# Plant model automatic update technology using parameter probability distribution

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Identification of changes in control characteristics, system identification, probability distribution, optimization, $CO_2$ reduction, SORTiA™

Azbil is working to reduce $CO_2$ emissions through control and optimization, and its SORTiA™ advanced control solution plays a part in this effort. Advanced control uses models that represent plant characteristics; however, if these characteristics change significantly for some reason and the models remain unchanged, the performance of control and optimization may deteriorate due to the resulting differences. To solve this problem, we have developed a technology to automatically estimate and update the model of a plant in operation. The developed technology estimates the probability distribution of the model parameters from the data of the plant in operation and automatically determines whether or not the model needs to be updated based on that distribution. This technology does not require any special operations on the plant and is characterized by the ease of maintaining the model.

## 1. Introduction

With the aim of helping to achieve a decarbonized society, Azbil works to reduce $CO_2$ at customer sites. There are a wide range of methods to reduce $CO_2$, and one of these methods is energy optimization. Azbil offers a solution for more advanced control called SORTiA [1], a solution that brings together all of the knowledge and control technology that we have accumulated through our onsite experience. SORTiA-MPC (Model Predictive Control) multi-variable model predictive control, which is found at the core of SORTiA, has been introduced at oil refining plants and other such manufacturing plants as well as in power units in a range of industries, and contributes to $CO_2$ reduction through energy saving based on control and optimization.

While the introduction of advanced control has a major effect in terms of $CO_2$ reduction and operational load reduction, the construction and maintenance of a model are issues that still need to be addressed. What "model" refers to here is mathematical expressions of the simplified behavior of a plant that forms the subject for control and optimization. The performance of advanced control depends largely on the model, and to produce value, the model needs to be able to represent the main aspects of a plant's behavior. The construction of a model upon introduction of advanced control with the requisite precision for control and optimization, and the subsequent maintenance of the model, are important aspects in the application of advanced control.

This post-introduction maintenance of the model presents a challenge caused by factors such as the potential change in plant characteristics due to the accumulation of changes to the plant over time as well as the repair and modification of equipment. To the degree that the characteristics of the plant change, the error in the model (that is to say, the difference with the plant) becomes larger. If the error is small, advanced control such as SORTiA-MPC is capable of suppressing the impact through feedback control. Therefore, small errors in a model never lead directly to a major deterioration in control performance. However, if the characteristics of a plant change significantly and the error in the model becomes increasingly large, then this can have an impact on performance. In such cases, it is considered desirable for the model to track the changes in the plant in order to maintain the effect of advanced control. This forms the background to why the technology to update plant models is required.

Azbil is developing technology to automatically estimate and update models using data from operating plants. While quantitatively a wealth of operational data is available, there is only a limited subset of it that can be used to estimate a model, and so it is necessary to identify and select this data. However, identifying and selecting this data takes a lot of time and effort, even for experts. As such, we have developed a new technique for automatically estimating and updating a model by identifying and selecting data based on the estimated probability distributions of the parameters in the mathematical expressions representing the model. In this paper, we will explain this technology.

## 2. Challenges in achieving automatic update of models

This section discusses plant models and their automatic updating, and explains the challenges that must be addressed to achieve this.

### 2.1 Plant models and the need for their updating

The plant model used here is a mathematical model in which a mathematical expression represents the behavior of output when an input is provided to the plant. That is to say, it represents an input-output relationship (fig. 1). Since plants in which advanced control is to be used have dynamic characteristics, their models also use things capable of expressing such dynamic characteristics, such as transfer functions, state-space representations, or differential equations. SORTiA-MPC employs transfer functions.

When provided with an input, the model simulates the plant's behavior using mathematical expressions and produces an output that closely matches that of the actual plant. Using this, it is possible to predict the output of the plant. It is also possible to calculate the required input to achieve a desired output. This enables control and optimization.

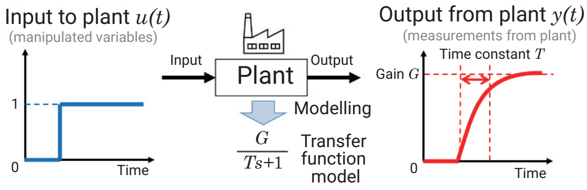


Fig. 1. Plant model

Control and optimization that use a model will be impacted by any changes in plant characteristics. If the change is small, the impact will be absorbed by the control and optimization to some extent, and so will not cause much of a problem. On the other hand, if the change is large, then the model will become unable to simulate the plant with the requisite precision and the control and optimization will no longer be able to perform the way they are supposed to. In order to avoid this, it is necessary to adapt the model to the plant in the event that the characteristics change greatly, and reduce the difference between the model and the plant to an inconsequential level. The purpose of updating a model is to maintain the effectiveness of advanced control by taking this action.

### 2.2 The goal of updating a model based on data from an operational plant

We aimed to realize a technique for updating a model using data from a plant in normal operation.

Estimating a plant model is actually made easier by adding perturbation for test purposes to the input of a plant. As such, in model construction when advanced control is to be introduced, it is common to provide test input to a plant in order to create an operational state that differs from normal. However, in addition to the fact that this method only allows estimating when perturbation for test purposes is added, it is also necessary to take into account the impact of perturbation for test purposes on operations, so it was our opinion that it was not suitable to apply this method directly to model updating. As such, in this development project, we decided to aim for a model update technique that does not require special operations that differ from normal.

Control data from a plant in normal operation is easy to obtain, so if a model of the plant can be estimated from this data, it is considered that such a technique would be easy to apply to a wide range of subjects and circumstances.

### 2.3 Challenges in model estimation based on data from an operational plant

This section explains the difficulty of model estimation based on data from a plant under normal operation, and the technical challenges that must be resolved.

Estimating the mathematical expression model of a plant from plant data means estimating the mathematical expressions that represent the relationship between plant input and output. As such, input/output data must fulfill the conditions below.

A) Input must have sufficient fluctuation
B) The output must clearly represent changes according to fluctuations in input, and the impact of disturbance must be small

In order to calculate the function that expresses the input-output relationship from data, input must fluctuate instead of being constant. Also, it is not possible to estimate a model to the requisite precision from data in which the input-output relationship has become unclear due to the impact of disturbance.

The conditions above give a suggestion of the difficulty of estimating a model during the course of normal operations. Plants where advanced control is properly implemented and carried out have stable input and output with only small fluctuations, and thus do not meet condition A. Plants are also subject to disturbance from a range of sources, and if the impact is large then condition B is not met. While active manipulation of input is possible with a technique for adding perturbation for test purposes, the method we are aiming for must passively wait for a state in which the operational data meets the above conditions. This is what makes it difficult to estimate a model during normal operations.

On the other hand, when we observed actual operating data, we noticed that there were some segments where input changes due to factors such as changes in upper and lower limit settings, and the impact of disturbance was small. We thought that seizing precious opportunities such as this and estimating a plant model would make the automatic updating of models we were aiming for possible. In other words, the challenge that needs to be overcome is to automatically identify and select segments that fulfill the aforementioned conditions in operating data and remove segments that are not suitable for model estimation.

## 3. The approach of the proposed technique and procedural overview

This section explains the approach of the proposed technique [2] and provides a procedural overview. While the key to the proposed technique is the automatic identification and selection of data segments suitable for use in estimation, in order to achieve this, the proposed technique estimates and uses the probability distribution of parameters for a model.

Probability distribution of parameters refers to the representation as a function of the probability that a parameter will take a certain value (fig. 2). Probability distribution of parameters has thus far been used to assess the reliability of estimated values in the form of confidence intervals. In the proposed technique, this is used in the identification and selection of segments. If the probability distribution of the estimated parameters in a certain segment is concentrated in a narrow range, the parameters are considered to have low uncertainty and high reliability in that segment, and the segment is judged to be suitable for model estimation (solid line in fig. 2). Conversely, if the distribution is over a wide range, it is determined that this segment is unsuitable for use in model estimation (dashed line in fig. 2). Thus, the greatest feature of the proposed technique is that it identifies and selects segments suitable for model estimation by using the probability distribution of parameters and updates the model.

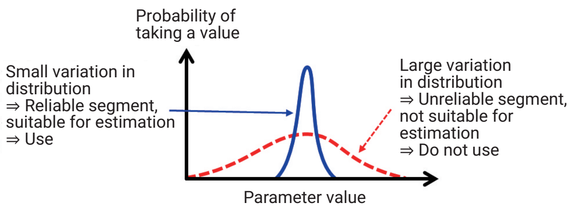


Fig. 2. Parameter probability distribution and segments suitable for estimating models

We will first describe the problem setting of the proposed technique in 3.1, and then explain the procedure of the technique in 3.2.

### 3.1 Problem setting

We shall assume that a model for a plant already exists, and that the initial value of the model's parameters can be obtained. As mentioned in Section 1, a model of a plant is normally constructed upon the introduction of advanced control, and so this shall be used. We shall also assume that changes in a plant can be expressed through changes in model parameters. This assumes that the order and structure of the model remain unchanged. This assumption can be considered valid if changes in a plant are caused by an accumulation of changes over time, equipment repairs, and changes to operational conditions. On the other hand, it cannot be considered to be applicable in cases of significant modification where the structure of a plant changes.

Based on these assumptions, input/output data is collected from a plant periodically, and the proposed technique is implemented.

### 3.2 Procedural overview of the proposed technique

The proposed technique divides the input/output data into segments, estimates the probability distribution of the model parameters within each segment, and updates the model when the following three conditions are fulfilled.

A)The probability distribution of parameters is narrow, and the segment used for estimation is suitable for model estimation.

B)The estimated output obtained from the newly estimated model tracks the plant output more accurately than the estimated values from the currently used model.

C)The parameters in the newly estimated model do not greatly deviate from the probability distribution obtained thus far.

The steps in the procedure for the proposed technique are set out below (fig. 3). First divide the collected time-series input/output data into segments of the same length (divided into three segments in fig. 3).

1.Using the data in the segments created, estimate the probability distribution for the plant model parameters in each segment (see Section 4 for the probability distribution estimation method).

2.Calculate the variance of probability distribution for each segment, and determine that a segment equal to or lower than the threshold value fulfills condition A, then move on to the next step. Do not use any segments that are greater than the threshold value.
- Segment 1 has a large probability distribution variance due to the impact of disturbance, so it is not used
- Segment 2 has only a small input fluctuation, so it is not used
- Segment 3 has a clear fluctuation that shows the cause and effect relationship between input and output, while the impact from disturbance is also small and variance is low, so it is used for estimation

3.Generate a model with the weighted average of the parameter probability distribution as the estimated value (here, a model is generated from the probability distribution estimated within Segment 3).

4.Provide input data to both the model currently used for control and the estimated model generated in step 3, implement a simulation for each model, and obtain a time-series of the predicted output values. Then calculate the error with the corresponding measured output from the actual plant.

5.Compare the errors of both models calculated in step 4, and if the error is smaller in the estimated model then determine that condition B is fulfilled and move on to the next step.
- In figure 3, the estimated model closely tracks the measured value and the error is small, so it can be determined that condition B is fulfilled.

6.Compare the estimated values from the model with past estimated probability distribution, and if they do not deviate greatly then determine that condition C is fulfilled. If conditions A through C are all fulfilled, then update the model.

## 4. Method for estimation of model parameter probability distribution

In order to realize the proposed technique, it is necessary to estimate the probability distribution for parameters in a dynamic model. This section explains the method for estimating the probability distribution of parameters. The content of this section is a detailed explanation of step 1 in Section 3.

The proposed technique uses Bayesian estimation as the technique to estimate the probability distribution for parameters in a model. Analytically estimating the probability distribution of parameters in a dynamic model is generally difficult for the following reasons.

(1)Information at a given time point is impacted by past information up to that point, meaning direct calculation is difficult.

(2)Information from all time points must be considered in order to obtain an overall view of behavior, and the calculation of this is complex in many cases.

Given that this makes it difficult to directly calculate the probability distribution of parameters, the proposed technique uses a technique called Markov Chain Monte Carlo (MCMC) for probability distribution estimation. MCMC

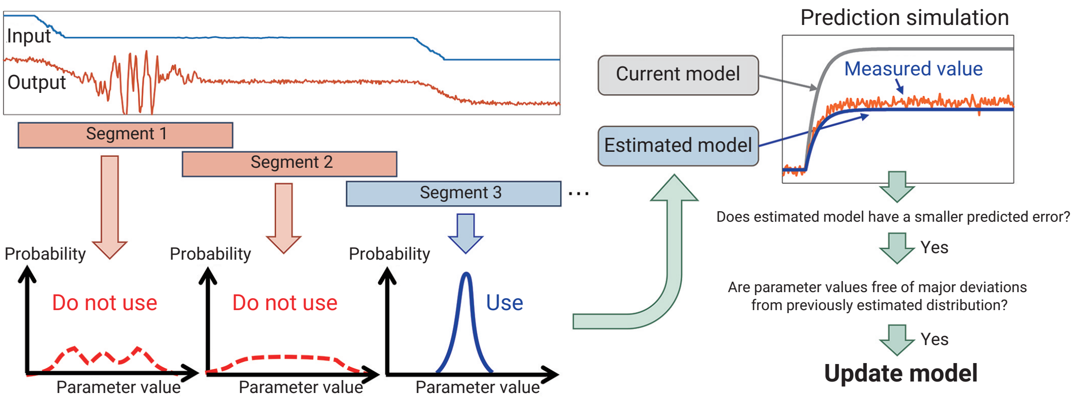


Fig. 3. Overview of procedure in the proposed technique

is a method that approximates the target distribution by generating a large number of samples using random numbers and performing statistical analysis.

The structure of this section is as set out below. 4.1 describes discrete-time state-space representation, while 4.2 describes procedure for estimating the probability distribution for parameters in a model. 4.3 explains the background to this probability distribution estimation technique.

### 4.1 Discrete-time state-space representation of the model structure

In SORTiA, models are represented with a continuous-time transfer function. However, this probability distribution estimation technique uses a parameter estimation technique based on discrete-time state-space representation. As such, it is necessary to convert continuous-time transfer functions to a discrete-time state-space representation. Here we will examine the conversion method.

This report covers systems that have a single output for a single input. As an example, consider a system represented by the following first-order lag transfer function with a time delay. Here, $G$ is gain, $T$ is the time constant, $t_d$ is the time delay, and $U(s)$ and $Y(s)$ are the Laplace transforms of the input $u(t)$ and the output $y(t)$, respectively.

$$Y(s)=\frac{G}{Ts+1}e^{-t_d s}U(s) \qquad \text{Eq. (1)}$$

By applying the inverse Laplace transformation to the above equation and using the backward difference approximation with a sampling cycle $\Delta_t$, the following discrete-time state-space representation is obtained. Here, system noise $v(t)$ and observation noise $w(t)$ are taken into account.

$$x(t)=Ax(t-1)+Bu(t-t_d)+Hv(t)$$

$$y(t)=Cx(t)+w(t) \qquad \text{Eq. (3)}$$

$$A=\frac{T}{T+\Delta_t},B=\frac{G\Delta_t}{T+\Delta_t},C=1,H=\frac{\Delta_t}{T+\Delta_t} \qquad \text{Eq. (4)}$$

Here, the average of $v(t)$ and $w(t)$ is 0, and the variance for each is assumed to be a random number that follows the normal distribution $\alpha^2$ and $\beta^2$. The parameters to be estimated are gain $G$, time constant $T$, and $\alpha$ and $\beta$. Henceforth, these parameters are collectively referred to as $\theta$. $x$ is referred to as the internal state.

The explanation in this report is only for systems that have a single output for a single input, but the same conversion is also possible for multi-variable systems.

### 4.2 Procedure for estimation of parameter probability distribution

The proposed probability distribution estimation technique for parameters in a model uses the same approach as a the SMC$^2$ technique for its parameter estimation method based on discrete-time state-space representation. SMC$^2$ is a technique that uses a particle filter (PF) on the subject of state-space representation and simultaneously performs sequential estimation on parameter $\theta$ and internal state $x$ [3]. A PF is a method for estimating probability distributions using samples called particles, and it is a type of Sequential Monte Carlo (SMC) method. Here, each particle's position corresponds to a random variable of the probability distribution being estimated. These particles have weights, and by using many particles, the probability distribution can be approximated by their positions and weights. A PF is an algorithm that estimates the desired probability distribution by sequentially updating the positions and weights of these particles based on observed values [4].

In this technique, a Kalman Filter (KF) [5] is used to estimate the internal state $x$. SMC$^2$ and MCMC that are used within this technique will be explained in 4.3.

The steps in the procedure for this technique are shown in sequence (fig. 4). As an example, in figure 4, a uniform distribution is set as the prior distribution for the parameter $\theta$. Note that the following procedure is applied to one segment of the divided time-series input/output data.

1. Set the prior distribution of the parameter $\theta$ based on prior knowledge.
   - For example, set a uniform distribution centered on the current parameter values used for control.
2. Generate an initial set of particles using random numbers based on the prior distribution. Assign an initial weight to each particle.
3. Repeat the following steps once for each pair of input and output values at a given time as an iterative process.
4. If the positions or weights of the particles are biased toward a limited area, perform resampling.
5. Update the positions of the particles using random numbers.

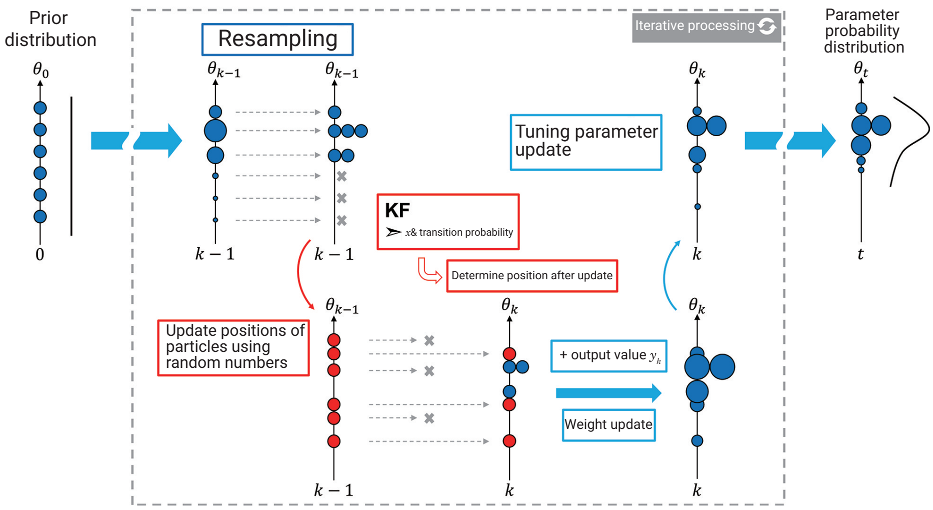

Fig. 4. Conceptual diagram of parameter probability distribution estimation

- The extent of the update is determined by tuning parameters.

6. Estimate the internal state $x$ of each particle using KF.
   - The particle's position and the value of the parameter θ in the state-space representation have a 1-to-1 correspondence.
   - Using the corresponding parameter θ value, estimate the internal state $x$ under these conditions.
7. Calculate the transition probabilities of the particle positions and determine the positions of the particles after the update.
   - Use the internal state $x$ of each particle to calculate the transition probability of each position. The transition probability is the probability that a particle changes from one state to another.
   - Particles with high probability move to new positions, and others remain in their original positions.
8. Update the weights of the particles based on the observed output.
   - Predict the output $y$ from the estimated internal state $x$ and calculate the error between the predicted value and the actual observed value.
   - Particles with small errors increase in weight, and those with large errors decrease in weight.
9. Update the tuning parameters in step 5 using the weighted particles.
   - If the positions and weights of the particles are concentrated, adjust so that the extent of the update is reduced.

By repeating the above steps until the final time of the segment, the positions and weights of the particles asymptotically approach the probability distribution of the parameters. As a result, the probability distribution of the model parameters can be estimated.

Figure 5 shows a heat map illustrating the transition of the weighted particles of the gain, one of the parameters in θ to be estimated, in a segment suitable for model estimation. The vertical axis represents the estimated value of the gain, and the horizontal axis represents the time within the segment. As time progresses, it can be observed that the particles converge from a dispersed distribution to a more concentrated and reliable probability distribution.

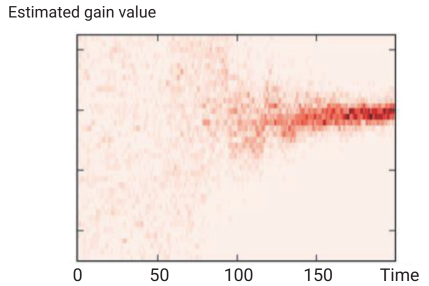


Fig. 5. Heat map of weighted particles

### 4.3 Background to the proposed technique for estimation of probability distribution

This part explains the algorithms used in each step of the parameter probability distribution estimation technique in the previous part.

First, we will explain the SMC² algorithm, which serves as a reference for this method. In step 6 of this method, a PF is used instead of a KF for estimating the internal state $x$. By using a PF, parameters can be estimated for a wider range of subjects. However, since SMC² uses a double PF structure, the computational cost is quite high and requires a significant amount of time for estimation.

Therefore, this technique aims to reduce computation time by using a KF for the estimation of the internal state $x$. Generally, it is difficult to directly replace a PF with a KF, but since the parameter θ is fixed to a certain value in this case, a KF can be applied to the discrete-time state-space representation described in 4.1.

Next, we will explain the MCMC algorithm used in each step.

In step 5, particle positions are updated randomly. In this step, the MCMC transition kernel m is used to update the particle positions. In this technique, the Metropolis-Hastings (MH) algorithm [3], which is a type of MCMC, is used as a design technique for the transition kernel m.

The transition probability calculated in step 7 is the MH ratio used in the MH method [3]. Using this MH ratio, a determination is made whether to accept the new sample that has transitioned or reject it and keep the current sample. With this operation, a sample that follow a distribution closer to the desired distribution is obtained.

In step 9, based on the distribution of weighted particles, the covariance matrix Σ of the Gaussian distribution and the number of transitions, which are the tuning parameters of the proposal kernel $\tilde{m}$, are updated. As the distribution of weighted particles becomes narrower, the transition distance of the particles becomes smaller, and through repeated transitions, the weighted particles converge into a highly reliable probability distribution.

## 5. Numerical simulation

This section demonstrates that the proposed technique can estimate a dynamic model from plant data during normal operation through a simulation assuming model updates for a plant controlled and optimized by model predictive control.

### 5.1 Simulation settings

The dynamic model that formed the subject was a first-order lag system with a single input and single output. A situation was assumed in which the gain $G$ differs between the plant and the model due to changes in the plant. The specific parameter values were set as shown in table 1.

Table 1. Parameter values

| | Plant | Model |
|---|---|---|
| Gain $G$ | −2.0 | −1.0 |
| Time constant $T$ | 20 | 20 |

A situation was simulated in which the input (manipulated variable) was adjusted as the target value changed in a plant controlled and optimized using SORTiA-MPC. The optimization objective was to minimize the input values. Initially, the output (controlled variable) was close to its upper limit due to optimization, but partway through, the upper limit of the output is changed as shown in table 2. The input was manipulated along with this, and it was hoped that this variation would enable the estimation of the model.

The input/output data obtained from this simulation is shown in figure 6. The horizontal axis represents elapsed time, and the vertical axis represents the variable values of input and output. The output and input values are shown as solid lines, and the upper limit of the output is shown as a dashed line. White noise with a mean of 0 and variance of 0.09 is constantly applied to the output. Additionally, to simulate a segment that is unsuitable for estimating a model due to the influence of large disturbances, white noise with a mean of 0 and variance of 1.0 was applied during the 2:30 - 5:00 segment. The control cycle is 1 minute.

Table 2. Output upper limit settings

| Time | From 0:00 | From 3:20 | From 7:30 |
|---|---|---|---|
| Upper limit | 48 | 50 | 54 |

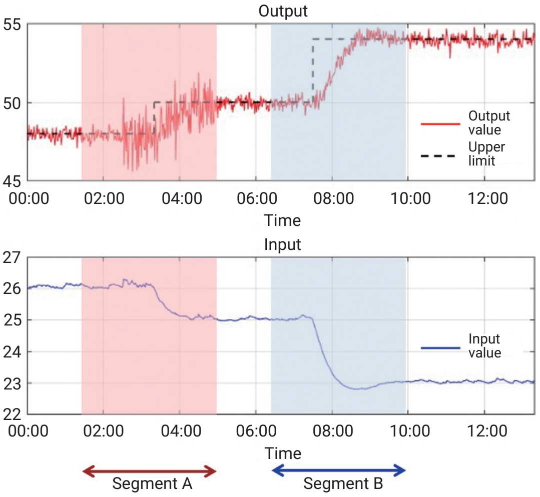


Fig. 6. Simulation input/output data

While the subject was controlled with model predictive control, prediction and control was performed with a model that has a smaller gain than the actual plant's gain, so the manipulated input was greater than the appropriate level. As such, an overshoot in the output value occurred around 9:00, and the output value temporarily violated the upper limit. However, SORTiA-MPC possesses robustness against model errors and can reduce the impact of errors through control, so the level of the violation remained low.

Note that in the settings of the proposed technique, the width of the divided segments was 200 minutes, and the gain $G$ and time constant $T$ were set as the subjects for estimation. The sampling cycle for data used in the estimation was 1 minute, which is the same as the control cycle.

### 5.2 Simulation results

Table 3 shows the results of estimation. Estimation was undertaken for the two segments of 01:40 to 05:00 (Segment A) and 06:34 to 09:54 (Segment B) (see fig. 6). Both segments include an input manipulation accompanying a change in the output upper limit. The probability distribution for the estimated gain and estimated time constant obtained from Segment A and Segment B are shown in figure 7 and figure 8, respectively.

Table 3. Results of estimation

| Estimation segment | Segment A<br>01:40 to 05:00 | Segment B<br>06:34 to 09:54 |
|---|---|---|
| Estimated gain | −2.10 | −2.03 |
| Estimated time constant | 15.2 | 20.6 |

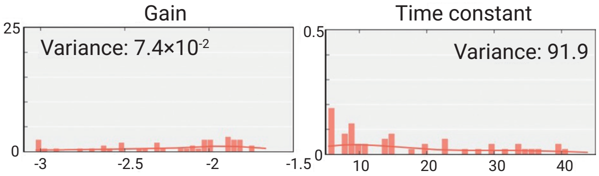


Fig. 7. Parameter probability distribution estimated within Segment A

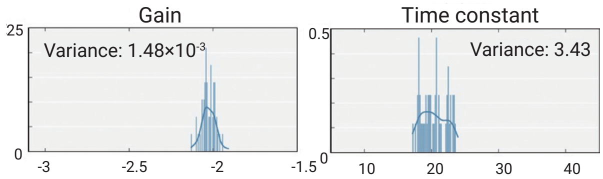


Fig. 8. Parameter probability distribution estimated within Segment B

In Segment A, the output contains a large disturbance and the change in output due to input manipulation is unclear, so the variance in the probability distribution of the parameters is large. In Segment B, on the other hand, the impact of the disturbance is small and the cause and effect relationship between input and output is clear, so the variance of the probability distribution is small. In other words, the estimated values obtained from Segment B are highly reliable, thus indicating that the segment is suitable for use in estimating a model. While we shall not set out the details here, a model using the estimated values obtained in Segment B also fulfills the remaining two conditions (conditions B and C) of the three conditions for updating a model set out in 3.2.

Next, the estimated values obtained in Segment B were set as parameters of the model, and the results of a simulation conducted with the same settings as table 2 are shown in figure 9.

Note that in this simulation, in order to make it easier to confirm the improvement in control performance achieved by updating the model, the large disturbance of variance 1.0 added upon estimation (fig. 6) in the segment from 2:30 to 5:00 was not applied.

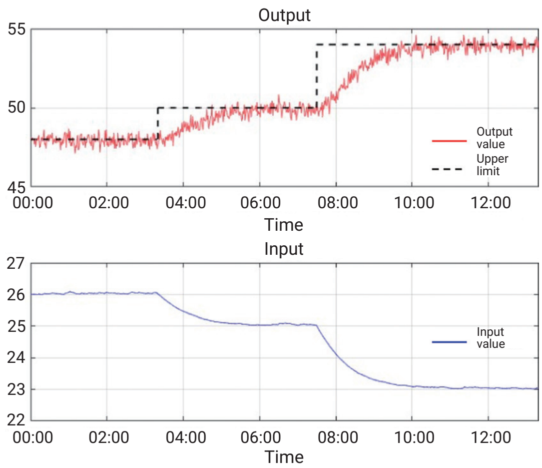


Fig. 9. Simulation using estimated parameters

This simulation shows that the output tracks the target value without overshooting and violating the upper limit when the gain of the model gets close to the value from the actual plant.

As such, the proposed technique enables the selection of segments suitable for estimating a model using data from a controlled and optimized plant in normal operation, thereby enabling the estimation of the model. And with this, it is possible to update a model with parameter values that offer the requisite level of precision. The simulation also showed that it is possible to maintain control performance.

## 6. Conclusion

In this report, we described technology for estimating a model for a plant from plant data obtained during normal operation, and automatically updating the model. This technology is considered effective in maintaining customer value by contributing to $CO_2$ reduction and other benefits through advanced control. A plant model update function that uses this technology has been developed as a new function for SORTiA, and is on offer as SORTiA-IMB (Intelligent Model Builder).

Data from plants in normal operation contains many segments that are not suitable for estimating a model. As such, we developed a new technique in which time-series data from a plant is split into multiple segments and segments that can be used to estimate a model are automatically selected. This was realized by estimating the probability distribution for model parameters and selecting the segments with low distribution variance. This technique can be applied if data from normal operations is available, so it offers the advantages of a low burden on users and no impact on plant operations.

In order to make this technique possible, a technique to estimate the probability distribution for parameters in a dynamic model was required. This was implemented through a Bayesian estimation of parameters using a technique based on a particle filter, which is a Sequential Monte Carlo method.

In addition, a numerical simulation assuming a plant controlled and optimized by model predictive control was conducted to demonstrate that the proposed technique selects segments suitable for model updating and that using the model estimated with those segments improves control performance compared to before the update.

Azbil intends to continue to contribute to $CO_2$ reduction and a decrease in operational load through its control and optimization technology.

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