

Technology of Controller Performance Monitoring and Diagnosis in Chemical Plants

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Hidekazu KUGEMOTO

The controller performance monitoring technique, which is based on the principle of minimum variance control, can evaluate the performance of many PID controllers in a plant at a time and is applicable in online. It is important that the origins of failure are analyzed for lower performance controllers. One of them is valve failure and is identified by the proposed methods. In this article, the technology of controller performance monitoring and diagnosis is mentioned and its applications in practical chemical plants are shown.

This paper is translated from R&D Report, "SUMITOMO KAGAKU", vol. 2005-II.

Introduction

In recent years, technology has been developed for evaluating and monitoring the performance of controllers in industrial plants, and this technology is beginning to be applied in large-scale commercial plants. There are a large number of PID controllers in chemical plants, and this is attracting attention as a method for the improvement and maintenance of the performance of these controllers. A large number of techniques that add exogenous signal to manipulated variable for grasping characteristics of controllers have been proposed, but they have not become popular because they give the fluctuations in the actual plant.

Control performance evaluation methods¹⁾ that are based on minimum variance control do not require these exogenous signals and manipulated variable data, and have convenient characteristics for actual applications, such as being able to evaluate controller performance from controlled variable data only and not being dependent on the controller structure. In addition, it is possible to monitor all controllers throughout the plant because evaluations can be done using comparatively simple calculations.

These control performance evaluations are an effective means for extracting controllers that are performing poorly and are deteriorating over time throughout the plant, but they cannot go as far as diagnosing the causes.

We must get a grasp on the causes to improve control performance, and diagnostic techniques for doing so are being sought. As causes for a drop in control performance, we have bad controller tuning, operational failures caused by valves sticking, insufficient capacity in equipment, mutual interference and the like, but out of these, we developed techniques for detecting valve stiction caused by friction through cooperation between industry and academia.²⁾

In this paper, we will outline control performance evaluation methods and detection methods for valve failure and introduce work Sumitomo Chemical has done using these methods.

Control Performance Evaluation Methods

The method of making minimum variance control was proposed by Harris, and it has been developed as a method capable of quantitatively evaluating controller performance using only controlled variables. The performance of PID controllers throughout a plant can be evaluated using this method, and this can be helpful for control improvement activities and plant monitoring.

1. Minimum Variance Control

Letting the controller be C , the process P and the transfer function for the disturbance D , the relationship between the controlled variable y and manipulated variable u for a discrete time system is expressed as follows for Fig. 1.

$$y(k) = P(q^{-1})u(k) + D(q^{-1})a(k) \quad (1)$$

$$u(k) = C(q^{-1})(r(k) - y(k)) \quad (2)$$

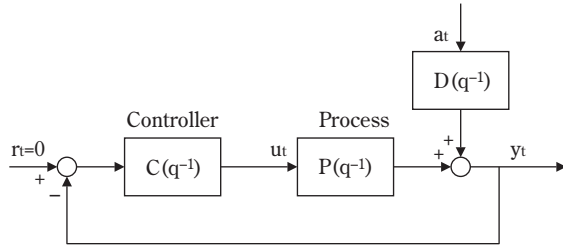


Fig. 1 Block diagram

Here, a is white noise and r is a set point. Letting there be $d-1$ steps of dead time in the process, the disturbance transfer function is divided into an inside dead time part and an outside dead time part to obtain Equation (3).

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

q^{-d} is known as the delay operator, and it expresses a delay of d steps. Controlled variable y is expressed by the following equation unless the settings are changed.

$$\begin{aligned} y(k) &= \frac{D}{1 + CP} a(k) \\ &= \frac{F + q^{-d}G}{1 + q^{-d}C\tilde{P}} \\ &= \left\{ F + q^{-d} \frac{G - FC\tilde{P}}{1 + q^{-d}C\tilde{P}} \right\} a(k) \\ &= Fa(k) + Ha(k-d) \end{aligned} \quad (4)$$

Here \tilde{P} represents the transfer function for a process with no dead time. If the entire process, including the controller, is perceived as a black box, it is possible to divide Equation (4) into the direct effects of white noise $Fa(k)$ on the process through the disturbance transfer function during the dead time and the effects $Ha(k-d)$ through feedback outside of the dead time. Since $Fa(k)$ and $Ha(k-d)$ are independent of each other, the variance of these gives rise to the following relationship.

$$\begin{aligned} \text{Var}\{y(k)\} &= \text{Var}\{Fa(k) + Ha(k-d)\} \\ &= \text{Var}\{Fa(k)\} + \text{Var}\{Ha(k-d)\} \\ &\geq \text{Var}\{Fa(k)\} = \sigma_{MV}^2 \end{aligned} \quad (5)$$

Var and σ^2 show the variance, and σ_{MV}^2 is called the minimum variance. If there is dead time in the process,

the controller cannot be affected in any way during the dead time, so the variance for controlled variable y must always be greater than the minimum variance σ_{MV}^2 . (4) The second term $Ha(k-d)$ in the equation shows the effects outside of the dead time, and this can be made small for operating control. Considering ideal control where there is a fluctuation of zero outside of the dead time, that is, $\text{Var}\{Ha(k-d)\} = 0$, the variance for controlled variable y is equal to the minimum variance, and control achieving this is called minimum variance control.

2. Control Performance Index

The variance when control is carried out by minimum variance control is σ_{MV}^2 , and control performance can be evaluated through the ratio with the variance σ_y^2 for controlled variable y .

$$\eta(d-1) = \frac{\sigma_{MV}^2(d-1)}{\sigma_y^2} \quad (6)$$

This is known as control performance evaluation method that is based on minimum variance control, and η is called the control performance index. The control performance index η is a value in the range of 0 – 1, and as η gets close to 1 control performance is judged to be better. As it approaches 0 control performance is judged to be poorer.

As an actual method for finding the control performance index η , there is what is called the filtering and correlation analysis algorithm (FCOR)³, and this can be found from the cross correlation function for controlled variable y and white noise a .

$$\bar{\rho}_{ya}(i) = \frac{\frac{1}{N-1} \sum_{t=1}^N y_t a_{t-i}}{\sqrt{\frac{1}{N-1} \sum_{t=1}^N y_t^2} \sqrt{\frac{1}{N-1} \sum_{t=1}^N a_t^2}} \quad (7)$$

$$\eta(d-1) = \sum_{i=0}^{d-2} \rho_{ya}^2(i) \quad (8)$$

Here, N indicates the number of pieces of time series data. To actually measure the white noise affecting the process, an autoregressive moving average (ARMA) model, which is a time series model, is used, and the white noise a is estimated from controlled variable y . ARMA models are the process dynamics under the presumption that the process is driven by white noise, and observed white noise a can be calculated at the same time. Control performance index η is calculated from

Equation (7) and Equation (8) using controlled variable y and white noise a .

Valve Failure Detection Methods

Though there are causes such as tuning problems and valve problems for drops in controller performance, valve failures take up a little under 10% in typical plants and 38% in plants where they are frequent in the experience of the authors. Sticking because of lack of grease in the valve or leakage of fluids, valve positioner failure, mechanical hysteresis and the like can be cited as direct causes of valve failure.

Both PID tuning problems and valve failures often produce periodic oscillations in the controlled variables, and for actual improvements, it is important to assess which of these is the cause. With tuning problems, retuning is sufficient, and with valve failures, the valves must be detached and repaired. If retuning is carried out erroneously for a valve failure, there may be a large fluctuation in the plant, and techniques for diagnosing this accurately in advance are needed.

1. Modeling of Valve Stiction

Let us look at the behavior when valves stick with the pneumatic control valves (Fig. 2) that are widely used. In pneumatic control valves there are three main forces operating, the air pressure used to drive the valve in response to a manipulated variable, the elastic force of the springs in the actuator and the frictional force arising in the grand packing. The frictional force increases with over tightening of the grand packing and leakage of fluids and hardening and disturbs the operation of the valve. Discontinuous action of this sort is called valve stiction.

Detailed models^{4), 5)} expressing the forces operating in the valve as equations of motion and simple models^{6), 7)} focusing on the relationship between the manipulated variable and valve position have been proposed as models representing valve stiction.

The action in Fig. 3 shows the relationship between the manipulated variable output by the controller and the actual valve position for valve stiction. The dashed lines are the ideal state where there is no friction. Letting point (a) be the initial state, static friction operates in the interval where the manipulated variable is gradually increased from point (a) to point (b), and the valve position does not change. If enough is added to the manipulated variable to overcome the maximum static

friction f_s , the static friction is transformed into dynamic friction f_D , and the slip jump J from point (b) to point (c) occurs.

$$J = f_s - f_D \quad (9)$$

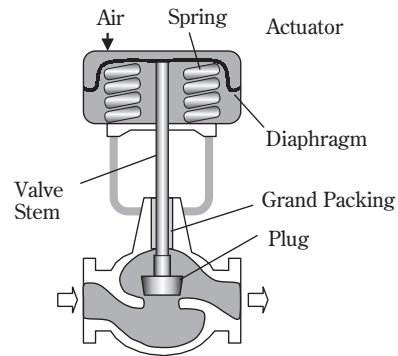


Fig. 2 Cross section diagram of control valve²⁾

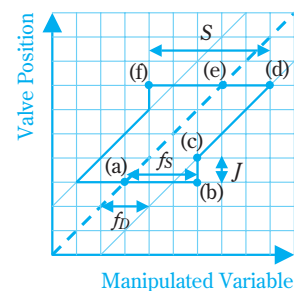


Fig. 3 Manipulated variable and valve position plot²⁾

After that it moves smoothly to point (d). Next, if the manipulated variable is gradually reduced from point (d), it returns to a state where there is no stress at point (e) where the dynamic friction f_D has dropped. Next, the static friction operates, and the valve position does not change up to point (f). The stationary interval where the valve does not move is the sum of the dynamic friction f_D and the maximum static friction f_s , and this is called the sticking width S .

$$S = f_s + f_D \quad (10)$$

Fig. 4 shows a flow chart for a model that expresses this behavior. Letting u be the manipulated variable and y the valve position, u_s is the manipulated variable at the point in time where the stationary or operating direction changes, and stp the static state of the valve and d the direction in which the dynamic friction works.

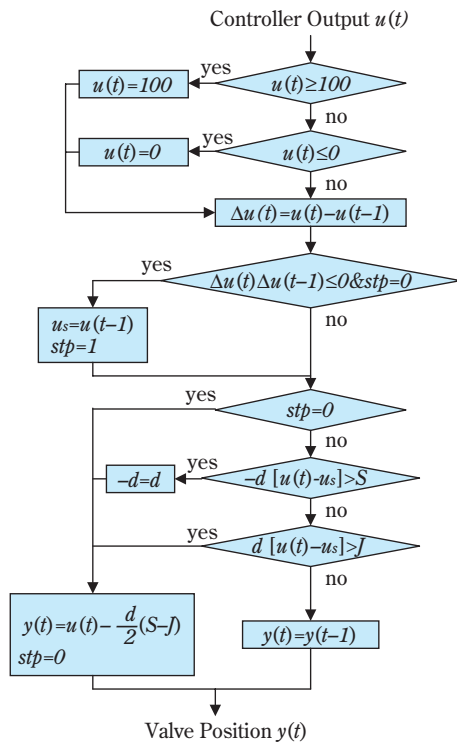


Fig. 4 Valve stiction model²⁾

2. Methods for Detecting Valve Failure

Valve failure detection methods can be roughly divided in two. One uses a diagnostic function incorporated into a fieldbus instrument or intelligent valve positioner and has the feature of being capable of high-speed diagnostics using detailed information about the equipment other than the manipulated variables and controlled variables. The other uses plant operating data, and it has the merit of not requiring the addition of any new hardware. This latter method, which uses plant operating data, is being studied enthusiastically in Europe and the United States, and various methods have already been proposed. For example, Horch, a pioneer in this field, has proposed a method for detection using phase delay information obtained from correlation functions and a detection method that uses the property that the valve opening exhibits behavior close to a square wave in closed loop.⁸⁾ Choudhury et al. have proposed a method that detects problems with valves by investigating nonlinearity using higher order statistics.⁶⁾

Thornhill et al. have proposed a method for identifying the location of valve failures by analyzing oscillating data transmitted throughout the plant from a different point of view.⁹⁾ In Japan, Kaseda et al. have proposed a detection method that uses a valve stem speed distribution found from the valve positions.⁴⁾ Since for many of the causes of valve failures there is periodic

oscillation in the controlled variable, most techniques make use of periodicity for detection.

① Frequency Analysis¹⁰⁾

With methods that make use of the periodicity of controlled variable data, it is important to be able to accurately distinguish between tuning problems and valve failures. Though tuning problems exhibit behavior close to a sine wave, valve failures have the characteristic of exhibiting behavior where the valve position or the flow rate is close to a square wave. Frequency analysis can be used for handling these at the same time and diagnosing the differences.

Fig. 5 shows the power spectra of sine, square and white noise data. There is one peak exhibiting periodicity in the sine wave power spectrum that simulates a tuning failure, and we see several harmonic peaks besides the fundamental wave in the square wave that simulates a valve failure. On the other hand, we can see no remarkable peaks in the white noise that simulates normal process data. Here, the peaks of the harmonic waves seen in the square wave power spectrum appear in each odd numbered multiple of the fundamental wave as is also apparent from the Fourier series progression for the square wave in Equation (11). The power attenuates $1/(2n+1)^2$ of the fundamental wave each time.

$$x(t) = \frac{4}{\pi} \left(\sin \omega t + \frac{1}{3} \sin 3\omega t + \frac{1}{5} \sin 5\omega t + \dots \right) \quad (11)$$

$$P_x = X \cdot X^*$$

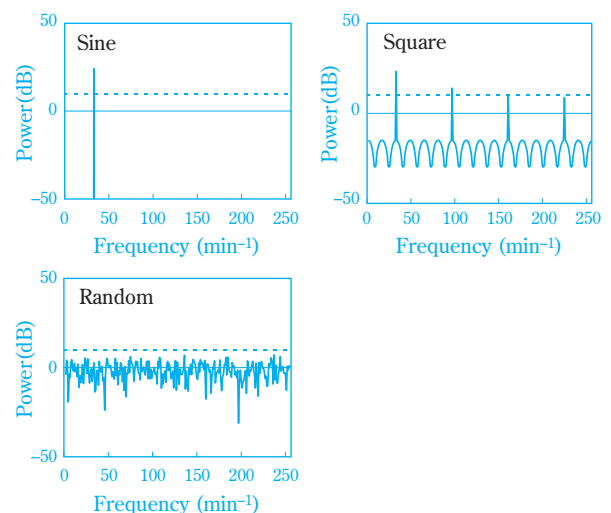


Fig. 5 Power spectra of sine, square and white noise data¹⁰⁾

X is the Fourier transform of $x(t)$, X^* the complex conjugate root and P_x the power spectrum.

The harmonics may be used to discriminate the difference between the sine wave and square wave, but there is the problem of identification being difficult with attenuation in power. Therefore, Equation (12) is used to amplify the power P_x .

$$P_x^1 = (f/f_0)^2 P_x \quad f = 1 \sim 256 \quad (12)$$

f is frequency, f_0 the fundamental frequency and P_x^1 the power after amplification. Since this amplification filter makes the low frequency component power smaller and the higher frequency component power greater based on the power of the fundamental wave, the result is an increase in the power of the harmonics to the level of the fundamental wave seen in the square wave.

Fig. 6 shows the results of amplification of the sine wave and square wave using this filter.

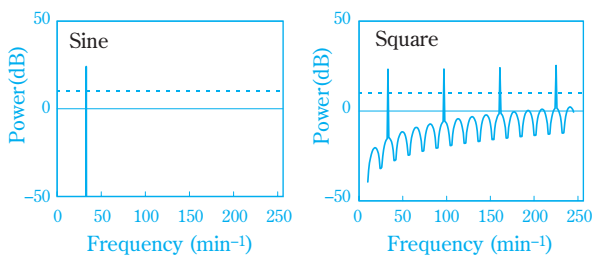


Fig. 6 Amplified power spectra of sine and square data¹⁰⁾

It can be seen that the harmonics are easy to grasp with the amplification filter processing. In the detection of valve failures we may check for the presence or absence of power exceeding a threshold value for the frequency bands higher than the fundamental wave, but since there effects from data drift and harmonic noise, there should be cutoffs in the low frequency band and high frequency band so that there is no effect on discrimination or preprocessing with a band-pass filter. This technique cannot be applied when there is periodic oscillation in the data, but it can detect tuning failures and valve failures at the same time.

② Detection of Valve Sticking

The cause of periodic oscillation may be valve failure, but not all valve failures make for periodic oscillation. It is desirable to make improvements for valve failures that cause periodic oscillation because they direct-

ly degrade control performance, but it is also desirable to detect valve failures that do not give rise to periodic oscillation as potential problems. Therefore, we developed techniques for detecting valve failures, including ones that do not give rise to periodic oscillations.⁷⁾

(i) Method for Counting the Stationary Interval (Method A)^{7), 11)}

As was discussed under the modeling of valve stiction, there is a stationary interval where there is no change in the valve position or the flow rate even if the manipulated variable changes. In this method, valve failures are detected by calculating the proportion taken up out of the whole by the stationary interval as index ρ , exclusive of the interval where there is no change in both the manipulated variable and the flow rate. Index ρ is obtained as a value from 0 to 1, and as it gets close to 1, there is judged to be a problem with the valve, and as it gets close to 0 the judgment is that there is no problem with the valve. From experience, the possibilities of a valve failure are high if ρ is 0.25 or higher. When diagnosis is made using the flow rate rather than valve position, a threshold value that takes measurement noise into consideration is established, and anything below the threshold value may be seen as no change in the flow rate. The threshold value can be derived directly from the standard deviation for the flow rate. In addition, the sticking width S can be found from the width for the manipulated variable in the interval where there was no change in flow rate. If the sticking width S exceeds 1%, there is often a problem in control, such as the controlled variable oscillating periodically.

(ii) Method of Identification Using the Backlash Inverse Function (Method B)^{7), 11)}

If there is a problem with a valve, the relationship between manipulated variable u and the valve position is close to the parallelogram in Fig. 3, and when there is no problem, the behavior is close to a straight line. This method determines the differences from the relationship between the manipulated variable and the valve position or flow rate using the backlash inverse function F in Equation (13).

$$F(t) = \max\{\min\{F(t-1) + \Delta u(t), F_{\max}\}, 0\} \quad (13)$$

Backlash inverse function F is a function that makes shifts the amount of the sticking width ($S = F_{\max}$) so

that the right side of the parallelogram in Fig. 3 is superimposed on the left side, and F_{\max} is found such that the relationship is linear after the conversion. It is sufficient to find F_{\max} , which is the sticking width S , such that the absolute value for the correlation coefficient for the backlash inverse function $F(t)$ and the flow rate is maximized by optimization, and from experience, it is highly possible that there is a valve failure if the correlation coefficient $|r|$ is 0.7 or higher and F_{\max} is 0.5 or greater. If an index is formed for this as in Method A, the following equation, for example, is used.

$$\phi = |r| \cdot \min(F_{\max}, 1) \quad (14)$$

The value for index ϕ is in the range from 0 to 1, and in a like manner, the determination of valve failure is made as it gets close to 1.

(iii) Method Using Qualitative Shape Analysis (Method C)^{7), 12)}

This method encodes the behavior of the manipulated variable and the flow rate using the symbols shown in Table 1, and searches a parallelogram pattern when there are valve failures is extracted from these. The encoding indicates the changes in the data with -, 0 and +, and nine qualitative behaviors are expressed from the combination of the two variables for the controlled variable and the flow rate. The proportion taken by +0 and -0 which signify the upper side and bottom side in this parallelogram is calculated as the index θ to detect valve failures. The value for index θ is in the range from 0 to 1, and the determination of valve failure is made as it gets close to 1. From experience, the possibilities of a valve failure are high if θ is 0.25 or higher. In addition, besides the combination of (+0, ++), (-0, --) shown in Fig. 7, the pattern during valve failures has (+0, 0+), (-0, 0-), (+0, -+) and (-0, +-). Of these, it is possible to find the sticking width S from the manipulated variables for +0 and -0.

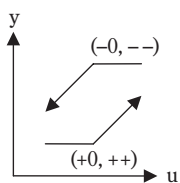


Fig. 7

A pattern of stiction²⁾

Table 1 Patterns of quadric matching²⁾

$\Delta u \setminus \Delta y$	-	0	+
-	--	-0	-+
0	0-	00	0+
+	+-	+0	++

3. Considerations of Periodic Oscillation during Valve Failure

Using flow rate control and liquid level control, which are frequently used in chemical plants as examples, we considered periodic oscillation during valve failure using simulations. We used the valve stiction model in Fig. 4 for the simulations.

① Flow Rate Control

Consider a typical flow rate control configured from a flow meter, the valve and a PID controller. The valve size is not limited, but to make the calculations easier, a 100 m³/h linear valve is used, with an initial value for the valve position of 50% and the initial flow rate value and flow rate setting both being 50 m³/h. Letting the valve follow a primary delay model with a time constant of 10 s, a PI controller with PID parameters of a proportional band (PB) of 100%, integral time (TI) of 20 s and derivative time (TD) of 0 s is used. I-PD control, which is typically used, is used for the PID algorithm. The sticking width is 1% and the slip jump width is 0.2%.

Fig. 8 shows the results when the flow rate setting is increased 0.2 m³/h one minute after the start of the simulation and when it is increased 1 m³/h. The case where there is a slip jump and the case where there is none are shown together.

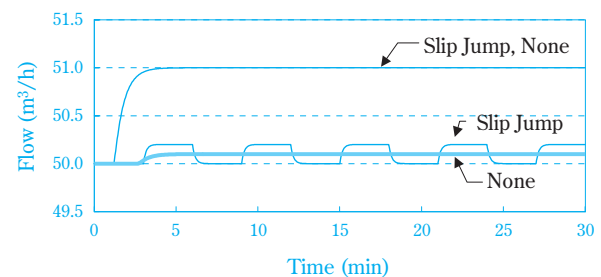


Fig. 8 Simulation results on flow control²⁾

From the results of this simulation, we find that there is no periodic oscillation in either case when there is no slip jump. On the other hand, when there is a slip jump, we found periodic oscillation only when there was a setting change within a slip jump width of 0.2 m³/h. Therefore, we can see that even if there is valve stiction, there is not always periodic oscillation.

Therefore, valve failures that do not produce periodic oscillation may not be diagnosed because the frequency analysis mentioned above is a diagnostic method that presupposes periodic oscillation. Thus, we must

be careful of potential failures with flow rate control.

② Liquid Level Control

Let us consider typical liquid level control, where a predetermined flow rate is fed into a tank with a liquid level meter and the same flow rate is removed through a valve. Assuming valves of the same size, let the feed flow rate and the removal flow rate both be $50 \text{ m}^3/\text{h}$ and the tank capacity be 10 m^3 . Letting both the initial value and setting for the fluid level be 50%, a PI controller with PID parameters of a proportional band (PB) of 30%, integral time (TI) of 900 s and derivative time (TD) of 0 s is used. I-PD control is used as the PID algorithm. The sticking width and slip jump width were set in the same manner at 1.0% and 0.2%.

Fig. 9 shows the results of a 0.5% increase in the fluid level setting 10 minutes after the start of the simulation. The case where there is a slip jump and the case where there is none are shown superimposed on each other. The flow rate are also shown with the fluid level. From the results of the simulation, periodic oscillation arises in the fluid level regardless of whether or not there is slip jumping, and if there is slip jumping, the oscillation periods become shorter. Furthermore, even though the flow rate exhibits square wave shaped behavior, the characteristics of the fluid level are exhibiting a triangular wave shaped behavior. When the process has a long delay or integral characteristic, periodic oscillation occurs readily, and the oscillation periods are very long, ranging from several minutes to several hours. A great deal of caution is necessary with this long-period oscillation because it makes the plant load change.

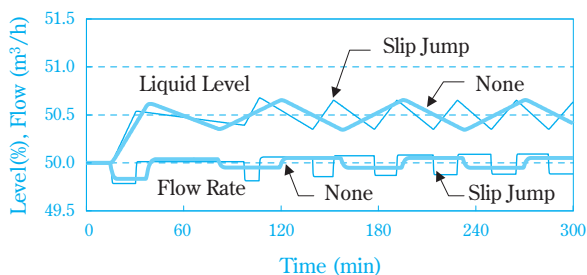


Fig. 9 Simulation results on level control²⁾

Applications in Actual Plants

We will give examples of evaluations of the diagnostic methods that have been described above using sam-

ple data acquired from actual plants and the results of applications in entire plants.

1. Examples of Control Performance Evaluation

Based on the algorithms described under the control performance evaluation methods at the beginning of this paper, we developed the control performance diagnostic tool *LoopDiag* (Fig. 10). Since this tool was developed in MATLAB®,^{Note 1)} it can be compiled and used as a general purpose software. The large MATLAB® mathematical library can be used, and in addition to control performance evaluation, time series data analysis and the like can be performed.

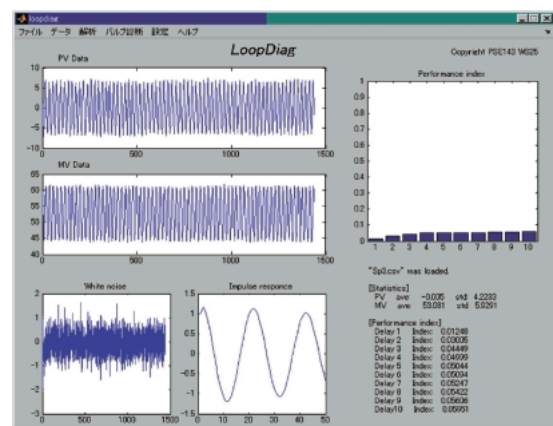


Fig. 10 Controller diagnostic tool "LoopDiag"

The two graphs in the upper left of Fig. 10 are process data, and in the lower left are shown white noise found from the ARMA model and closed loop impulse response. The graph in the upper right is the control performance index, and indices corresponding to the each of the dead times is shown in a bar graph. In control performance evaluation that is based on minimum variance control, the dead time in the process must already be known, and the control performance index corresponding to the dead time is its evaluation value. The results of fluid level control where there is periodic oscillation caused by a valve failure are shown as an example. All of the control performance indices are less than 0.1, and there is an accurate evaluation that control performance is poor.

Table 2 gives the results of control performance evaluations for 13 groups of sample data acquired from actual plants. The table shows what was evaluated in order from the lowest control performance evaluation, and the cause of the failure is entered in the right col-

umn. #1 and #3–#8 are data where the control performance was poor because of tuning problems or valve failures, and the performance evaluation method made accurate evaluations. #10 is data following maintenance for the #3 valve, and we can see that the original control performance is restored by repairing the valve. The evaluation values for #9–#13 are high, and the diagnosis is that there is no problem with control performance. On the other hand, the resolution of the data for #2 and #12 is coarse, and the control performance is erroneously diagnosed as being poor for #2. This is not caused by the precision of hardware such as sensors or converters, but rather by truncation (rounding) due to data compression in the data acquisition system for the plant. Therefore, there is a danger of erroneous diagnosis if the settings for the filtering coefficients in the data acquisition system are unsuitable, so we must be cautious.

Table 2 Results of controller performance evaluation

No.	Tag	Index	Comment
#1	Data10(PC)	0.002	Bad turning
#2	Data9(PC)	0.011	Low resolution
#3	Data3(LC)	0.050	Valve stiction
#4	Data1(FC)	0.119	Quantized output
#5	Data11(LC)	0.150	Bad turning
#6	Data8(FC)	0.222	Valve stiction
#7	Data5(LC)	0.523	Bad turning
#8	Data2(FC)	0.657	Bad turning
#9	Data13(FC)	0.833	Disturbance
#10	Data12(LC)	0.995	After maintenance #3
#11	Data7(FC)	0.998	
#12	Data6(PC)	1.000	Low resolution
#13	Data4(FC)	1.000	

FC: Flow Controller LC: Level Controller

PC: Pressure Controller

2. Examples of Detecting Valve Failure

Of the 13 groups of data used as control performance evaluation examples, we will evaluate four groups of data that exhibit typical behavior. Data3 and Data8 are data containing valve failures, Data11 a tuning problem and Data13 disturbance. Moreover, Data3 is data with periodic oscillation caused by a valve failure, and Data8 is data for a valve failure but without periodic oscillation.

① Frequency Analysis

Frequency analysis was used on these four groups of

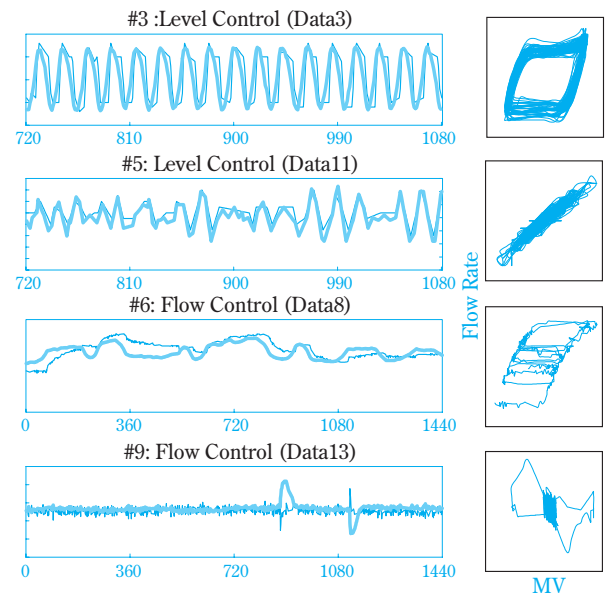


Fig. 11 Sample data for evaluation²⁾

data. Data3 and Data11 were found to have peaks that exhibit periodicity, and the results for Data3 and Data11 after amplification filtering are shown in Fig. 12. Since harmonics that exceed the threshold value were detected in Data3 with amplification filtering, the diagnosis is valve failure for Data3 and tuning problems for Data11. No remarkable peaks are seen for Data8 and Data13, so they are diagnosed as normal, and since there is no periodic oscillation in Data8, it was diagnosed erroneously. Valve failure cannot be detected where there is no periodic oscillation in the frequency analysis as in Data8. However, most of the periodic changes for valve failures have the merit of being detectable even without manipulated variable data.

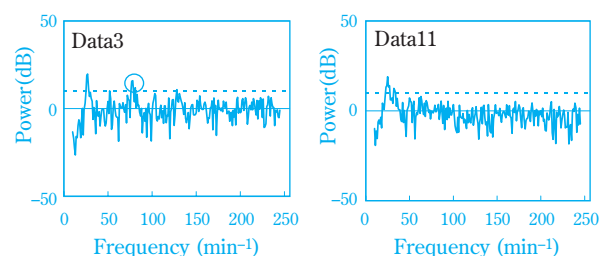


Fig. 12 Amplified power spectra of Data3 and Data11

② Detection of Sticking Valves

The results of using three detection methods on the same four groups of data are given in Table 3. With Method A and Method C, the indices for Data3 and

Data8 are over 0.25, and with Method B, the indices for Data3 and Data8 are over 0.7. From these results it was possible to make accurate diagnoses of each valve failure. These methods require manipulated variable data in addition to flow rate data, but they can also detect valve failures that do not exhibit periodic oscillation.

Table 3 Results of valve evaluation

	Method A	Method B	Method C	
	ρ (>0.25)	ϕ (>0.7)	θ (>0.25)	
Data3	0.58	0.98	0.58	stiction
Data11	0.14	0.16	0.10	
Data8	0.32	0.97	0.43	stiction
Data13	0.04	0.00	0.02	

3. Application in Entire Plants

Performance evaluations were carried out for a PID controller with approximately 300 loops in an entire plant to evaluate control performance, and work was done on improvements for loops with lower performance. Many tuning problems and manual mode loops were included in the ones evaluated as having poor control performance. Reassessment of whether or not the control mode is suitable is underway for the manual mode loops. The loops with tuning problems were classified as unresponsive and hypersensitive for control actions.

We developed a tool that could be run in Microsoft® Excel^{Note 2)} for valve failure detection. A link can be created with the plant operating data through Excel, and if the tags being analyzed are registered in advance valve failures can be diagnosed with the touch of a button. When this tool was used a different plant from the one where the sample data was obtained, there were 12 valve failures diagnosed in 118 loops, and of these four were actually valve failures. Fig. 13 shows an example of a valve failure that was identified. In this example a valve failure with a sticking width of 1% was detected. Causes of the remaining eight instances were collection system data compression, noise, changes in pump pressure during process startup and the like, but it was effective in narrowing down the locations of valve failures in the large number of loops. To deal with the erroneous diagnoses, it is practical to use combinations where judgments of valve failure are made when detected by two or more methods among multiple methods.

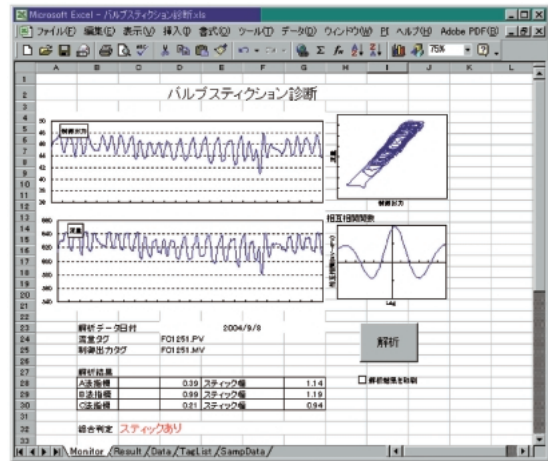


Fig. 13 Valve diagnosis tool on Microsoft® Excel²⁾

Conclusion

We have described control performance evaluation methods for controllers that are based on minimum variance control and valve failure detection methods. With the goal of making competitive plants, there have been advances in technology and reductions in the number of personnel, and support systems that monitor controller status and give precise guidance to operators if there is a problem are necessary. In Europe and the United States, there have been reports of large-scale control performance monitoring systems in operation that carry out control performance evaluation for plants online. In Japan, there have been no reports of applications of large-scale control performance monitoring systems, but the sections into which control performance evaluations are divided differ and progress is being made on plant monitoring systems that make use of operating support systems.

The valve failure detection methods developed in this cooperation between industry and academia is only part of control performance diagnostic technology, but we think it can diagnose one main cause and make daily maintenance operations more efficient. From here on, we want to develop techniques that will make it possible to carry out wide-ranging monitoring, not just of controllers, but also equipment capabilities and process status based on control performance diagnostic techniques, and our goal is the construction of process monitoring and a Boardman support system.

Acknowledgements

Except for part of the valve failure detection methods, this study is based on joint results from the Japan

Society for the Promotion of Science, The 143rd Committee on Process Systems Engineering, Workshop No. 25 "Control Performance Monitoring". We would like to thank everyone from this society and Dr. Manabu Kano of Kyoto University.

References

- 1) T. J. Harris, *Canadian Journal of Chemical Engineering*, **67**, 856 (1989).
- 2) H. Kugemoto and M. Kano, *Journal of the Society of Instrument and Control Engineers*, **44**(2), 143(2005).
- 3) B. Huang and S. L. Shah, "Performance Assessment of Control Loops: theory and applications", Springer-Verlag London (1999).
- 4) C. Kaseda, A. Ohtsuka, F. Nagasaka and T. Kagawa, *Transactions of the Society of Instrument and Control Engineers*, **35**, 594 (1999).
- 5) F. Muller, *Proceedings of the 1994 Summer Computer Simulation Conference*, 742 (1994).
- 6) M. A. A. S. Choudhury, S. L. Shah and N. F. Thornhill, *Automatica*, **40**, 1719 (2004).
- 7) Y. Yamashita, H. Kugemoto, M. Kano and H. Maruta, *Proceedings of SCEJ 69th Annual Conference*, 113 (2004).
- 8) A. Horch, PhD thesis, Royal Institute of Technology, Stockholm, Sweden (2000).
- 9) N. F. Thornhill, J. W. Cox and M. A. Paulonis, *Control Engineering Practice*, **11**, 1481 (2003).
- 10) H. Kugemoto, *Proceedings of SICE 3rd Annual Conference on Control Systems*, 347 (2003).
- 11) H. Maruta, M. Kano, H. Kugemoto and K. Shimizu, *Transactions of the Society of Instrument and Control Engineers*, **40**, 825 (2004).
- 12) Y. Yamashita, *Control Engineering Practice*, In Press.

Note 1) MATLAB® is registered trademark of The MathWorks, Inc.

Note 2) Microsoft® is registered trademark of the Microsoft Corporation.

PROFILE



Hidekazu KUGEMOTO

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Research Associate