC is able to utilize MPC as if it were PID control. Since

Fig.7 MPC system configuration using MICREX-SX

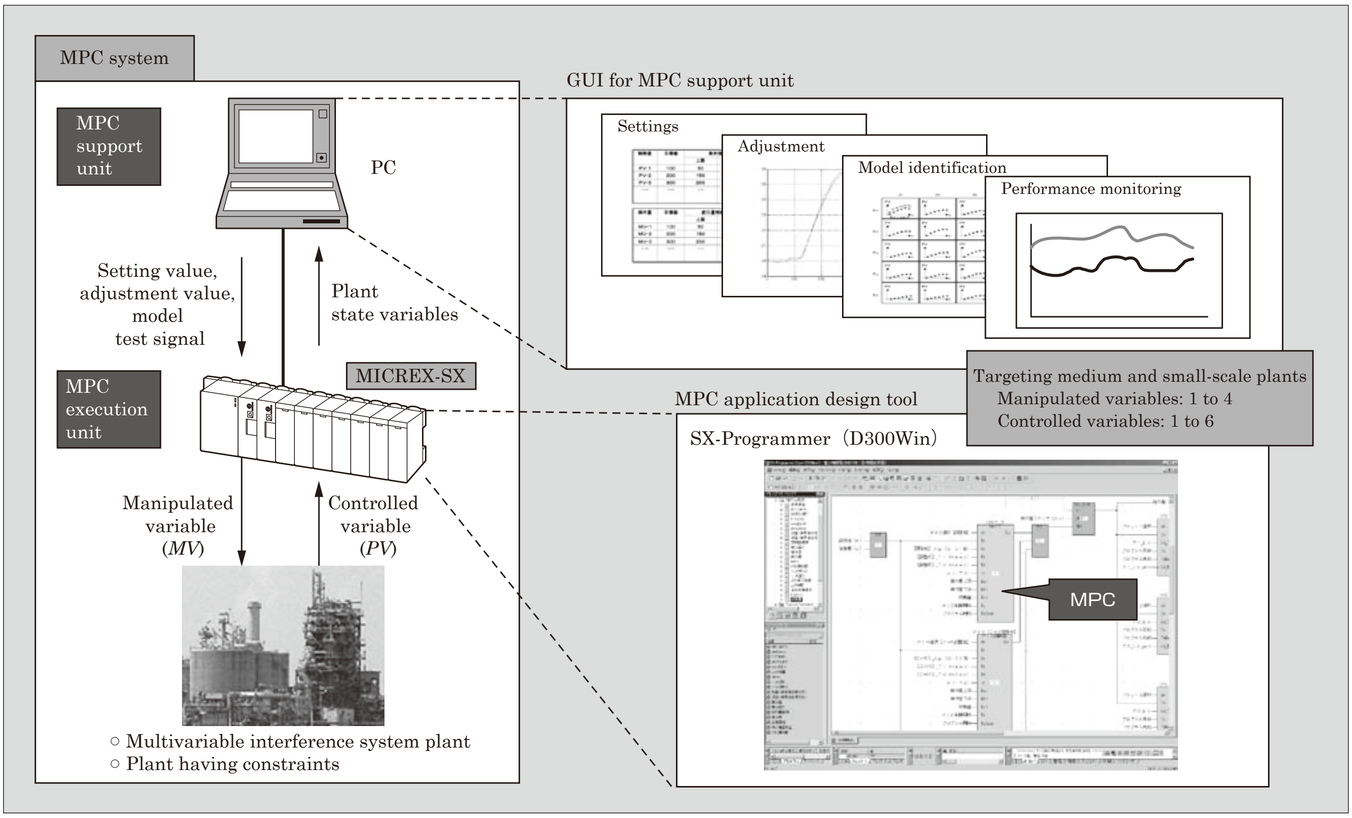
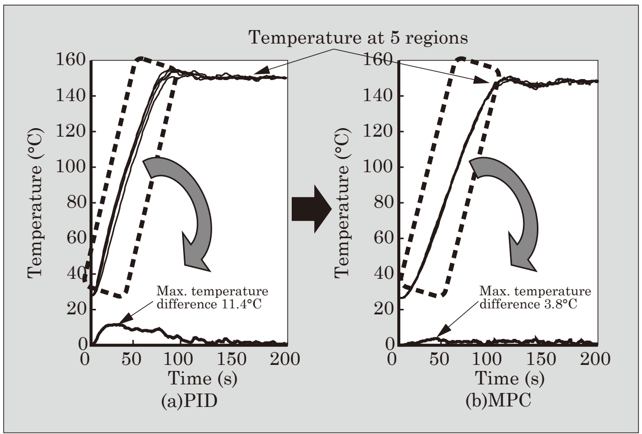


Fig.8 Results of application of MPC to glass substrate synchronous heating



the MPC module is embedded in the control panel that houses the PLC, the user will not be inconvenienced with respect to installation efficiency.

3.3 Application example of MPC to manufacturing process

MPC was applied to the heat treatment of glass substrates which are a basic unit in the manufacture of flat panel displays (FPDs). In the manufacturing process, the glass substrates must be heat-treated with an annealing process or the like. To prevent cracks and display unevenness, while being heated, the entire surface to be processed must be controlled to a uniform temperature (synchronous heating). Previously, for this process, a glass substrate was subdivided into multiple regions, and for each region, PID control having the controlled variables for the temperature and the heater as its inputs and outputs was used to implement multi-point synchronous heating. Using MPC to perform synchronous heating, we investigated whether the temperature difference between the region having the highest temperature and the region having the lowest temperature, i.e. the maximum temperature difference, would decrease. Figure 8 shows the results of a comparison of the maximum temperature difference when using PID and MPC. By using MPC, the maximum temperature difference in the heating process was found to be 3.8 °C which is significantly lower than the value of 11.4 °C when PID control was used.

4. Postscript

This paper has discussed MSPC and MPC as control technology for the advancement of automation. The application of MSPC to quality simulation technology for making thin-film solar cells more efficient has been described. For MPC, Fuji Electric's proprietary disturbance observer function, the implementation of MPC functions with a PLC, and application examples have been introduced.

Fuji Electric's future plans regarding MSPC are to embed the newly developed engine into various packages and to expand the range of applications mainly in the industrial field. Fuji Electric will actively pursue applications of MPC to medium and small control systems in addition to applications to control systems for large-scale energy plants such as petrochemical and iron and steel plants.

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