Development of Control Performance Diagnosis System and its Industrial Applications

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The control performance diagnosis system, **PID *Monitor***, and the PID tuning tool, **PID *Tune***, have been developed. These systems are useful in improving the control and maintaining high productivity of plants. PID *Monitor* observes the performance of all controllers in the plant, and it picks out the loops which have problems. The diagnosis report is displayed as a Web page on the intranet. The operator and the staff can efficiently improve the control by supervising it. PID *Tune* is used to tune extracted loops. It is able to do the tuning safely without process changes, as it does not need specific plant tests. This paper introduces the technical background of these systems and some applications in a real plant.

This paper is translated from R&D Report, "SUMITOMO KAGAKU", vol. 2010-II.

Introduction

There are many controllers working in plants, and they are supporting the safety and stable operation of the plants. PID controllers make up approximately 90% of these controllers, and they play an important role as the basic control part. On the other hand, tuning problems with PID controllers have been pointed out. It has been reported that the loops having acceptable performance are only 32%, and 36% are in manual mode.[1] In this situation, control improvement activities based on total productive maintenance (TPM) concepts became popular from the latter half of the 1990s to the first half of the 2000s for improving plant productivity, and attractive work was done by domestic Japanese firms. For example, there have been reports on cases where hands-off operation was achieved by systemizing control improvement techniques,[2), 3)] cases of expanding to all factories the developed control improvement tools to support PID controller tuning,[4)] and cases of developing novel control algorithms and PID tuning methods.[4)] At Sumitomo Chemical, efforts to reduce the DCS alarms and operations have been executed by applying advanced control and operator support systems, and we have moved ahead with activities focusing on automation. As TPM activities moved forward, some measures for making control improvements more efficient and maintaining the activities up to now were required, and the need for control performance diagnostic systems increased.[5)]

As a technique for evaluating controller performance from plant operation data, there is a control performance evaluation method based on minimum variance control theory.[6)] It is available as a benchmark for controllers. The loops with lower performance existing in the plant can be extracted efficiently by combining this control performance evaluation method and various diagnostic techniques. A control performance diagnosis system (PID *Monitor*) with this technology integrated into it can perform controller diagnosis in an entire plant, and with improvements by running a plan-do-check-action (PDCA) cycle, it can play a role in improving and maintaining plant productivity.

On the other hand, the tuning work for PID controllers required a great deal of time and effort, as well as the other companies enforcing TPM activities. Therefore, a PID tuning tool (PID *Tune*) was developed to make tuning more efficient. In recent years, data-driven PID controllers,[7)] VRFT, FRIT,[8)] tuning methods based on oscillation data,[9), 10)] and other PID tuning methods that use plant operation data have attracted attention. The methods based on oscillation data uses the closed loop data oscillating because of tuning problems, and their salient feature is being able to carry out tuning safely without process changes. PID *Tune* makes use of this method.

In this article, we will introduce our construction of the control performance diagnosis system and the PID tuning tool as well as some applications in a real plant.

Control Performance Diagnosis System (PID *Monitor*)[11]

There has been progress in increasing the use of information technology in plants, and plant information management systems (PIMS) are collecting a large amount of plant operation data. It has become possible to construct online control performance diagnosis systems like the one in **Fig. 1**. PID *Monitor* runs on a web server. It analyzes plant operation data according to a tag list that has been registered in advance, and the results of diagnosis are output to a web file. The diagnostic results can be referred to from a PC existing at the site, and control performance in the entire plant can be improved by moving forward with improvements based on the diagnostic results. Since control problems are eliminated one by one by running a PDCA cycle of control improvements in this manner, it is easy to gain the understanding of operators. In addition, it is effective for work on maintaining improved controllability.

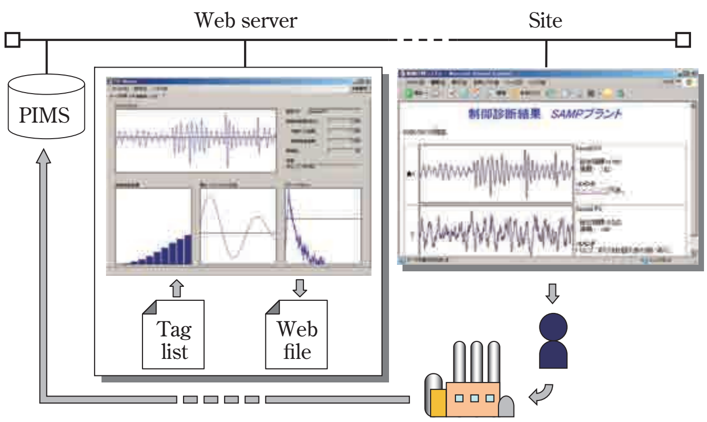

Fig. 1 Control performance diagnosis system[11]

1. Indices for control performance

First of all, a method for evaluating controller performance from plant operation data is discussed. Letting the controller be C, the process be P and the transfer function for disturbance be D as is shown in **Fig. 2**, the relationship between the controlled variable y and the manipulated variable u is given by the following equations.

$$y(t) = P(z^{-1})\,u(t) + D(z^{-1})\,w(t) \tag{1}$$

$$u(t) = C(z^{-1})\big(r(t) - y(t)\big) \tag{2}$$

where w is white noise and r is the set-point. Letting there be $d-1$ steps of dead time in the process, the disturbance transfer function is divided into effect F during the dead time and effect G that follows the dead time, yielding the following equation.

$$D(z^{-1}) = F(z^{-1}) + z^{-d}G(z^{-1}) \tag{3}$$

z^{-d} is the delay operator, and it gives the delay for d steps.

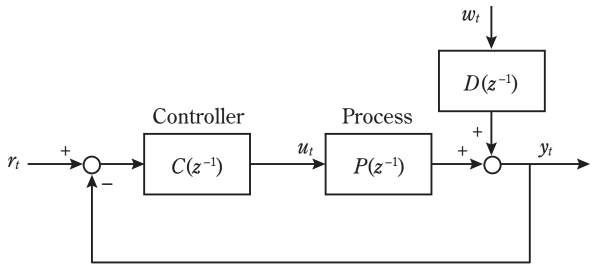

Fig. 2 Block diagram

The set-point for controlled variable y is defined as $r(t) = 0$ unless the setting is changed, and it is expressed by the following equation.

$$\begin{aligned} y(t) &= \frac{D}{1+CP}\,w(t) \\ &= \frac{F+z^{-d}G}{1+z^{-d}C\tilde{P}}\,w(t) \\ &= \left\{F + z^{-d}\frac{G-FC\tilde{P}}{1+z^{-d}C\tilde{P}}\right\} w(t) \\ &= Fw(t) + Hw(t-d) \end{aligned} \tag{4}$$

$\tilde{P}$ is the transfer function for processes with no dead time. Equation (4) means the entire process including the controller as a black box and is divided into the first term that gives the direct effects of white noise within the dead time on the process through the disturbance transfer function and the second term that gives the effects after the dead time through a feedback loop. Here, $Fw(t)$ and $Hw(t-d)$ are independent of each other, and the variance between these gives rise to the following relationship.

$$\begin{aligned} Var\{y(t)\} &= Var\{Fw(t) + Hw(t-d)\} \\ &= Var\{Fw(t)\} + Var\{Hw(t-d)\} \\ &\geq Var\{Fw(t)\} = \sigma^2{}_{MV} \end{aligned} \tag{5}$$

Var and σ^2 show the variance, and $\sigma^2{}_{MV}$ is called the minimum variance. From Equation (5), the controller cannot be affected in any way during the dead time, so the variance σ^2_y of controlled variable y is either equal to or greater than the minimum variance σ^2_{MV}. The second term $Hw(t-d)$ in Equation (4) shows the effects after the dead time, and this can be made small by control. Ideal control where this variance become to zero, that is, the second term in Equation (5), $Var\{Hw(t-d)\} = 0$, is minimum variance control.

The variance when control is carried out by minimum variance control is σ^2_{MV}, and control performance can be evaluated though the ratio with the variance σ^2_y for the current controlled variable y.

$$\eta(d-1) = \frac{\sigma^2_{MV}(d-1)}{\sigma^2_y} \qquad (6)$$

The control performance index η is a value in the range of 0 to 1, and as η approaches 1, control performance can be judged to be better. As it approaches 0 control performance can be judged to be poorer. Since the white noise w affecting the process is not measured, it and the process model are estimated from controlled variable y using an auto-regressive moving average (ARMA) model, which is a kind of time series model, in a calculating process for the control performance index. Modeling is carried out under the assumption that the process is driven by the white noise, and the control performance index based on minimum variance control does not depend on the form of the controller. It is calculated from controlled variable y alone.

A variety of other control performance evaluation methods have been proposed, and the simplest techniques would be methods that use the variance in the controlled variable y or the variance in the controlled variable y and the manipulated variable u. **Fig. 3** shows

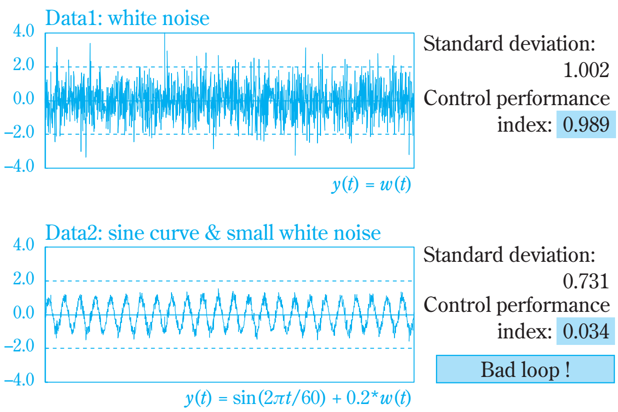

Fig. 3 Comparison between standard deviation and control performance index

examples of evaluation with the standard deviation σ_y for controlled variable y and with control performance index η based on minimum variance control. The graph at the top is white noise data simulating measurement noise, and the graph at the bottom is a sine wave with white noise added simulating bad tuning. In the standard deviation case, the value of Data 1 is larger than Data 2, and it is assessed as poor performance, which is wrong. Meanwhile, in the control performance evaluation case, the assessments are correct with the performance of Data 1 being good, and the performance of Data 2 being poor.

Besides control loops that run in automatic mode, it is desirable to detect the loops that have a large number of manual operations within controllers which are normally in manual mode as control problems. Therefore, manual operations obtained from DCS event data are coupled with this, and it is reflected in comprehensive index γ.

$$\gamma = \eta \times \exp(-N \cdot 24/100) \qquad (7)$$

N is the number of manual operations per day, and the comprehensive index γ is expressed as the product with the control performance index η.

Since the control performance evaluation method depends on the ideal minimum variance control, the control performance index η for PID controllers generally tends to be low. Therefore, it is considered to be sufficient performance even if η is around 0.7, and the control performance diagnosis system extracts loops which are the comprehensive index γ of less than 0.3 or have oscillation as control problems.

2. Various diagnostic methods

Next, various diagnostic methods for identifying the causes of controllers extracted as having control problems are discussed. We evaluated the control performance of 60 loops for controllers in a real plant, and investigated the causes of poor control performance. With this, the following classifications were obtained.

1) Erroneous detection caused by data acquisition precision
2) Manual mode loops
3) Poor controller tuning
4) Valve failures
5) Interaction with other loops
6) External disturbance due to batch use, cleaning operations, etc.

Of these, 1) and 2) have nothing to do with controller performance, and they must be eliminated as targets of evaluation in pre-processing. There is not still effective detection means for 6), and detection methods for plants including many batch operations are being developed.

(1) Manual mode determination

The control mode data is generally not collected from the relationship with PIMS volume, and it is conjectured from the relationship between controlled variable y, set-point r and manipulated variable u, based on the following equation.

Manual mode

$$r > \bar{y} + 3\sigma_y \quad or \quad r < \bar{y} - 3\sigma_y \tag{8}$$

or

when u = constant,

Loops corresponding to 2) that are determined to be in the manual mode set control performance index $\eta = 1$ are removed from analysis.

(2) Determination of valve failure [5), 12), 13)]

Besides bad tuning, there are also control problems that are valve failures due to valve sticking. Causes of valve failures include over-tightening of the gland packing parts, running out of grease from the valve body, sticking because of fluid leakage, valve positioner failure and mechanical hysteresis. To detect these valve failures using the control performance diagnosis system, an identification method that makes use of the frequency analysis and backlash inverse function shown in **Fig. 4** is utilized. The detection precision is greater with the latter, and it should be used if the flow rate data is obtained.

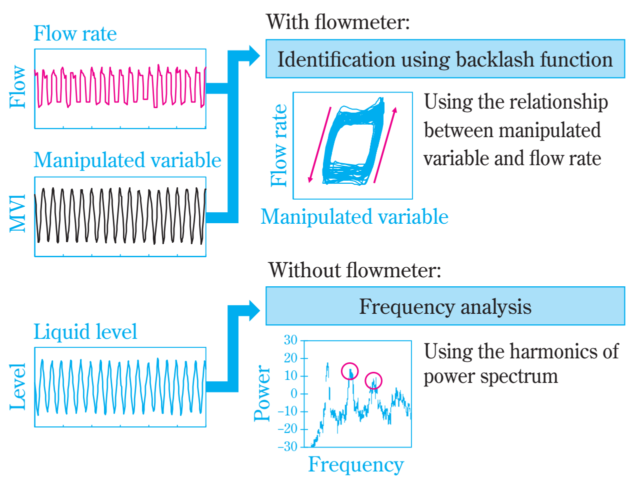

Fig. 4 Methods for detecting valve failure (example of liquid level control)[14)]

1) Frequency analysis

If there is a failure in a valve, there is a characteristic where waves similar to rectangles are displayed in the case of flow rate control, and where waves similar to triangles are displayed in the case of liquid level control. In this method, the characteristics of the waveform are detected using frequency analysis. It is used in casees where flow rate data is not obtained. The Fourier series expansion of rectangular waves and the power spectrum give

$$x(t) = \frac{4}{\pi}\left(\sin wt + \frac{1}{3}\sin 3wt + \frac{1}{5}\sin 5wt + \ldots\right)$$
$$P_x = X \cdot X^* \tag{9}$$

and X is the Fourier transform, X^* the complex conjugate root and P_x the power spectrum. It is clear from equation (9) that the harmonics appear in the power spectrum of the rectangular wave for each odd number period multiple in addition to the fundamental frequency, and the power is attenuated $1/(2n+1)^2$ for each. Triangular waves also exhibit a similar tendency, and harmonics are observed in the power spectrum. Thus it is possible to use the peaks of the harmonics appearing in the power spectrum to identify the differences between these waves and the sine waves which occur due to bad tuning.

2) Method of identification using backlash inverse function

If there is a problem with a valve, the relationship between manipulated variable u and the flow rate is close to the parallelogram in **Fig. 4**. This method makes use of this characteristic, and it uses the backlash inverse function F given by the following equation to detect the shape of this parallelogram.

$$F(t) = \max[\min\{F(t-1) + \Delta u(t), F_{\max}\}, 0] \tag{10}$$

Backlash inverse function F is a function that makes shifts in the amount of the sticking width (F_{max}) so that the right side of the parallelogram is superimposed on the left side, and F_{max} is found such that the relationship between manipulated variable u and the flow rate is linear after conversion. F_{max}, which is the sticking width, is found such that the absolute value for the correlation coefficient for the value of the backlash inverse function and the flow rate is maximized using an optimizing calculation, and it is detected as valve failure if at a correlation coefficient of 0.7 or higher and F_{max} is 0.5 or greater.

(3) Method for detecting root cause loop

Fig. 5 shows an example where insufficient tuning propagates to the other loops and makes the control performance deteriorate. The graphs on the left show the trends and those on the right show the cross-correlation coefficients and the auto-correlation coefficients.

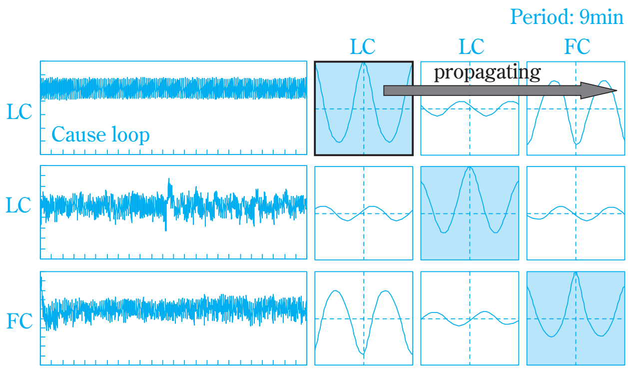

Fig. 5 Method for detecting root cause[11)]

Since the cross-correlation coefficient takes the correlation coefficient in shifting the time for one of two sets of time series data, it is given by the following equation.

$$C_{xy}(\tau) = E\{x(t)y(t+\tau)\}$$
$$R_{xy}(\tau) = \frac{C_{xy}(\tau)}{\sqrt{C_{xx}(0)C_{yy}(0)}} \tag{11}$$

$x(t)$ and $y(t)$ are the time series data, C_{xy} the cross-correlation function and R_{xy} the cross-correlation coefficient. The relativity of the two sets of time series data and the delay time can be found from the cross-correlation coefficient. Similarly, the auto-correlation coefficient takes the correlation coefficient in shifting one of the same two sets of time series data, and the intensity of the periodicity of the data and period can thus be found.

$$C_{xx}(\tau) = E\{x(t)x(t+\tau)\}$$
$$R_{xx}(\tau) = \frac{C_{xx}(\tau)}{C_{xx}(0)} \tag{12}$$

C_{xx} is the auto-correlation function and R_{xx} is the auto-correlation coefficient. Identification for loop cause is done by first extracting data oscillating in the same period from the plant operation data and then analyzing the relativity using the cross-correlation coefficient. If, at this time, the maximum value of the absolute value for cross-correlation coefficient is 0.5 or greater, it is determined to have relativity. Next, the loop with the greatest auto-correlation coefficient from related loops is identified as the root cause loop.

(4) Determination of PID tuning failures

From among the data causing oscillation, loops that oscillate alone other than (2) and loops identified as root causes are assessed as PID tuning problems. In addition, loops with lower performance are detected as the tuning targets even if they are not causing oscillation.

PID Tuning Tool (PID *Tune*)[10), 15)]

The insufficient tuning loops diagnosed by the control performance diagnosis system can be tuned efficiently by using the PID tuning tool shown in **Fig. 6**. PID *Tune* identifies a process model from closed loop plant operation data using a genetic algorithm (GA), and the optimal parameters are calculated by a PID tuning method based on generalized minimum variance control. This method does not require step tests, and it has an industrial advantage that enables short-time tuning without process changes.

Fig. 6 PID tuning tool

1. Identification using genetic algorithm (GA)

Genetic algorithms (GA) simulating the process of biological evolution are one optimization method, and besides Discrete GA dealing with discrete values, there is Real-corded GA which is composed of real number values. This has the merit of being able to apply the same algorithm not only to linear systems, but also to optimization problems that include nonlinear functions, discrete values and integer values.

As shown in **Fig. 7**, the controller model and process model are identified from plant operation data using GA. The process assumes the following to be approximated: below the second-order delay + dead time system that includes an integral. The controller is assumed to be a PID controller.

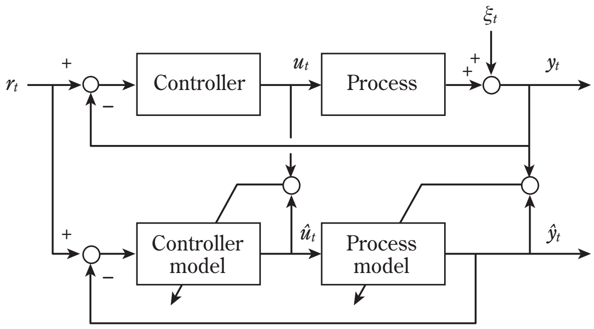

Fig. 7 Identification structure based on GA[10)]

$$\text{Case1:}\quad \frac{K}{(1+Ts)}\, e^{-Ls} \tag{13}$$

$$\text{Case2:}\quad \frac{K}{(1+T_1 s)(1+T_2 s)}\, e^{-Ls} \tag{14}$$

$$\text{Case3:}\quad \frac{1}{Ts}\, e^{-Ls} \tag{15}$$

$$\text{Case4:}\quad \frac{K}{s(1+Ts)}\, e^{-Ls} \tag{16}$$

Here, s is the Laplace operator, and K, T and L are the system gain, time constant and dead time, respectively. Case 1 through Case 4 can be expressed as the following equation if converted to a discrete time system.

$$\begin{aligned} y(t) &= -a_1 y(t-1) - a_2 y(t-2) \\ &\quad + b_0 u(t-d-1) + b_1 u(t-d-2) + \frac{\xi(t)}{\Delta} \end{aligned} \tag{17}$$

where ξ is noise and Δ is the differential operator, a and b are system parameters, and for Case 1, $a_2 = 0$, for Case 3, $a_1 = -1$, $a_2 = 0$, and for Case 4 $a_2 = -(a_1 + 1)$. Case 2 has no constraints. Equation (17) is known as a Controlled Auto-Regressive and Integrated Moving Average (CARIMA) model, and it is often used as one of the system identification methods.

On the other hand, the I-PD controller which is a kind of PID controller with negative feedback is given by the following equation.

$$\Delta u(t) = \frac{k_c \cdot T_s}{T_I} e(t) - k_c \left(\Delta + \frac{T_D}{T_s} \Delta^2 \right) y(t) \tag{18}$$

$$e := r(t) - y(t)$$

where k_c, T_I and T_D are PID parameters and are proportional gain, integral time and derivative time, respectively. T_s is the sampling period, and e is the difference between the set-point and the controlled variable.

If we take the difference between equation (17) and equation (18), the predictive models are

$$\begin{aligned} \hat{y}(t) &= y(t-1) - a_1 \Delta y(t-1) - a_2 \Delta y(t-2) \\ &\quad + b_0 \Delta \hat{u}(t-d-1) + b_1 \Delta \hat{u}(t-d-2) \end{aligned} \tag{19}$$

$$\begin{aligned} \hat{u}(t-d-1) &= u(t-d-2) \\ &\quad - k_c \Delta y(t-d-1) + k_c \frac{T_s}{T_I} e(t-d-1) \\ &\quad - k_c \frac{T_D}{T_s} \Delta \{ y(t-d-1) - y(t-d-2) \} \end{aligned} \tag{20}$$

and the fitness function for system identification using GA is defined as follows.

$$f = \sum_{t=d+1}^{\tau} \left[\{ \hat{y}(t) - y(t) \}^2 + \{ \hat{u}(t-d-1) - u(t-d-1) \}^2 \right] \tag{21}$$

For the process given by equation (19), equation (20) and the predictive model for the controller, parameters a_1, a_2, b_0, b_1, d, k_c, T_I and T_D are composed as a gene sequence shown in **Fig. 8**, and randomized genes are generated. Selection, crossover and mutation procedures are carried out repeatedly, and the parameter sequence

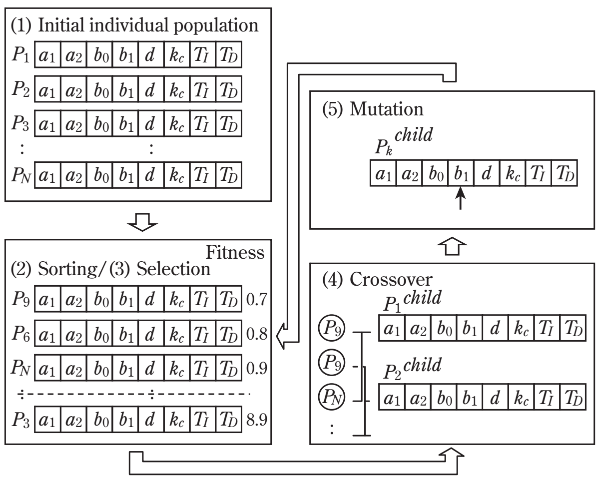

Fig. 8 Process of evolutionary identification using GA[10)]

that minimizes the fitness function in equation (21) can then be found.

2. PID parameter tuning

Next, a method for calculating optimal PID parameters from the process model found by system identification based on generalized minimum variance control (GMVC) is discussed. The discrete time process model in equation (17) can be rewritten as

$$A(z^{-1})y(t) = z^{-(d+1)}B(z^{-1})u(t) + \xi(t)/\Delta \quad (22)$$

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2}$$
$$B(z^{-1}) = b_0 + b_1 z^{-1}$$

and the controller in equation (18) as

$$C(z^{-1})y(t) = \Delta u(t) - C(1)r(t) = 0 \quad (23)$$

$$C(z^{-1}) := k_c\left\{\left(1+\frac{T_s}{T_I}+\frac{T_D}{T_s}\right)-\left(1+\frac{2T_D}{T_s}\right)z^{-1}+\frac{T_D}{T_s}z^{-2}\right\}$$

The GMVC evaluation criteria[16] is

$$J = E\left[\{P(z^{-1})y(t+d+1) + \lambda\Delta u(t) - P(1)r(t)\}^2\right] \quad (24)$$

and the polynomial expression for $P(z^{-1})$ is designed as follows.

$$P(z^{-1}) = 1 + p_1 z^{-1} + p_2 z^{-2} \quad (25)$$

$$p_1 = -2e^{\frac{\rho}{2\mu}}\cos\left(\frac{\sqrt{4\mu-1}}{2\mu}\rho\right)$$
$$p_2 = e^{\frac{\rho}{\mu}}$$
$$\rho := T_s/\alpha$$
$$\mu := 0.2(1-\delta) + 0.51\delta$$

where λ is the weight parameter, α a parameter expressing the rise-time and μ a parameter expressing the attenuation characteristics of the response. It is desirable for α to be 0.3 to 1.0 times the total of the time constant and dead time, and here it is set at 0.75. μ is adjusted by δ, and δ is set at 0.0. The Diophantine equation that takes dead time into consideration is given by the following equation.

$$P(z^{-1}) = \Delta A(z^{-1})E(z^{-1}) + z^{-(d+1)}F(z^{-1}) \quad (26)$$

$$E(z^{-1}) = 1 + e_1 z^{-1} + \ldots + e_d z^{-d}$$
$$F(z^{-1}) = f_0 + f_1 z^{-1} + f_2 z^{-2}$$

From this and Equation (22) the following is obtained as a control row that minimizes Equation (24).

$$F(z^{-1})y(t) + \{E(z^{-1})B(z^{-1}) + \lambda\}\Delta u(t) - P(1)r(t) = 0 \quad (27)$$

If the second term in Equation (27) is replaced by a static gain, we have

$$F(z^{-1})y(t) + \{E(1)B(1) + \lambda\}\Delta u(t) - P(1)r(t) = 0 \quad (28)$$

and from the relationship with Equation (23), the PID parameters can be found from the following equation.

$$k_c = -\frac{1}{E(1)B(1)+\lambda}(f_1+2f_2)$$
$$T_I = -\frac{f_1+2f_2}{f_0+f_1+f_2}T_s \quad (29)$$
$$T_D = -\frac{f_2}{f_1+2f_2}T_s$$

Next, a method for finding the weight parameter λ that minimizes the sum $I(\lambda)$ of variances for difference e and manipulated variable Δu is described.

$$I(\lambda) = E[e^2(t)] + K^2 E[\Delta u(t)^2] \quad (30)$$

K is system gain, and the following relation holds true for difference e and manipulated variable Δu in a steady-state condition.

$$e(t) = -\frac{1}{T(z^{-1})}\xi(t) \quad (31)$$

$$\Delta u(t) = -\frac{C(z^{-1})}{T(z^{-1})}\xi(t) \quad (32)$$

$$T(z^{-1}) = \Delta A(z^{-1}) + z^{-1}B(z^{-1})C(z^{-1}) \quad (33)$$

If at this time the variants for each are calculated using the H_2 norm, Equation (30) becomes:

$$I(\lambda)' = \left\|-\frac{1}{T(z^{-1})}\right\|_2^2 + K^2\left\|-\frac{C(z^{-1})}{T(z^{-1})}\right\|_2^2 \quad (34)$$

The λ that minimizes Equation (34) is found, and the values for $E(z^{-1})$ and $F(z^{-1})$ are calculated. Finally, the optimal PID parameters are calculated.

3. Example of Application

An example of controller tuning in a real plant using this method is shown. We carried out liquid level control tuning based on the result calculated by PID *Tune*, and achieved the stabilization shown in **Fig. 9**.

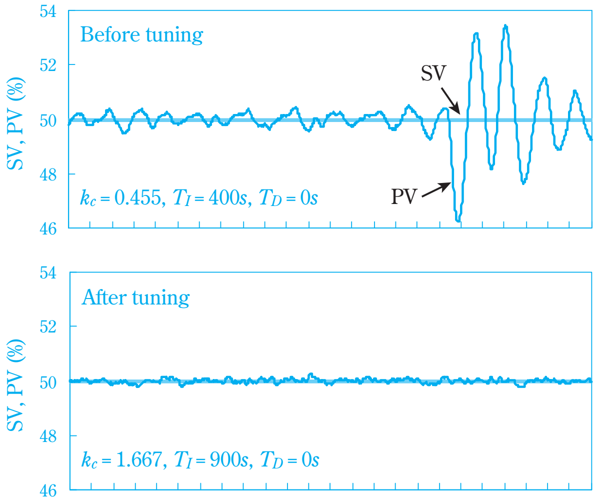

Fig. 9 Result of tuning (liquid level control)[10]

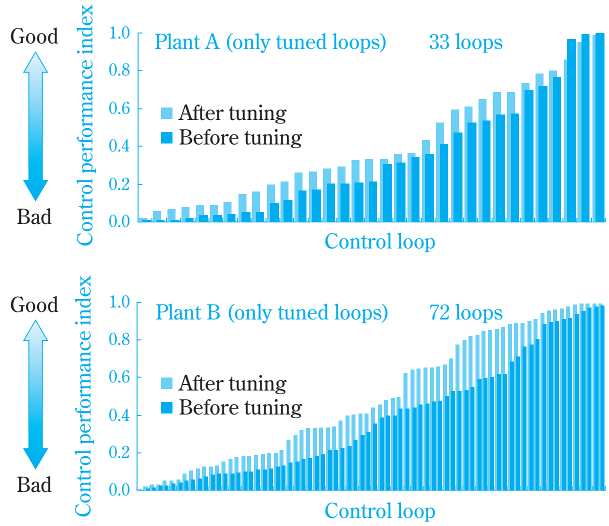

Fig. 10 Comparison of control performances in plants A and B[14]

Applications in Real Processes[14]

Finally, an example of improving the control plant-wide using the control performance diagnosis system and PID tuning tool are introduced.

We implemented these in two plants with around 170 loops and worked on improvements. In the loops diagnosed as having control problems, the 33 loops and 72 loops that underwent PID tuning are compared in **Fig. 10**. One can see that overall control performance was improved by the tuning.

In addition, in a distillation process where multiple oscillations were found in the same period, the loops causing problems were identified using the control performance diagnosis system. An example of stabilization by PID tuning is shown in **Fig. 11**. The oscillation disappeared, and the process as a whole was stabilized.

Furthermore, several loops with suspected valve failures were detected, and valve inspections were carried out on these loops. Cleaning and maintenance were performed on ones that were dirty inside, and positioners were installed in valves that had no positioners installed. **Fig. 12** is an example of the improved control with the installation of a valve positioner.

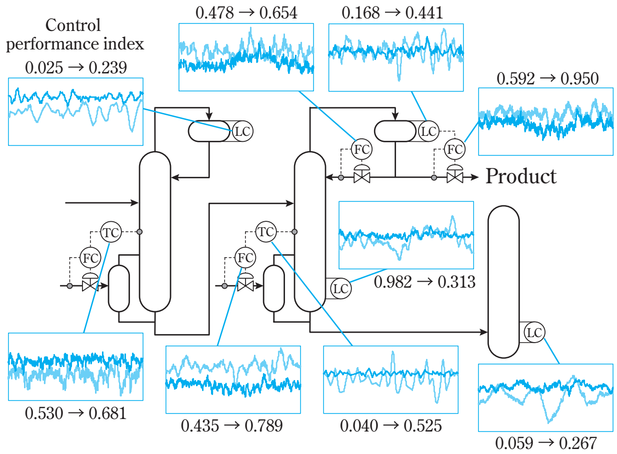

Fig. 11 Improved control performance in distillation process[14]

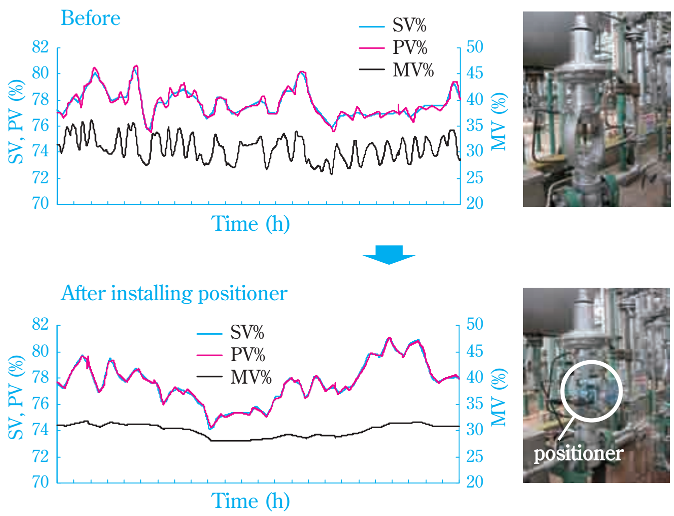

Fig. 12 Improvement of control performance by installing valve positioner[14]

Conclusion

In this article, we have given an introduction to the technical background of our control performance diagnosis system (PID *Monitor*) and PID tuning tool (PID *Tune*) as well as an example of application in a real plant. These systems are useful to improve the controllability of entire plants, and now, we are moving forward with deploying them company-wide as tools for maintaining productivity in plants.

These have been found to be powerful tools not only for control improvements in existing plants, but also for stabilization of new plants in the short term. In addition, we have better records on not only chemical plants and petrochemical plants this time, but also oil refining plants. We would like to move forward while aiming at improving the functions and expanding the range of applications.

Acknowledgments

Part of the control performance diagnosis technology in the first half of this article is based on joint results from Workshop No. 25 “Control Performance Monitoring” of the 143rd Committee on Process Systems Engineering held by the Japan Society for the Promotion of Science , and the PID tuning method in the second half is results obtained jointly with Hiroshima University. We would like to express our gratitude to all the members of this society and to Toru Yamamoto of Hiroshima University.

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