The State of the Art in Advanced Chemical Process Control in Japan

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Abstract: In this age of globalization, the realization of production innovation and highly stable operation is the chief objective of the process industry in Japan. Obviously, modern advanced control plays an important role to achieve this target; but it is emphasized here that a key to success is the maximum utilization of PID control and conventional advanced control. This paper surveys how the three central pillars of process control – PID control, conventional advanced control, and linear/nonlinear model predictive control – have been used and how they have contributed toward increasing productivity. In addition to introducing eminently practical methods, emerging methods, and their applications, the authors point out challenging problems. In Japan, industry and academia are working in close cooperation to share their important problems and develop new technologies for solving them. Several methods introduced in this paper are results of such industry-academia collaboration among engineers and researchers in various companies and universities. Furthermore, soft-sensor or virtual sensor design is treated with emphasis on its maintenance, because soft-sensors must cope with changes in process characteristics for their continuous utilization. Maintenance is a key issue not only for soft-sensors but also for controllers. Finally, we will expand our scope and briefly introduce recent activities in tracking simulation and alarm management. A part of the results of our recent questionnaire survey of process control are also introduced; the results are extremely helpful in clarifying the state of the art in process control in Japan.

Keywords: Advanced process control, Alarm management, Industrial application, Model-based control, Model predictive control, PID control, Process control, Production innovation, Soft-sensor, Tracking simulator.

1. INTRODUCTION

The Japanese chemical and petroleum refining industries has focused on *production innovation* and *highly stable operation*. The embodiment of these two concepts is believed to be indispensable. In fact, production innovation and highly stable operation have led to remarkably increased productivity at advanced chemical companies. Daicel Chemical Industries, for example, has tripled the productivity per plant employee since *Intellectual and Integrated Production System* was established in the Aboshi plant in 2000 (Daicel Chemical Industries, Ltd. (2008)). This reputable activity was motivated by the effort in Mitsubishi Chemical Corporation (MCC) in the 1990's (Shoda (1998)). MCC has developed *Super-stable Operation Technologies* (SSOTs) and *Super-stable Maintenance Technologies* (SSMTs) to maintain production stability and prevent facility accidents (Mitsubishi Chemical Corporation (2005)). SSOTs aim to keep stable plant operation by prevention and prediction of various troubles such as fouling, plugging, corrosion, and so on, and SSMTs are facility management technologies used to ensure high standards of stability.

In the 1990's, Japanese companies realized that many skilled operators were approaching retirement age. This social problem was called "year 2007 problem" in Japan. We are in the middle of this. Since the achievement of stable and efficient operation has largely depended on skilled operators in Japan, the year 2007 problem has heightened a sense of crisis and has motivated companies to initiate production innovation. Production innovation requires thorough review of personnel training, organizations, production methods as well as operation control systems.

To realize highly stable operation, process control plays an important role. In Japan, a task force was launched in 2007 to sift through problems regarding process control and investigate solutions. The task force, named "Workshop No.27 Process Control Technology," consists of 32 engineers from industry and 12 researchers from universities. It is supported by the 143rd committee on process systems engineering, the Japan Society for the Promotion of Science (JSPS). Currently, the following topics are being investigated by the members.

- Practical closed-loop system identification
- Practical tuning techniques of PID controllers
- Systematization of the control performance improvement activity based on control performance assessment

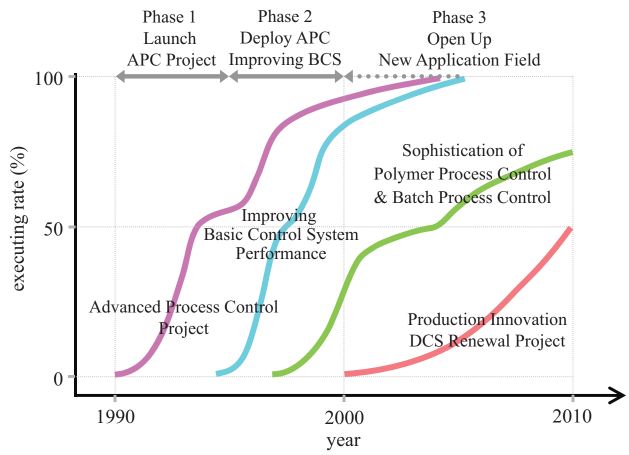


Fig. 1. Chronology of project execution in MCC

- Control system design from the viewpoint of plant-wide control
- Evaluation and maintenance of model predictive control
- Design and maintenance of soft-sensors

Most of these topics are also covered by the status report of the IFAC Coordinating Committee 6 (Dochain et al. (2008)). These are key issues not only in the Japanese chemical industry but also internationally.

This paper aims to reveal the state of the art in advanced chemical process control in Japan. First, the projects that process control sections of a general chemical corporation of Japan have executed in the last two decades are described in section 2. Then, several key technologies are investigated in more detail: PID control in section 3, conventional advanced control in section 4, model predictive control (MPC) in section 5, soft-sensor or virtual sensor in section 6, and other issues including an operation support system based on an on-line process simulator and alarm management in section 7. In each section, eminently practical techniques with successful application results are introduced, and challenges are clarified. Furthermore, this paper introduces results of a questionnaire to member companies of the JSPS 143rd committee on their process control applications including MPC and soft-sensors. The results will be extremely useful for grasping the state of the art in process control.

2. MILESTONE IN THE HISTORY OF PROCESS CONTROL APPLICATION

There are three phases in process control application projects in Mitsubishi Chemical Corporation (MCC), to which the second author had belonged for many years, as shown in Fig. 1: the advanced process control (APC) projects for large-scale continuous processes, the improvement activity of the control performance of basic control systems for small-to-medium-scale processes, and the advancement of polymer and batch process control.

2.1 Project Chronology

In the first phase in the early 1990's, multivariable MPC was applied to large-scale continuous processes such as olefin production units for generating a large profit. The APC project was conducted for 15 production units of 5 production sites by using DMCplus® as a standard tool, and satisfactory results were achieved. The key to success is nurturing process control engineers who can accomplish the projects independently on their own. They learned procedures and methods of planning, control system design, plant tests, tuning, and operation. In addition, they joined seminars on advanced control theory given by prominent researchers and professors. By accumulating experience on the projects, they grew into capable engineers who understood theory and had business acumen. These 15 process control engineers took a leading part and accomplished APC projects in MCC.

In the second phase, the performance of PID control systems was assessed and improved. All production units which APC projects did not cover were targeted. Both the operation section and the instrumentation section jointly carried out this project as a daily improvement activity in cooperation with the process control section. As a result, the operator workload was reduced through the improvement in service factors of PID control systems and a reduction in frequency of alarms and operator interventions. In addition, the improvement in control performance contributed toward the economic profit because it made operations energy-efficient through optimally changing set-points. It was also the perfect opportunity for finding applications of conventional advanced control such as override control and valve position control (VPC).

In the third phase, the advancement of polymer process control was investigated. It is important to achieve rapid grade transition while satisfying quality specification in polymer plants, because transitions among a wide variety of products are made frequently. Therefore, an original control algorithm that is based on precise first-principle models of polymerization reactions and quality models relating polymerization reaction conditions and product quality has been used since the 1980's. In this phase, process models such as catalyst activity were reviewed, and a new nonlinear MPC algorithm was developed and applied. As a result, the control performance was significantly improved, off-specification products were reduced, and quality was stabilized.

The focus of the process control section has shifted to problem-solving regarding process control of small-to-medium-scale processes and the maintenance of APC systems. The targets include 1) accumulating energy-saving effects by applying an in-house linear MPC algorithm to distillation, reforming furnace, and air separation processes, 2) developing soft-sensors, which are substituted for process gas chromatographs, for shortening the control interval and improving control performance, and 3) adapting APC systems for reinforcement of process units.

Since the 1990's, the movement to reform the whole production activity has started at advanced chemical companies as mentioned in the introduction. In addition to integration of control rooms, such production innovation requires the review of operation management, alarm management, emergency shutdown system, maintenance management, etc., and also it requires modernizing the control information system. Such an activity is triggered by the

Table 1. Classification of process control methodologies and the numbers of applications in the MCC Mizushima plant

classification	methodology	application
modern advanced control	linear MPC	54
	nonlinear MPC	2
	LQI with preview action	2
conventional advanced control	feed-forward control override control valve position control analyzer feedback control model-based control etc	500+
regulatory control	PID/I-PD control	5006

opportunity for DCS introduced in the 1980's to enter a renewal period as well as the year 2007 problem. Process control engineers are or will be involved in this movement.

2.2 Process Control Methodology

Control methodologies which bear the central role in process control systems can be classified into regulatory control such as PID control, conventional advanced control such as feedforward control and override control, and modern advanced control such as MPC. The number of applications of these control methodologies in the MCC Mizushima plant is summarized in Table 1. The ratio of applications of PID control, conventional advanced control, and MPC is 100:10:1. PID control is used in 5006 loops in 24 production units. The number of control loops repeatedly increases and decreases corresponding to new establishment, reinforcement, or stopping of production units. Conventional advanced control is effective in many cases, but the number of its applications is not as many as expected. MPC has become established as a standard technique for multivariable control which realizes economical operation of large-scale processes.

2.3 Survey Result of Control Methodology

A part of the questionnaire survey results of process control application is summarized in Table 2. This questionnaire asked control engineers to evaluate the level of their application of conventional advanced control, model-based control, adaptive control, modern-control-theory-based control, knowledge-based control, statistical process control, and soft-sensor in four grades.

This survey result clarifies the state of the art of process control application in Japan. As expected, linear MPC is the only methodology of modern advanced control that has been applied practically. Most companies have not used nonlinear MPC, adaptive control including self-tuning control, state feedback control, preview control, H_∞ control, or knowledge-based control including neural-network-based control. These control techniques have not been used because they are not available as a practical, easy-to-use tool and in-house development is troublesome. In particular, self-tuning control is a black box and has incurred a vague distrust of engineers and operators. In addition, it is not superior to gain scheduling control or robust PID tuning, which is more intuitive and understandable. On the other hand, the modern control theory has not been accepted in the chemical and petroleum refining industries. This situation is in stark contrast to that

Table 2. Level of control application (from the survey JSPS143 WS27 2009)

control methodology	level of application			
	A	B	C	D
conventional advanced control				
feedforward control	3	9	6	2
override control	2	6	5	7
valve position control	4	5	6	5
sampled-data control	1	5	9	5
dead-time compensation	0	2	11	7
gain-scheduled PID control	1	1	9	9
model-based control				
internal model control	2	5	3	9
linear model predictive control	4	6	6	3
nonlinear model predictive control	0	1	2	16
adaptive control				
self-tuning PID control	0	1	1	17
model reference adaptive control	0	0	1	18
modern-control-theory-based control				
state feedback control	0	0	4	15
preview control	0	0	1	18
H_∞ control	0	0	0	19
knowledge-based control				
fuzzy control	0	0	5	14
artificial-intelligence-based control	0	0	2	17
neural-network-based control	0	0	4	15
statistical process control	0	1	3	15
soft-sensor	3	7	4	5

Explanation of level of application:
A: standardized and always applied if necessary.
B: applied, but not standardized.
C: applied sometimes.
D: not applied.
The numbers in this table show the numbers of answers.

in the steel industry, for example, where there are many applications of modern control such as H_∞ control. This is because there have already been a number of successful MPC applications in the chemical and petroleum refining industries; thus control engineers are not motivated to use more theoretical control algorithms. Knowledge-based control is useful for complementing PID control and MPC, but it is difficult to generalize knowledge-based control so that it can be applied to a variety of processes.

3. PID CONTROL

In Japanese chemical companies, KAIZEN activities aimed at safe and stable operation are actively continuing. One important activity is improvement in the control performance of PID control systems. The aims of this improvement activity, in which controllers are retuned appropriately, are 1) to realize stable operation by reducing the influence of disturbances, 2) to realize automatic rapid transition of operating conditions such as production rate, 3) to gain the ability to achieve economical operation, and 4) to allow operators to be released from taking care of PID controllers. Additional effects are to find out problems with sensors and actuators, and to clarify possible targets of advanced control application.

In the KAIZEN activities, improving the control performance with retuning should be stressed, rather than spending time and effort to strictly assess the control performance of PID control loops. The following simple indexes are sufficient to determine good or bad control performance: 1) Is the controller in auto mode at all times? 2) Are PID parameters in the proper range? 3) Is fluctuation of the controlled variable and the manipulated variable sufficiently small? 4) Is the PID tuning agreeable to the control purpose such as flow-averaging level control? Other than these, it is necessary to check the range propriety of sensors and actuators, the necessity of filtering of measurement noise, the presence of stiction of control valves, and so on.

Experience leads us to believe that 80% of PID control loops can be successfully tuned with a method based on rule of thumb and trial and error. For example, initial settings for PID parameters should be "wide proportional band and fast reset time" for flow control and "narrow proportional band and slow reset time" for level control. After the initial PID setting, PID parameters are tuned gradually to strengthen control action while the control performance is verified.

The control performance improvement activity introduced in this section has attracted the attention of many enterprises in the chemical and petroleum refining industries in Japan, and the number of enterprises starting this activity has increased rapidly. Such a movement seems to be the result of the process control section not directly recognizing the reality that the operation section had an awareness of control performance issues and was dissatisfied with the control performance.

3.1 Actual Project Examples

The result of a project on a large-scale monomer plant, which has 190 PID control loops, is introduced here. In this plant, 90% of the PID controllers were in auto mode for 30 days. This value outperforms the average of 70% in the literatures (Desborough and Miller (2001); Ender (1993)). Operators had adjusted PID parameters to realize very loose control action. As a result, the process was easily affected by disturbances and a long time was required for production rate changes, thus the operators made frequent adjustments such as set-point changes and manual operation.

In all, 112 loops having a margin of improvement in control performance were retuned in 12 days. The standard deviations of controlled variables (CVs), σ_e, and manipulated variables (MVs), σ_u, were reduced by an average of 37% and 28%, respectively, as shown in Fig. 2. Here $\tilde{\sigma}$ denotes the standard deviation before the retuning. The reduction is almost the same as the value reported by Shah et al. (2004). A pronounced effect was achieved in tray temperature control loops of distillation columns. Temperature fluctuation was reduced to one-fourth up to one-seventh, and composition was also stabilized.

Figure 3 shows PID parameters for 29 level control loops before and after the retuning. Here PB and T_i denote proportional band and reset time, respectively. With the exception of a part such as six loops for a heat recovery boiler, the purpose of these control loops is flow-averaging level control (FALC). Operators made the proportional gain small (wide proportional band) in order for the manipulated variable not to change. However, the manipulated variable had been oscillatory due to small reset time. To solve this problem, Ogawa et al. (1998) developed

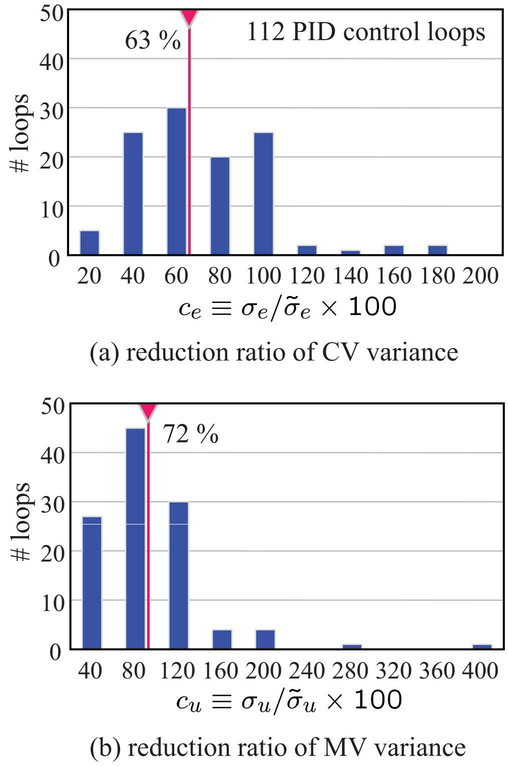


Fig. 2. Improvement in PID control performance: project on a large-scale monomer plant in MCC

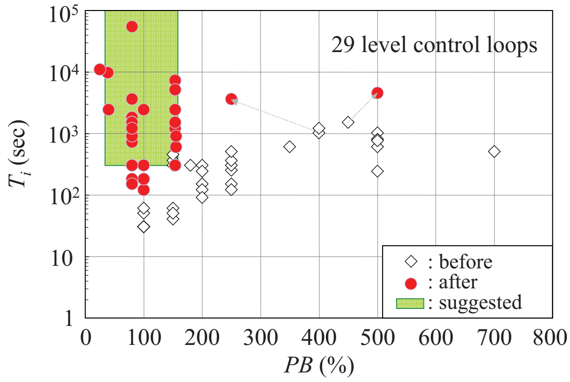


Fig. 3. PI parameters of 29 level controllers before and after retuning

a design method of flow-averaging level controllers and applied it to those loops. As a result, it became possible to suppress the oscillation of the manipulated variable by allowing the fluctuation of the level, utilizing the capacity of the drum, and absorbing flow disturbances. This FALC, explained in section 3.3, was very effective for decreasing changes in feed/product flow rate to distillation columns and lightening the burden of tray temperature control.

The above-mentioned example is the result for MCC. Generally, each company has its own in-house tool for assessing and improving PID control performance. In Sumitomo Chemical, for example, Kugemoto (2005) developed a control loop diagnostic tool "LoopDiag" that can execute control performance assessment, valve stiction detection, as well as time series data analysis. LoopDiag is a re-

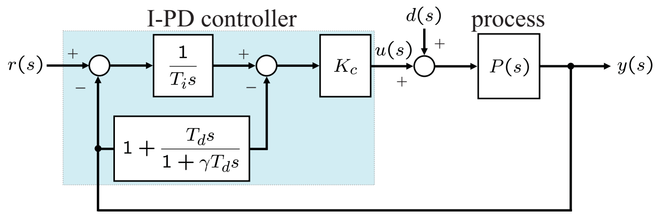


Fig. 4. I-PD control system

sult of industry-academia collaboration in the task force "Workshop No.25 Control Performance Monitoring" supported by the JSPS 143rd committee. In LoopDiag, control performance is evaluated on the basis of the minimum variance control benchmark concept (Harris (1989)), and valve stiction is detected by using the methods developed by Maruta et al. (2005) and Yamashita (2006). By the year 2005, control performance assessment was carried out for 300 PID control loops by using LoopDiag, and performance improvement was achieved. In addition, 12 valve failures were diagnosed in 118 control loops, and four of 12 valves had actually developed trouble.

Mitsui Chemicals has utilized "Plant Control Estimation & Tuning System (PCETS)" (Nishimura and Ootakara (2007)). The functions of PCETS include 1) control performance assessment based on operation data of controlled variables, set-points, and manipulated variables, 2) plant performance assessment, and 3) optimal PID tuning support. The function of control performance assessment has been applied to more than 5000 control loops, and more than 250 control loops whose performance was identified as poor were retuned by the function of optimal PID tuning support. The control performance was greatly improved in most control loops.

In Idemitsu Kosan, one-parameter tuning PID control has been used (Fujii and Yamamoto (2008)). This unique technique was developed to integrate control performance assessment and controller design and to make PID tuning easier and more intuitive for plant operators. It allows PID parameters to be tuned by adjusting just one user-specified parameter that corresponds to control strength or robustness. So far, one-parameter tuning PID control has been successfully applied to hundreds of control loops. This technique clarifies when controllers should be retuned and enables operators who do not have controller design experience to tune PID parameters effectively.

These examples would reveal the state of the art in PID control, which still plays a very important role in chemical process control. In the following part of this section, a few practical control techniques are introduced.

3.2 Robust I-PD Controller Tuning

Since most PID controllers have the I-PD algorithm at least in Japan, Ogawa and Katayama (2001) derived a robust model-based PID tuning method for the I-PD controller shown in Fig. 4. This method is suitable for specific control loops such as temperature and composition control, which are required a proper control performance in the presence of plant-model mismatch.

The advantage of I-PD control over conventional PID control is that I-PD control can realize milder response to set-point changes than PID control, while both control algorithms achieve the same performance against disturbances. When the set-point is changed stepwise in PID control systems, an abrupt change of the manipulated variable is unavoidable due to derivative and proportional actions. In practice, such an abrupt change is undesirable. On the other hand, in I-PD control systems, both derivative and proportional terms act only on the controlled variable; thus milder changes in the manipulated variable can be realized.

Here, the I-PD controller tuning method for a first-order plus time-delay (FOPTD) model is explained. The desired response $W_r(s)$ of the controlled variable y for the set-point r is specified by

$$W_r(s) \equiv \frac{y(s)}{r(s)} = \frac{1}{(1+T_F s)^n} e^{-T_L s} \tag{1}$$

where T_F denotes a tuning parameter and $n = r+1 = 2$ for the relative order $r = 1$ of the process model. T_L, T_p, and K_p denote time-delay, time constant, and steady-state gain of the process model, respectively. By using the 1/1 Pade approximation and ignoring the derivative filter, the partial model matching method (Kitamori (1981)) provides the following PID setting rule.

$$K_c = \frac{p-2q+4}{K_p\,(p+2q)} \tag{2}$$

$$T_i = \frac{(p+2q)\,(p-2q+4)}{2p+4} T_p \tag{3}$$

$$T_d = \frac{p\left(p+4q-2q^2\right)}{(p+2q)\,(p-2q+4)} T_p \tag{4}$$

where $p \equiv T_L/T_p$ represents the difficulty of control and $q \equiv T_F/T_p$ is a tuning parameter. Although the parameter q can be tuned so that ISE (Integral of Squared Error) is minimized, such tuning is not preferable in practice. To realize robust PID control that is intuitive and practical, a constraint on the maximum change of the manipulated variable $u(t)$ against a stepwise set-point change is introduced. Given $U_{\max}(\%)$, the parameter q is determined by solving the following equation.

$$\max_q \|u(t)/u(\infty)\|_\infty \le U_{\max}/100 \tag{5}$$

where $u(\infty)$ is the steady-state value of $u(t)$ after the set-point change. The relationship among q, p, and $U_{\max}$ is shown in Fig. 5.

This robust I-PD controller tuning method is derived not only for FOPTD models but for integral plus FOPTD models and second-order plus time-delay (SOPTD) models with/without an unstable pole.

3.3 Flow-Averaging Level Control

Consider a process described by

$$P(s) = \frac{y(s)}{u(s)} = \frac{1}{T_p s}, \quad T_p = \frac{K_m A}{K_u} \tag{6}$$

where T_p (h) denotes reset time constant, K_m (m/%) sensor gain, K_u (m^3/h/%) actuator gain, and A (m^2) sectional area.

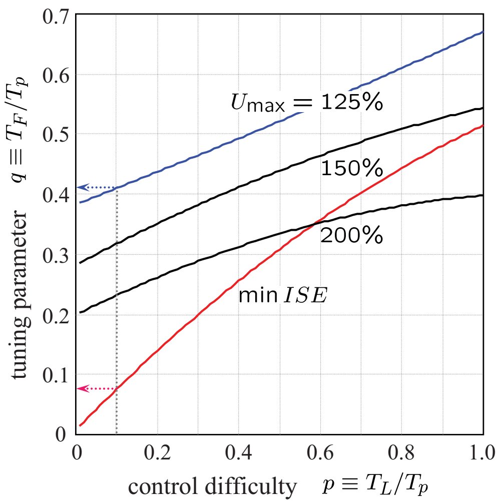


Fig. 5. Tuning of robust I-PD controllers

I-P control is used for FALC. Its block diagram is shown in Fig. 4 and derivative time T_d is set equal to 0. The control response to set-point r (%) and disturbance d (%) becomes the following second-order standard form.

$$y(s) = \frac{1}{1 + 2\zeta T_n s + T_n^2 s^2}\left(r(s) + \frac{T_i s}{K_c} d(s)\right) \tag{7}$$

The damping coefficient ζ and the natural frequency T_n are given by

$$\zeta = \sqrt{\frac{K_c T_i}{4T_p}}, \quad T_n = \sqrt{\frac{T_p T_i}{K_c}} \tag{8}$$

By defining the performance index of FALC under a stepwise disturbance as

$$\min\ J = \frac{1}{2}\int_0^{\infty} \left(q^2 y^2(t) + r^2 \dot{u}^2(t)\right) dt \tag{9}$$

and solving the optimization problem similar to the LQI problem, the control parameters can be related to the process parameter.

$$K_c T_i = 2T_p \tag{10}$$

As a result, the damping coefficient becomes $\zeta = 1/\sqrt{2}$ and the second-order standard form becomes Butterworth-type.

Given the size of the step-wise disturbance d_s and the maximum allowable level change y_s, the proportional gain and the reset time can be determined as follows:

$$K_c = \frac{\sqrt{2}e^{-\pi/4}}{y_s/d_s} \approx \frac{0.645}{\eta}, \quad T_i = \frac{2T_p}{K_c} \tag{11}$$

Here, $\eta \equiv y_s/d_s$ is the disturbance rejection ratio.

This tuning method has been widely used in industry to improve the performance of level control, in particular, to achieve FALC with the specified characteristics, because the calculation of PI parameters is very easy.

3.4 Direct PID Controller Tuning

Discussions with control engineers in the Japanese process industries confirm that PID controller tuning is still a key

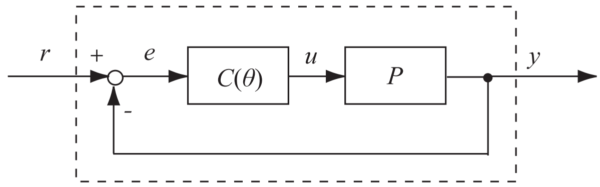


Fig. 6. Feedback control system

issue. A typical chemical plant has thousands of control loops whose maintenance is vital to efficient operation of the entire plant. The conventional approach to tackling this problem is to use an efficient open/closed-loop identification method and reduce the burden of modeling. However, any control system based on an identified model suffers from modeling errors and requires retuning of control parameters. In addition, identification is still one of the critical tasks in control system design. Control engineers and operators would prefer to avoid identification and manual tuning of PID controllers.

Extended fictitious reference iterative tuning (E-FRIT) is a new direct tuning method, which can optimize PID or I-PD control parameters directly from operation data without a process model (Tasaka et al. (2009); Kano et al. (2009b)). E-FRIT is a kind of extension of other direct tuning methods such as iterative feedback tuning (IFT) proposed by Hjalmarsson et al. (1998), virtual reference feedback tuning (VRFT) by Campi et al. (2002), and fictitious reference iterative tuning (FRIT) by Soma et al. (2004).

E-FRIT is briefly explained here. Figure 6 shows a block diagram of a feedback control system, where P denotes a process, $C(\boldsymbol{\theta})$ a controller with parameters $\boldsymbol{\theta}$, r set-point, and u and y are a manipulated variable and a controlled variable, respectively. When PID control is used,

$$C(\boldsymbol{\theta}) = K_{\mathrm{P}}\left(1 + \frac{1}{T_{\mathrm{I}} s} + T_{\mathrm{D}} s\right) \tag{12}$$

$$\boldsymbol{\theta} = (K_{\mathrm{P}}, T_{\mathrm{I}}, T_{\mathrm{D}})\ . \tag{13}$$

In E-FRIT, a virtual output variable is formulated as a function of PID parameters by using input and output data together with a reference model. PID parameters are determined so that the difference between the real and virtual output variables is minimized. The following is the PID tuning procedure based on E-FRIT. Here, $G(s)x(t)$ or $Gx(t)$ is defined by $\mathcal{L}^{-1}\{G(s)\mathcal{L}\{x(t)\}\}$, which represents the discrete time series data collected at certain sampling intervals.

[Step 1] After the control system is stabilized with initial PID parameters $\boldsymbol{\theta}_0$, change the set-point and collect input and output data, $u_0(t)$ and $y_0(t) (t = 1, 2, \cdots, N)$.

[Step 2] Derive the fictitious reference (virtual set-point) $\tilde{r}(\boldsymbol{\theta}, t)$ that generates $u_0(t)$ and $y_0(t)$ even when $\boldsymbol{\theta} \neq \boldsymbol{\theta}_0$.

$$\tilde{r}(\boldsymbol{\theta}, t) = C(\boldsymbol{\theta})^{-1} u_0(t) + y_0(t) \tag{14}$$

[Step 3] Formulate the reference output $\tilde{y}(\boldsymbol{\theta}, t)$ by using a reference model M as shown in Fig. 7.

$$\tilde{y}(\boldsymbol{\theta}, t) = M\tilde{r}(\boldsymbol{\theta}, t) \tag{15}$$

The closed-loop system is close to the reference model when $\tilde{y}(\boldsymbol{\theta}, t)$ is close to $y_0(t)$.

[Step 4] Solve the following optimization problem and determine the optimal control parameters $\boldsymbol{\theta}^*$.

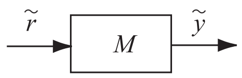


Fig. 7. Reference model of closed-loop system

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} J_{\text{ext}}(\boldsymbol{\theta}) \tag{16}$$

$$J_{\text{ext}}(\boldsymbol{\theta}) = \frac{1}{N}\sum_{t=1}^{N}\left\{(y_0(t) - \tilde{y}(\boldsymbol{\theta},t))^2 + \lambda\Delta\tilde{u}(\boldsymbol{\theta},t)^2\right\} \tag{17}$$

$$\Delta\tilde{u}(\boldsymbol{\theta},t) = \tilde{u}(\boldsymbol{\theta},t) - \tilde{u}(\boldsymbol{\theta},t-1) \tag{18}$$

$$\tilde{u}(\boldsymbol{\theta},t) = C(\boldsymbol{\theta})\,(r_0(t) - Mr_0(t)) \tag{19}$$

where λ is a weighting coefficient.

A reference model plays an important role in defining the desirable control response. It is difficult, however, to determine an appropriate reference model in advance without information on the process. Therefore, parameters in the reference model are optimized together with the control parameters in E-FRIT. For example, when the reference model M is defined as the second-order binomial coefficient standard form given by

$$M = \frac{\omega_0^2}{s^2 + 2\omega_0 s + \omega_0^2} e^{-L_{\text{M}}s} \tag{20}$$

the optimization variables are

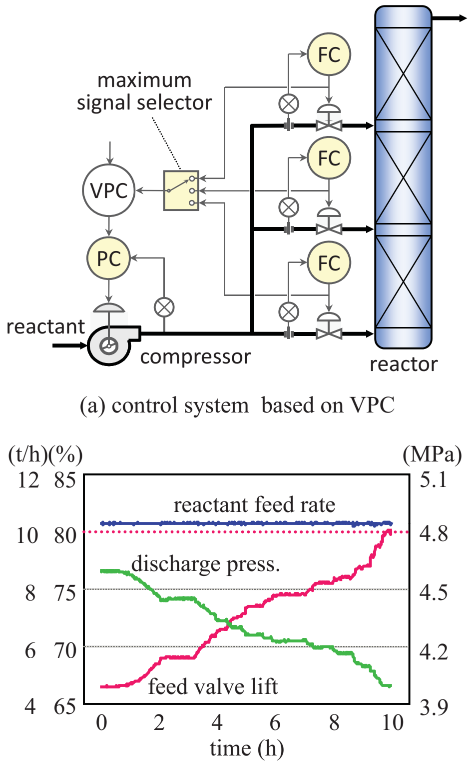
$$\boldsymbol{\phi} = (K_{\text{P}}, T_{\text{I}}, T_{\text{D}}, L_{\text{M}}) \tag{21}$$

instead of $\boldsymbol{\theta}$. This extension makes it possible to determine the reference model that is more suitable for the process.

Kano et al. (2009b) proposed useful guidelines for applying E-FRIT to industrial processes: 1) use the fourth-order binomial coefficient standard form with dead time as a reference model, 2) set a parameter ω_0 of the reference model on the basis of the rise time of the closed-loop response, 3) optimize the dead time of the reference model together with control parameters, and 4) use a fixed value as a weighting coefficient λ for a penalty term for variation of the manipulated variable. A recommended value is $\lambda = 0.01$ for tight control and $\lambda = 1$ for mild control. E-FRIT with these guidelines was validated through industrial applications. The results have clearly shown the usefulness of E-FRIT for chemical process control. A software tool that can execute E-FRIT was developed as a result of industry-academia collaboration in the task force "Workshop No.27 Process Control Technology," and it has been used in industry.

4. CONVENTIONAL ADVANCED CONTROL

The status report of the IFAC Coordinating Committee 6 (Dochain et al. (2008)) stated that high performance multivariable control is key to achieving the desired high profits and that the technology for the design and realization of high performance model-based constrained control systems at reasonable engineering effort is one of the key challenges faced by industrial practice. In fact, MPC has contributed toward achieving high profitability for many years. However, the profit can also be realized by utilizing conventional advanced control such as valve position control and override control in particular. The following question arises here: do we make the most use of conventional advanced control? In this section, let us introduce one



(a) control system based on VPC

(b) control result

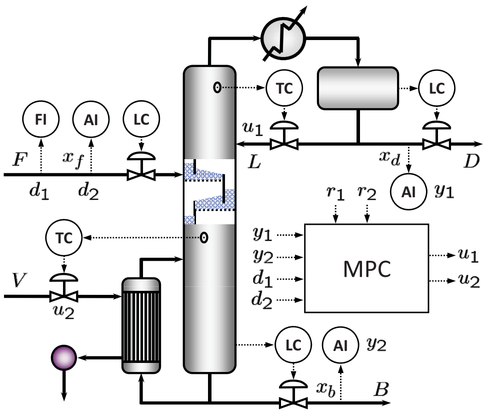
Fig. 8. Compressor-power-saving control

example showing the potential of conventional advanced control.

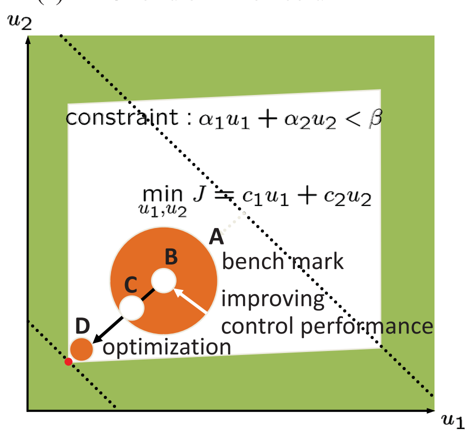
Conventional advanced control is effective for various processes and easy to implement on DCS. However, there has been a trend for control engineers to take little account of its application. This is the result that MPC became a standard tool for the advancement of process control. However, there is no doubt that production cost can be decreased by accumulating the effect of conventional advanced control.

The application of energy-saving control of the compressor with VPC is described here. As shown in Fig. 8, the feed gas is pressurized with the turbo compressor and supplied to three different stages of the reactor. Each flow rate of the feed gas is controlled. The discharge pressure of the compressor is controlled by using guide vane opening as the manipulated variable. To reduce compressor power, the discharge pressure is lowered gradually with VPC, until the largest valve opening among three feed flow control valves reaches the upper limit, while feed flow rate is kept constant. In this application, the discharge pressure was decreased from 4.6 MPa to 4.0 MPa by increasing the largest valve opening from 67% to 80%. As a result, motor electric power consumption was saved by 16%.

Shinsky (1977) listed the following objects in which there is an opportunity of the energy conservation by applying conventional advanced control: 1) excessive reflux of distillation column, 2) excessive combustion air of furnace, 3) high steam to oil ratio of reactor, and 4) fouled heat exchanger. In addition to these, excessive compression



(a) MPC for distillation column



(b) optimal operation using MPC

Fig. 9. MPC for distillation process

ratio provides an opportunity for the energy conservation as illustrated.

In the enterprise, it is important to find any loss that usually has been overlooked, to make the most use of conventional advance control, and to continue the effort at minimizing the loss. In comparison with the APC project of using MPC, profitable results can be obtained much more quickly without any further expense.

5. MODEL PREDICTIVE CONTROL

In this section, the present state of linear and nonlinear MPC is described through the typical applications and the survey results.

5.1 Linear MPC

The process that MPC is applied to most is distillation. A simple example of MPC for a distillation process is shown in Fig. 9(a). The controlled variables are the purity of products extracted from the column top and bottom, and the manipulated variables are the set-points of temperature PID control at the column top and bottom. The disturbance variables are flow rate and composition of feed. The constraints are upper and lower limits of the manipulated variables and the controlled variables and upper limits of changes in the manipulated variables.

The economic benefit that MPC brings is illustrated in Fig. 9(b). Since the achievable performance of PID control is limited due to interaction, which is a feature of multivariable processes, it is assumed that the current operating region corresponds to region A in the figure. In such a situation, the operating condition bound has to be set far from the real constraints to ensure a sufficient margin of safety. Using MPC can improve control performance and reduce variation. As a result, the operating region becomes small from A to B. This improvement makes it possible to move the operating region from B to C, which is close to the bound of operating conditions. Furthermore, more economical operation D can be realized by optimizing set-points to minimize operational costs. MPC takes on the responsibility of this set of functions. The benefit is not only the improvement of the control performance by using model-based control, but also the realization of stable operation close to the optimal point under disturbances by using optimization.

Implementation of MPC releases operators from most of the adjustment work they had to do in the past because the optimal operating condition is automatically determined and maintained under disturbances. In addition, MPC makes it possible to maximize production rate by making the most use of the capability of the process and to minimize cost through energy conservation by moving the operating condition toward the control limit. Both the energy conservation and the productive capacity were improved by an average of 3 to 5% as the result of APC projects centered on MPC at MCC.

The control performance of MPC depends on the accuracy of the process model and the appropriateness of tuning, but MPC has outstanding robustness. For example, stable operation is realized by MPC in spite of large model parameter errors of about 50%. However, it is difficult to assess the control performance of MPC due to a large number of variables. A plant test for modeling sometimes requires two weeks. The engineers who have experienced it can readily understand that the implementation of MPC including modeling and tuning is a demanding job.

MPC is highly effective, but it has several weak points (Hugo (2000)). First, it is not good at level control when the process has an integrator. For such a case, PI control is easy to design and superior to MPC in control performance. Second, the control performance of MPC deteriorates against ramp-wise disturbances because the MPC algorithm is developed by assuming step-wise disturbances (Lundstrom et al. (1995); Hugo (2000)). In addition, linear programming (LP) is usually used for optimizing set-points under constraints, and the optimal point is located at one of the extreme points of a polyhedron consisting of linear constraints. When the gradient of the objective function and that of constraints are similar to each other, the optimal point jumps from one extreme point to another and the set-points change suddenly (Forbes and Marlin (1994); Hugo (2000)). Research and development are continuing to solve these problems.

Ohshima et al. (1995), who wrote about the state of MPC application in the petroleum and chemical enterprises in Japan, reported that 154 MPC controllers were in operation and 43 under implementation. The total number

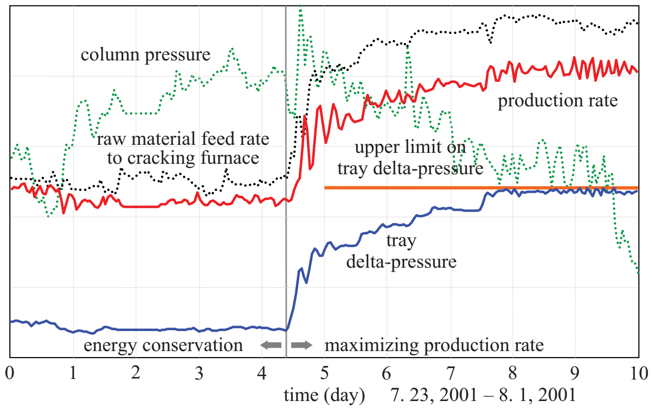


Fig. 10. Actual performance of the large scale MPC in the olefins unit

of 197 was 2.5 times as much as the number of 75 in 1990. At present, the number of MPC controllers is 169 only at MCC (Ogawa (2006)).

At the very end of this subsection, the MPC application for energy conservation and production maximization of the olefins unit at MCC Mizushima plant is briefly explained (Emoto et al. (1994)). Qin and Badgwell (2003) reported that this application was the largest MPC application in the world, consisting of 283 manipulated variables and 603 controlled variables. The process was operated in energy conservation mode for the first four days in Fig. 10. Since the productive capacity was beyond the demand, the temperature difference between vapor and coolant in the overhead condenser was increased by making the column pressure higher. As a result, an amount of heat exchanged was increased, and the amount of coolant used was decreased. This operation made it possible to reduce the refrigerator power. On the other hand, the process was operated in production maximization mode for the last five days. To maximize the production rate for fulfilling the demand, the separation performance was improved by decreasing the column pressure and increasing the relative volatility. The feed flow rate to the cracking furnace was increased until the tray delta-pressure reached its upper limit, that is, the flooding limit. In this production maximization mode, the MPC system is large because MPC controllers for many cracking furnaces and distillation columns function in cooperation.

A skilled operator made the following comment on this MPC application: "We had operated the Ethylene fractionator in constant pressure mode for more than 20 years. I was speechless with surprise that we had made an enormous loss for many years, when I watched the MPC decreased the column pressure, improved the distillation efficiency, and maximized the production rate." Another process control engineer said "I had misunderstood that set-points were determined by operation section and process control section took the responsibility only for control. I realized MPC for the first time; it makes the most use of the capability of equipments, determines set-points for economical operation, and maintains both controlled variables and manipulated variables close to the set-points."

Table 3. Statistics of MPC applications (from the survey JSPS143 WS27 2009)

in-house vs vendor			
in-house development			6 %
introduction from vendor			94 %
targeted process			
distillation			32 %
reaction			23 %
others			45 %
product			
DMCplus®			46 %
RMPCT®			36 %
Connoisseur®			5 %
SMOC®			4 %
others			9 %
number of MV, CV, and DV			
	MV	DV	CV
0	0	28	0
1	40	45	24
2	57	50	33
3-5	83	103	58
6-9	47	40	59
10-19	59	27	48
20-29	12	5	25
30-39	1	3	29
40-49	1	3	16
50 or more	5	1	13

MV: manipulated variable
CV: controlled variable
DV: disturbance variable

5.2 Nonlinear MPC

Nonlinear MPC has attracted attention in recent years (Qin and Badgwell (2003)). It is suitable for control of a nonlinear process operated in a wide range, e.g. polymerization reaction processes. In MCC, an independently developed nonlinear MPC has been applied to polymerization reactors at the polyolefin production units, and it has been put successfully to practical use (Seki et al. (2001)).

However, application of nonlinear MPC has not spread as well as was expected. It is difficult to build a nonlinear model of a process, or process control engineers have slackened their efforts at modeling nonlinear processes. On the other hand, most polymer production processes are operated without any quality problem by existing control systems supported with operators' suitable manual intervention. Therefore, it is difficult to justify any benefit of using nonlinear MPC. These obstacles should be overcome to expand nonlinear MPC application.

5.3 Survey Result of MPC

A part of the questionnaire survey results, related to MPC, is introduced here. The total number of MPC applications answered is 305, which is 1.5 times as much as the number of 197 in 1995. The statistics of 305 MPC applications are summarized in Table 3. Most of them are introduced from vendors; DMCplus® and RMPCT® are dominant tools. Distillation and reaction processes cover half the applications.

Table 4 clarifies objectives and effects of MPC. In addition to disturbance rejection and set-point tracking, the time to achieve the optimal condition and the realization of

Table 4. Effects of MPC applications (from the survey JSPS143 WS27 2009)

objective of tuning	
disturbance rejection	56 %
set-point tracking	38 %
time to optimal condition	6 %
major effect on control performance	
disturbance rejection	43 %
automatic operation	36 %
set-point tracking	18 %
others	3 %
major effect on productivity	
saving resources and energy	38 %
increasing production capacity	31 %
reducing operators' load	17 %
improving product quality	10 %
increasing flexibility toward changes	4 %
major key to success	
careful modeling	37 %
suitability for objective	33 %
education of operators and engineers	15 %
suitability for process characteristics	11 %
hardware/software environment	4 %

automatic operation are important. Saving resources and energy, increasing production capacity, reducing operators' load, and improving product quality are major effects achieved by MPC. Furthermore, process control engineers have identified the following major keys to success: 1) a process model should be developed with care, 2) MPC should be suitable for objectives, 3) operators and engineers should be adequately educated, and 4) MPC should be suitable for process characteristics.

Although MPC has been widely and successfully applied in the chemical and petroleum refining industries, problems still remain to be solved as summarized in Table 5. The major problem would be described as follows. To achieve desirable performance, it is necessary to build an accurate model and to tune control parameters appropriately. However, both of them are difficult in practice due to process nonlinearity and changes in process characteristics. To keep sufficient control performance and to prevent or at least cope with performance deterioration, the maintenance of MPC is crucial. Control engineers need to know the reason of performance deterioration and the effective countermeasure. In addition, they would like to know the relationship between model accuracy and achievable control performance. Modeling of a multivariable process is an exceedingly laborious engineering task; thus it needs to be clarified how accurate a model should be to achieve the goal. Of course, not only clarifying the relationship but also improving modeling and tuning methods is necessary. In addition, the implementation of MPC should be easier. As for the maintenance of MPC, very recently, Badwe et al. (2008) proposed a model-plant mismatch detection method by using partial correlation analysis, and Huang (2008) proposed the used of Bayesian methods. Another problem is how to transfer engineering technology from skilled engineers to others. Unfortunately, a lack of process control engineers aggravates the situation. Furthermore, it is also crucial in practice to answer the question: how can we estimate the economical benefit of installing MPC to justify the project? Most APC suppliers and users are required to report the benefit to management. Bauer and

Table 5. Problems of MPC applications (from the survey JSPS143 WS27 2009)

problem: general	
low robustness against model error	26 %
difficulty in tuning	23 %
inability to cope with specific objective	15 %
difficulty in modeling	12 %
others	24 %
problem: maintenance	
transfer of engineering technology	44 %
response to performance deterioration	33 %
education of operators	7 %
difficulty in tuning	7 %
others	9 %
need for improvement: general	
to improve modeling technology	28 %
to clarify method of estimating effect	25 %
to simplify implementation	22 %
to increase process control engineers	14 %
others	11 %
need for improvement: theory	
to cope with changes in process characteristics	26 %
to clarify relations between model accuracy and control performance	24 %
to cope with unsteady operation (SU/SD)	16 %
to incorporate know-how in control system	16 %
to cope with nonlinearity	13 %
others	5 %
need for improvement: response to changes/nonlinearity	
to switch multiple linear models	28 %
to improve robustness of linear MPC	25 %
to use time-varying/nonlinear model	18 %
to add adaptive function to linear MPC	18 %
to integrate other technique with MPC (e.g. knowledge-based control)	11 %

Craig (2008) reported that benefit estimation methods based on variance reduction are still carried out, but they are sometimes rudimentary and based on experience.

6. SOFT-SENSOR

A soft-sensor, or a virtual sensor, is a key technology for estimating product quality or other important variables when on-line analyzers are not available. In chemical processes, for example, soft-sensors have been widely used to estimate product quality of distillation columns, reactors, and so on. Artificial neural network (ANN) has been dominant in the literature since the middle 1990's, while partial least squares (PLS) is popular in industry (Kano and Nakagawa (2008)). ANN is a useful tool for building nonlinear models and supposed to be suitable for industrial processes. However, linear models have produced satisfactory results in many cases because industrial processes are operated within certain range to produce the required products and linear approximation functions well. In addition, collinearity has to be taken into account for developing reliable soft-sensors. Thus, PLS has been very popular as a tool for soft-sensor design (Mejdell and Skogestad (1991); Kresta et al. (1994); Kano et al. (2000)). In recent years, support vector machine (SVM), support vector regression (SVR), and other kernel-based methods have emerged (Boser et al. (1992); Cortes and Vapnik (1995)). These methods have attracted researchers' and engineers' attention and have been used for soft-sensor design (Yan et al. (2004); Desai et al. (2006)). Another method for developing soft-sensors is subspace identification (SSID), which can build a state space model from input and output data (Verhaegen and Dewilde (1992); Overschee and Moor (1994)). SSID is a useful tool to build a dynamic inferential model of a multivariable process, and it is suitable for soft-sensor design because the performance of soft-sensors can be greatly improved by taking process dynamics into account (Kano et al. (2000)). Amirthalingam and Lee (1999) used SSID for inferential control of a continuous pulp digester. Amirthalingam et al. (2000) developed a two-step procedure to build SSID-based inferential control models, in which the stochastic part was idetified from historical data and the deterministic part was identified from plant test data. Kano et al. (2009a) proposed two-stage SSID to develop highly accurate soft-sensors that can estimate unmeasured disturbances without assumptions that the conventional Kalman filtering technique must make. Thus it can outperform the Kalman filtering technique when innovations are not Gaussian white noises or the properties of disturbances do not stay constant with time. The superiority of the two-stage SSID over conventional methods was demonstrated through their application to an industrial ethylene fractionator.

6.1 Reliability of Soft-sensor

A great deal of research has been conducted to develop data-based soft-sensors for various processes. A data-based soft-sensor, however, does not always function well, because a black-box model is not valid when a process is operated outside certain conditions where operation data used for modeling were obtained. The product quality and process performance will deteriorate if estimates of the soft-sensor are blindly believed by operators and used in a control system. On-line monitoring of the validity of the soft-sensor will avoid such a dangerous situation. The simplest approach is to check whether an estimation error exceeds its control limit when a measurement becomes available. This approach enables us to detect the inconsistency between the analyzer and the soft-sensor, but the cause of the inconsistency cannot be identified. In industry practice, it is assumed that an estimation error is caused by inaccurate estimation; however, this assumption is not always true because analyzers are not always reliable. For example, when blockage occurs within a sampling line, a hardware sensor cannot provide accurate measurements. To address such practical problems, Kamohara et al. (2004) proposed a PLS-based framework for developing a soft-sensor and monitoring its validity on-line. The on-line monitoring system was based on the multivariate statistical process control (MSPC) technique (Jackson and Mudholkar (1979); Kresta et al. (1991)) in which the dynamic PLS model designed for estimating the product quality is used. In addition, simple rules were established for checking the performance of a process gas chromatograph by combining the soft-sensor and the statistical monitoring system. The effectiveness of the developed system was demonstrated through its application to an ethylene production plant.

6.2 Changes in Process Characteristics

Generally, building a high performance soft-sensor is very laborious, since input variables and samples for model construction have to be selected carefully and parameters have to be tuned appropriately. Even if a good soft-sensor is developed successfully, its estimation performance deteriorates when process characteristics change. In chemical processes, for example, equipment characteristics are changed by catalyst deactivation or scale adhesion. Such a situation may lead to a decline of product quality. Therefore, from the practical viewpoint, maintenance of soft-sensors is very important to keep their estimation performance. Soft-sensors should be updated as the process characteristics change, and manual and repeating construction of them should be avoided due to its heavy workload.

To cope with changes in process characteristics and to update statistical models automatically, recursive methods such as recursive PLS were developed (Qin (1998)). These methods can adapt models to new operating conditions recursively. However, the prediction performance would deteriorate if the model is updated with an abnormal sample. Kaneko et al. (2009) used independent component analysis (ICA) to detect abnormal situations and improve the prediction accuracy. Recently, ICA is recognized as a useful technique for fault detection and diagnosis (Kano et al. (2003, 2004); Lee et al. (2004)). The combination between soft-sensors and fault detection is effective to a certain extent. But, as far as a recursive method is used, the model will adapt excessively and will not function in a sufficiently wide range of operating condition when a process is operated within a narrow range for a certain period of time. In addition, recursive methods cannot cope with abrupt changes in process characteristics.

Just-In-Time (JIT) modeling or lazy learning was proposed to cope with changes in process characteristics as well as nonlinearity, and it has been used for nonlinear process monitoring as well as soft-sensing (Atkeson et al. (1997); Bontempi et al. (1999)). In JIT modeling, a local model is built from past data around a query point only when an estimated value is requested. JIT modeling is useful when global modeling does not function well. However, its estimation performance is not always high because the samples used for local modeling are selected on the basis of the distance from the query point and the correlation among variables is not taken into account. A good model cannot be developed when correlation among input and output variables is weak even if the distance between samples is small. Conversely, a very accurate model can be developed when the correlation is strong even if the distance is large. On the basis of this idea, recently, correlation-based JIT (CoJIT) modeling was proposed by Fujiwara et al. (2009). In this technique, the samples used for local modeling are selected on the basis of correlation together with distance, and the Q statistic is used as an index of the correlation dissimilarity. The Q statistic is derived from principal component analysis (PCA), and it is a measure of dissimilarity between the sample and the modeling data from the viewpoint of the correlation among variables (Jackson and Mudholkar (1979)). CoJIT can cope with abrupt changes of process characteristics and also achieve high estimation performance. It can also cope with process nonlinearity.

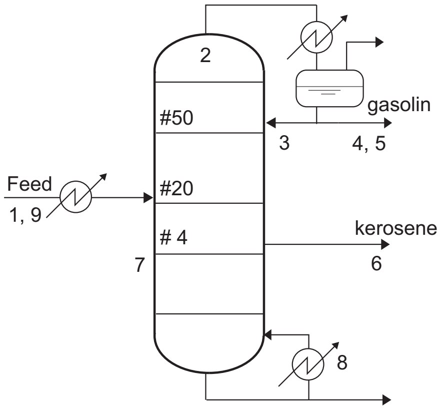


Fig. 11. Schematic diagram of the cracked gasoline fractionator of the ethylene production process at the Showa Denko K.K. (SDK) Oita plant

6.3 Industrial Case Study of CoJIT

Here, an application of CoJIT to an industrial chemical process is introduced (Fujiwara et al. (2009)). A soft-sensor for estimating the aroma concentration was constructed to realize highly efficient operation of the cracked gasoline fractionator of the ethylene production process at the Showa Denko K.K. (SDK) Oita plant in Japan. A schematic diagram of the cracked gasoline (CGL) fractionator of the ethylene production process is shown in Fig. 11. The CGL fractionator is controlled by applying multivariable MPC with an optimizer, and the aroma concentration in the CGL (aroma denotes the generic name for benzene, toluene, xylene and styrene, etc.) is used as one of the constraints in the optimizer. Although the operation data of the CGL fractionator are stored in the database every hour, the aroma concentration is analyzed in a laboratory usually once a day because of its long analysis time. For safety, the process must be operated in a condition that has a wide margin and is far from constraints. Therefore, a soft-sensor that can estimate the aroma concentration accurately in real time needs to be developed for realizing efficient operation.

In addition to eight variables measured in the CGL fractionator, the coil outlet temperature of the cracking furnace, measured four hours before, was used as an input variable, since the product composition is affected by the operating condition of the cracking furnace which is located in the upstream of the ethylene production process, and it takes about four hours for materials to reach the CGL fractionator from the cracking furnace. The selected input variables of the soft-sensor are listed in Table 6 and Fig. 11.

First, the aroma concentration was estimated with recursive PLS. The model was updated every 24 hours when the aroma concentration was analyzed in the laboratory. The estimation result is shown in Fig. 12(top). There is a bias between the measurements and the estimates after the 100th day when the pressure of the compressor was changed.

Next, the aroma concentration was estimated with CoJIT. In the initial state, the operation data obtained from April 30, 2006 to February 23, 2007 were stored in the database.

Table 6. Input variables of the soft-sensor for the CGL fractionator

No.	variable
1	Feed flow rate
2	Tower top temperature
3	Reflux volume
4	Outlet cracked gasoline temperature
5	Outlet cracked gasoline flow rate
6	Outlet cracked kerosene flow rate
7	Tray #4 differential pressure
8	Reboiler flow rate
9	Cracked furnace coil outlet temperature

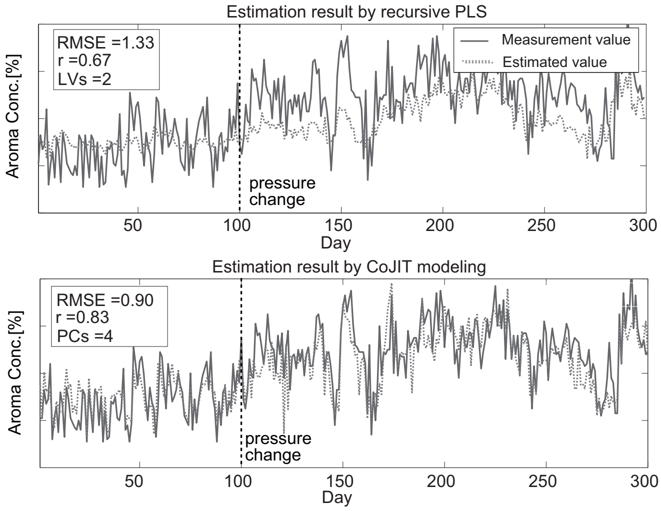


Fig. 12. Prediction results of aroma concentration: recursive PLS (top) and CoJIT modeling (bottom)

Then, the soft-sensor was updated and the aroma concentration was estimated for the next 300 days, February 24, 2007 to December 25, 2007. The estimation result is shown in Fig. 12(bottom). The estimation performance of CoJIT is high and RMSE (root mean squared error) is improved by about 28% in comparison with recursive PLS. CoJIT would have a potential for realizing efficient maintenance of soft-sensors in the real world.

6.4 Survey Result of Soft-sensor

A part of the questionnaire survey results related to soft-sensors is introduced here. This questionnaire asked control engineers the number of soft-sensor applications, targeted processes, methods for designing soft-sensors, and problems to be solved. The total number of soft-sensor applications answered was 439. The number is rapidly increasing. The survey result is summarized in Table 7.

This survey result clarifies the state of the art of soft-sensor application in Japan. First, a major targeted process is distillation (331/439), followed by reaction (86/439) and polymerization (20/439). Second, a major modeling method is multiple regression analysis (MRA) (293/439), followed by PLS (93/439). Nonlinear modeling methods are rarely used in the Japanese chemical and petroleum refining industries. It is confirmed that linear regression such as MRA and PLS can achieve sufficient estimation accuracy for most distillation and reaction processes. On the other hand, polymerization reaction processes are more difficult to model by linear regression than distillation and

Table 7. Statistics of soft-sensor applications (from the survey JSPS143 WS27 2009)

process	Phys	MRA	PLS	O.L.	ANN	JIT	Gray	total
	methodology							
distillation	20	256	41	6	0	5	3	331
reaction	5	32	43	0	0	5	1	86
polymerization	0	4	8	0	3	0	5	20
others	0	1	1	0	0	0	0	2
total	25	293	93	6	3	10	9	439

Phys: physical model
MRA: multiple regression analysis
PLS: partial least squares regression
O.L.: other linear regression
ANN: artificial neural network
JIT: just-in-time model
Gray: gray-box model or hybrid model between physical model and statistical model

Table 8. Problems of soft-sensor applications (from the survey JSPS143 WS27 2009)

accuracy deterioration due to changes in process characteristics	29 %
burden (time/cost) of data acquisition	22 %
burden of modeling itself	14 %
burden of data preprocessing	7 %
inadequate accuracy since installation	7 %
inadequate accuracy due to changes in operating conditions	7 %
difficulty in evaluating reliability	7 %
unjustifiable cost performance	7 %

other reaction processes. Thus, some companies have used gray-box models (5/20) or ANN models (3/20).

In addition, we have asked engineers what are problems related with applications of soft-sensors. The answers are summarized in Table 8. This result confirms that the maintenance of models is the most important issue concerning soft-sensors.

7. RELATED ISSUES

In this section, other important issues related to process operation are described: tracking simulator and alarm management.

7.1 Tracking Simulator

As process engineers, we have a dream that one day a plant simulator based on a rigorous first-principle model is realized and it provides functions such as 1) estimation and visualization of all states and parameters, 2) prediction of plant behavior in the future, 3) optimization of operating conditions, and 4) detection and diagnosis of abnormal situations. This plant simulation technology will become the core of future operation support system and lead to production innovation.

As mentioned before, the achievement of stable and efficient operation has largely depended on skilled operators in Japan, and many skilled operators are approaching retirement age. Thus, an advanced operation support system and an efficient operator training system are required. A training simulator for teaching operators to cope with start-up, shut-down, and other operations under abnormal situation has been developed and widely used in the process industry. The training simulator aims at faithful reproduction of real plant behavior. On the basis of the training simulator, a *tracking simulator* is now under development to realize the above-mentioned functions (Fukano et al. (2007)). The tracking simulator works simultaneously with an actual plant, adjusts parameters, estimates states, analyzes the plant, and optimizes operation by using plant models and measurements. The tracking simulator consists of a mirror model for visualizing plant states, an identification model for parameter estimation, and an analysis model for realizing the other necessary functions.

Such a tracking simulator has been developed by a few companies and introduced and tested in real plants in Japan. Further development is required to realize our dream, and various challenging problems confront us.

7.2 Alarm Management

Recently, alarm management has attracted considerable attention to achieve highly stable operation in the process industry. General recognition for current alarm systems in Japan is as follows (Higuchi et al. (2009)). With the advance of distributed control systems (DCS) in the chemical industry, it has become possible to install many alarms cheaply and easily. While most alarms help operators detect and identify faults, some are unnecessary. A poor alarm system may cause alarm floods and nuisance alarms, which reduce the ability of operators to cope with plant abnormalities because critical alarms are buried in many unnecessary alarms.

If an alarm system does not work as designed, the effects can be very serious. The explosion and fires at the Texaco Milford Haven refinery in 1994 injured 26 people and caused around £48 million of damage and a significant loss in production. The Health and Safety Executive's (HSE) investigation (1997) mentions that there were too many alarms and these were poorly prioritized and the control room displays did not help operators understand what was happening.

To improve the quality and safety of industrial plants, and to reduce cost of the design and maintenance of plant alarm systems, the Engineering Equipment and Materials Users Association (EEMUA) provided the general design and evaluation principles of plant alarm systems (The Enginnering and Equipment Materials Users' Association (EEMUA) (2007)). While this guide gathered many valuable plant engineers' experiences, it is only a general guide, and some of the design methods are only conceptual, such as the selection of alarm source signals and the decisions on alarm limits (Yan et al. (2007)). In addition, the role of operators in Japan is far different from that in other countries; thus, it is recognized that direct application of the EEMUA 191 Guide is not appropriate in Japan. In fact, a bottom-up approach has succeeded in reducing the number of alarms, average alarm frequency standards proposed by EEMUA are achieved in some plants, and further improvement is required. Generally, Japanese companies are excellent at such a bottom-up approach as TPM (total productive maintenance), which combines preventive maintenance with Japanese concepts of total quality control (TQC) and total employee involvement (TEI). It is true, however, the alarm management in Japan has been short of a viewpoint of such a top-down approach as EEMUA suggested. In Japan, the industry-academia collaboration task force "Workshop No.28 Alarm Management" supported by the JSPS 143rd committee was established in 2007. This task force aims at developing new methodologies and standardizing alarm management by emphasizing distinctive culture in Japanese industries.

8. CONCLUSIONS

The state of the art in process control in Japan was described in this paper on the basis of the authors' experience and the questionnaire survey results. The realization of *production innovation* and *highly stable operation* is the chief objective of the process industry in Japan. To achieve this objective and solve the year 2007 problem, i.e., retirement of skilled operators, process control and operation need to be further improved. This improvement does not necessarily mean the adoption of novel advanced technologies. Rather, it is important to reform the whole production activity through reviewing it as leading chemical companies have done and consequently have increased productivity remarkably.

In Japan, several industry-academia collaboration task forces have been organized to sift through problems related to process operation and solve them. Such task forces include Workshop No.25 Control Performance Monitoring, Workshop No.27 Process Control Technology, Workshop No.28 Alarm Management, and so on; they are supported by the JSPS 143rd committee. More than a few methods and tools have been developed by task forces and utilized in various companies. Several examples were introduced in this paper together with practical methods developed outside task forces. The topics discussed here include PID control, advanced conventional control, model predictive control, soft-sensor, tracking simulator, and alarm management. The current situation and the problems were clarified.

In recent years, there has been a strong trend to produce polymer products having special functions in a small amount in a batch process. At the forefront of production, the necessity of practical technological development is being recognized: for example, precise control of reaction temperature, estimation of reaction state, and batch-to-batch control. Process control engineers have been committed to continuous process control so far. In the future, however, they need to open their eyes to batch process control and to meeting the challenges to its advancement.

This paper has surveyed what process control engineers have done in the last two decades and what they might do in the future, especially focusing on the projects at a Japanese chemical company. The authors expect that engineers share practical methods and best practice and also that they spare no effort in developing their own methods to solve their own problems.

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