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Modeling and Detection of Stiction in Pneumatic Control Valves

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Control performance monitoring is an important technology that ensures highly efficient operation of production plants. Bad control performance is caused mainly by inadequate controller tuning or equipment malfunction. Valve stiction is the most common problem in pneumatic control valves, which are widely used in the process industry. Stiction causes persistent fluctuation of process variables. Therefore, developing a method to detect stiction and distinguish it from inadequate controller tuning is crucial to help operators take appropriate action for improving control performance. In the present work, valve stiction is modeled by taking into account its physical mechanism, and then new stiction detection algorithms are proposed. The usefulness of the proposed detection methods is demonstrated by comparing them with conventional methods. It is shown that the proposed methods can successfully detect valve stiction, distinguish it from bad tuning or disturbances, and quantify the degree of stiction by using simulation data sets and real operation data sets obtained from several chemical processes.

Key Words: control valve, stiction, control performance monitoring, fault detection, fault diagnosis

1. Introduction

The variability of process variables makes it difficult to keep operating conditions close to their bound; thus it causes economical loss including poor product quality and excessive energy consumption. To maximize productivity, control systems should achieve their best performance. However, there are thousands of control loops in plants and it is difficult to clarify which loop is a bottleneck for efficient operation of the entire plant. To detect control loops that require improvement, it is necessary to develop systematic and practical methods for evaluating the performance of control loops. From this viewpoint, much research concerning control performance assessment and monitoring has been conducted [1)~3)]. A basic method of control performance assessment uses minimum variance control as its benchmark [4)].

Poor control performance is caused not only by bad controller tuning but also by undesired characteristics of control valves. Among the many types of undesired characteristics of control valves, stiction is the most common problem in the process industry. Therefore, it is important to develop a practical method that can detect stiction and distinguish it from other causes including inadequate controller tuning.

In the present work, new methods that use only routine operation data for detecting valve stiction are proposed. Although several methods have been proposed [5),6)], they are based on the assumption that valve opening or a controlled variable such as flow rate follows a predefined probability distribution, and thus their judgment is not reliable when the assumption is not satisfied. In addition, conventional methods cannot quantify the degree of stiction even if they can detect it. Therefore, in the present work, a valve stiction model is built first to understand the stiction phenomenon and simulate it. The proposed model is not a rigorous first-principles model but a simple model aimed at describing the behavior of control valves with stiction, in particular, the relationship between controller output and valve opening. Then, new valve stiction detection methods are proposed on the basis of the proposed valve stiction model. Not only can these methods detect valve stiction with accuracy, but they can also quantify the degree of stiction. The accuracy of the valve stiction model is validated by comparing simulation results with real operation data of chemical processes. In addition, the usefulness of new valve stiction detection methods is demonstrated by applying them to simulation data generated by using the developed model and real operation data obtained from several chemical processes.

2. Valve Stiction Model

The present research focuses on pneumatic control valves, which are widely used in the process industry. Two

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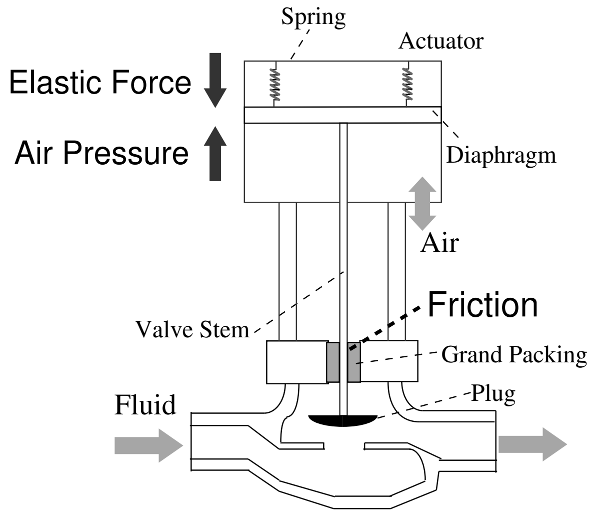

Fig. 1 Structure of pneumatic control valve

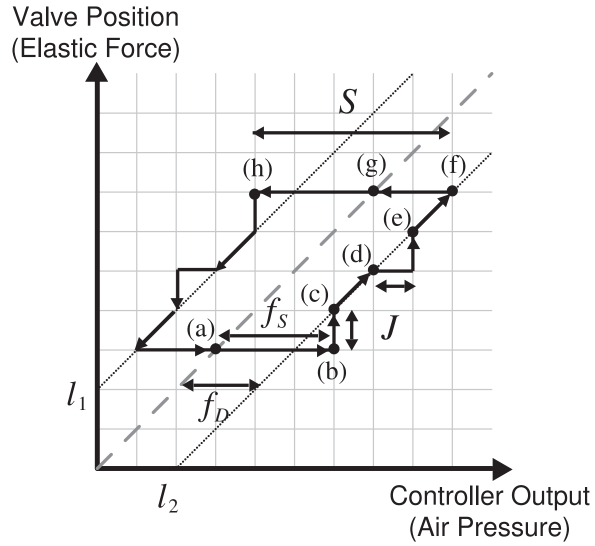

Fig. 2 Relation between controller output and valve position under valve stiction

types of valve stiction models have been proposed: 1) a detailed physical model that formulates the stiction phenomenon as precisely as possible [7], and 2) a data-driven model that describes the relationship between a controller output and a valve position [8]. Since a detailed physical model has numbers of unknown physical parameters, it is not only time-consuming but impractical to simulate an actual control valve by using such a model. A data-driven model, on the other hand, is useful because it has only a few parameters and these are easy to identify and simple to understand. In the present work, a valve stiction model than can precisely describe the stiction phenomenon with as few parameters as possible is developed. In this section, the proposed stiction model of a pneumatic control valve is explained in detail.

2. 1 Pneumatic Control Valve and Stiction

The general structure of a pneumatic control valve is shown in **Fig. 1**. This valve is closed by elastic force and opened by air pressure. Flow rate is changed according to the plug position, which is determined by the balance between elastic force and air pressure. The plug is connected to the valve stem. The stem is moved against static or kinetic frictional force caused by packing, which is a sealing device to prevent leakage of process fluid. Smooth movement of the stem is impeded by excessive static friction. The valve position cannot be changed until the controller output overcomes static friction, and it is suddenly and considerably changed when the difference between elastic force and air pressure exceeds the maximum static frictional force.

2. 2 Stiction Model

To model the relationship between the controller output and the valve position of a pneumatic control valve, the balance among elastic force, air pressure, and frictional force needs to be taken into account. The relationship can be described as shown in **Fig. 2**. The dashed line denotes the states where elastic force and air pressure are balanced. The controller output and the valve position change along this line in an ideal situation without any friction.

The ideal relationship is disturbed when friction arises. For example, the valve is resting at (a) where elastic force and air pressure are balanced. The valve position cannot be changed due to static friction even if the controller output, i.e., air pressure, is increased. The valve begins to open at (b) where the difference between air pressure and elastic force exceeds the maximum static frictional force. Since the frictional force changes from static f_S to kinetic f_D when the valve starts to move at (b), a slip-jump of the size

$$J = f_S - f_D \tag{1}$$

happens and the valve state changes from (b) to (c). Thereafter, the valve state changes along the line l_2 which deviates from the ideal line by f_D because the difference between air pressure and elastic force is equal to f_D. When the valve stops at (d), the difference between air pressure and elastic force needs to exceed f_S again for the valve to open further. Since the difference between them is f_D at (d), air pressure must increase by J to open the valve. Once air pressure exceeds elastic force by f_D, the valve state changes to (e) and then follows l_2.

Air pressure begins to decrease when the controller or-

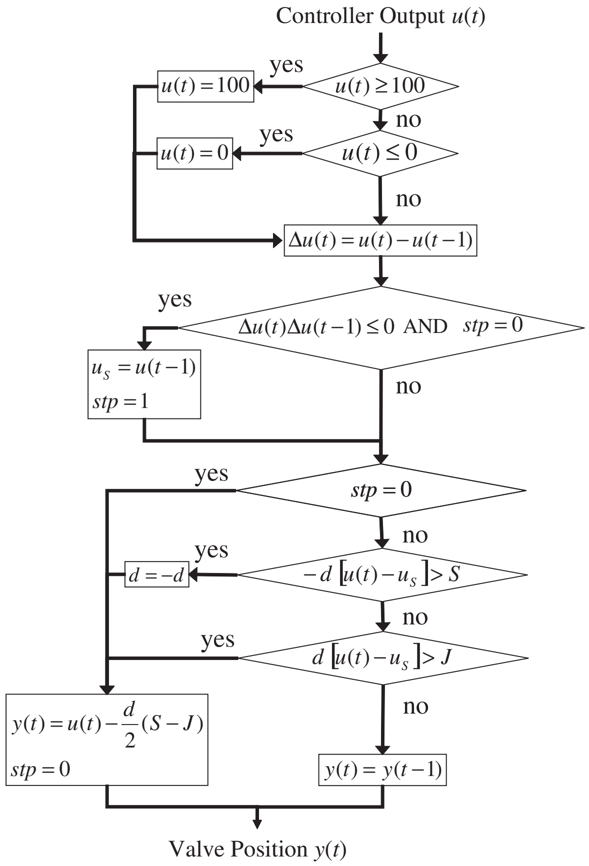

Fig. 3 Flowchart of valve stiction model

ders the valve to close at (f). At this moment, the valve changes its direction and comes to rest momentarily. The valve position does not change until the difference between elastic force and air pressure exceeds the maximum static frictional force f_S. The valve state (h) is just point-symmetric to (b). The difference of air pressure between (f) and (h) is given by

$$S = f_S + f_D \,. \tag{2}$$

The valve state follows the line l_1 while the valve position decreases.

The above-mentioned phenomena can be modeled as a flowchart shown in **Fig. 3**. The input and output of this valve stiction model are the controller output u and the valve position y, respectively. Here, the controller output is transformed to the range corresponding to the valve position in advance.

The first two branches check if the upper and the lower bounds of the controller output are satisfied. In this model, two states of the valve are explicitly distinguished: 1) a moving state ($stp = 0$), and 2) a resting state ($stp = 1$). In addition, the controller output at the moment the valve state changes from moving to resting is defined as u_S. u_S is updated and the state is changed to the resting state ($stp = 1$) only when the valve stops or changes its direction ($\Delta u(t)\Delta u(t-1) \leq 0$) while its state is moving ($stp = 0$). Then, the following two conditions concerning the difference between $u(t)$ and u_S are checked unless the valve is in a moving state. The first condition judges whether the valve changes its direction and overcomes the maximum static friction (corresponding to (b) and (h) in Fig. 2. Here, $d = \pm 1$ denotes the direction of frictional force. The second condition judges whether the valve moves in the same direction and overcomes friction. If one of these two conditions is satisfied or the valve is in a moving state, the valve position is updated via the following equation:

$$y(t) = u(t) - df_D = u(t) - \frac{d(S-J)}{2} \tag{3}$$

On the other hand, the valve position is unchanged if the valve remains in a resting state.

To demonstrate the validity of this stiction model, simulation results are compared with operation data of a chemical process that suffers from valve stiction. The flow rate is estimated by calculating the valve position from the controller output with the stiction model and by assuming dynamics from the valve position to the flow rate is given by a first order model.

$$P_F(t) = \frac{1}{0.2s + 1} \tag{4}$$

Measurements and estimates of the flow rate are shown together with the controller output in **Fig. 4**. The flow rate measurements proved coincident with that estimated by the stiction model. The parameters in Eq. (4) are set at typical values observed in chemical processes [9].

The valve stiction model developed here is based on the balance among the elastic force, the air pressure, and the frictional force, and it can describe the behavior of pneumatic control valves with only two parameters S and J. For example, an ideal situation exists when $S = J = 0$ and no slip-jump when $J = 0$. In addition, the developed

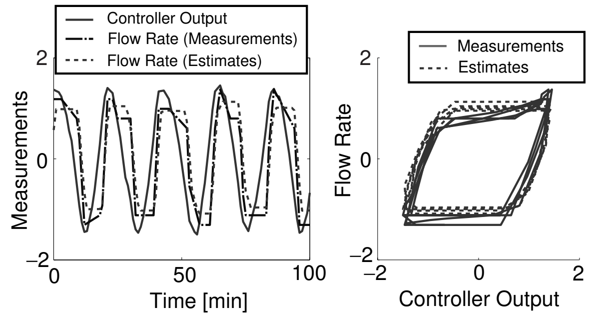

Fig. 4 Comparison between flow rate measurements and estimates for validating valve stiction model

model has several advantages compared with the conventional model [8]. First, it can cope with stochastic input as well as deterministic input. Second, u_S can be updated at appropriate timings by introducing the valve state *stp*. Third, it can change the degree of stiction according to the direction of the valve movement.

3. Stiction Detection Methods

In this section, two new methods for detecting valve stiction are proposed. In addition, conventional methods are briefly introduced. The superiority of the proposed methods over conventional methods is not only detection performance but their ability to quantify the degree of stiction.

3.1 Detection Methods Based on Stiction Model

As shown in Fig. 2, the following characteristics are observed when stiction occurs.

(1) There are sections where the valve position does not change even though the controller output changes. Stiction is stronger as such sections are longer.

(2) The relationship between the controller output and the valve position takes the shape of a parallelogram if slip-jump J is neglected. Stiction is stronger as the distance between l_1 and l_2 is longer.

On the basis of these characteristics, new methods for detecting valve stiction are proposed. The first method, referred to as method A, is based on characteristic (1); and the second, method B, is based on characteristic (2).

The algorithm of method A is summarized as follows:

(1) Calculate the difference of valve position y.

$$\Delta y(t) = y(t) - y(t-1) \tag{5}$$

(2) Find time intervals when the following condition is satisfied.

$$|\Delta y(t)| < \varepsilon \tag{6}$$

where ε is a threshold.

(3) During each time interval found, calculate the difference between the maximum and the minimum of the controller output u and define it as $\tilde{u}$. Similarly, calculate the difference between the maximum and the minimum of the valve position y and define it as $\tilde{y}$. In addition, determine thresholds: ε_u for $\tilde{u}$ and ε_y for $\tilde{y}$.

(4) Conclude that stiction occurs when $\tilde{u} \geq \varepsilon_u$ and $\tilde{y} \leq \varepsilon_y$. Otherwise, conclude that stiction does not occur.

(5) Calculate the ratio ρ of total length of intervals when stiction occurs to total length of all intervals. In addition, calculate σ that is the mean of $\tilde{u}$ when stiction occurs.

There is higher possibility of stiction as the normalized measure ρ is closer to one. On the contrary, it is confirmed that no stiction occurs when ρ is zero. Furthermore, the degree of stiction can be quantified by using σ.

Method B is based on the fact that the relationship between the controller output and the valve position takes the shape of a parallelogram and the distance between l_1 and l_2 increases as stiction becomes stronger. To capture the difference of shapes, a function F is introduced.

$$F(t) = \max\{\min\{F(t-1)+\Delta u(t), F_{max}\}, 0\} \tag{7}$$

$$F(0) = F_0 \tag{8}$$

The function F indicates the difference between the controller output u and the value on the line l_1 at the same valve position. Therefore, $u-F$ will have a strong correlation with the valve position y. In addition, the maximum value F_{max} of F corresponds to $S-J$. Thus, the degree of stiction or deadband can be quantified by F_{max} because slip-jump J is much smaller than deadband S and F_{max} is usually close to S. This is the most important advantage of using method B. To date, no stiction detection method that enables one to quantify stiction has been proposed. F_{max} and its initial value $F(0)$ can be identified from operation data by solving an optimization problem that aims to maximize a correlation coefficient r between $u-F$ and y. As a result, the possibility of stiction gets larger as F_{max} becomes larger. However, the results of method B are reliable only when the correlation coefficient r is close to one.

3.2 Conventional Detection Methods

To compare the proposed methods and conventional methods in the next section, two conventional methods are briefly explained here.

The first method is proposed by Kaseda et al. [5]. When a controlled variable fluctuates due to valve stiction, the velocity of the valve stem v becomes zero under stiction. The distribution of the valve stem velocity is assumed to be

$$p(v) = \frac{1}{S(a)} \exp\left\{-\left|\frac{v^{\frac{1}{a}}}{\lambda(a)}\right|\right\} \tag{9}$$

$$S(a) = 2a\lambda(a)^a\Gamma(a) \tag{10}$$

$$\lambda(a) = \left\{\overline{|v|}\left[\frac{\Gamma(a)}{\Gamma(2a)}\right]\right\}^{\frac{1}{a}} \tag{11}$$

$$\Gamma(a) = \int_0^\infty e^{-t}t^{a-1}dt \tag{12}$$

where a is a positive shape parameter and $\overline{|v|}$ denotes the mean valve stem velocity [5]. However, the validity of the distribution is not explained or verified with operation data. An index ξ for stiction detection is introduced as the ratio of the root mean square of stem velocity $\sqrt{\overline{v^2}}$ to mean velocity $\overline{|v|}$.

$$\xi \equiv \frac{\sqrt{\overline{v^2}}}{\overline{|v|}} = \frac{\sqrt{\Gamma(a)\Gamma(3a)}}{\Gamma(2a)} \tag{13}$$

ξ monotonically increases with the shape parameter a and its lower bound is one. Since the valve stem velocity distribution $p(v)$ reaches a higher peak around zero as a becomes larger, it is concluded that the larger ξ indicates a higher possibility of valve stiction and ξ close to one indicates no stiction.

On the other hand, Horch proposed another method focusing on the response of a controlled variable by assuming that the controlled variable fluctuates periodically [6]. In concrete terms, the response of a controlled variable becomes square or choppy waves when the fluctuation is caused by valve stiction, whereas the response becomes sinusoidal when the fluctuation is caused by bad tuning. Therefore, a first or second derivative signal x of the controlled variable becomes spiky under valve stiction and sinusoidal in other cases. The probability distributions of the spiky signal and the sinusoidal signal are assumed to be

$$p_1(x,\sigma_1) = \begin{cases} (1-\varepsilon_H)\frac{1}{\sqrt{2\pi}\sigma_1}\exp\left\{-\frac{x^2}{2\sigma_1^2}\right\} \\ \qquad (|x| > A_1) \\ (1-\varepsilon_H)\frac{1}{\sqrt{2\pi}\sigma_1}\exp\left\{-\frac{x^2}{2\sigma_1^2}\right\} + \frac{\varepsilon_H}{2A_1} \\ \qquad (|x| \le A_1) \end{cases} \tag{14}$$

$$p_2(x,\sigma_2) = \frac{1}{\sigma_2\sqrt{2\pi^3}} \int_{-A_2}^{A_2} \frac{\exp\left\{-\frac{(x-y)^2}{2\sigma_2^2}\right\}}{\sqrt{A_2^2-y^2}} \mathrm{d}y \tag{15}$$

respectively by taking account of measurement noise. A_1 denotes the size of spike and A_2 the amplitude of the sinusoidal wave. ε_H is a weighting coefficient and is recommended to be set at 0 to 0.3. The standard deviation of measurement noise σ_j is determined so that the mean squared error of $p(x_i)(i = 1, 2, \cdots, k)$ and p_j $(j = 1, 2)$ is minimized.

$$\mathrm{MSE}_j = \frac{1}{k}\sum_{i=1}^{k}\{p_j(x_i,\sigma_j) - p(x_i)\}^2 \tag{16}$$

where $p(x_i)$ is the probability distribution transformed from a histogram of time series of a controlled variable with k classes. If $\mathrm{MSE}_1 < \mathrm{MSE}_2$, that is, the signal is more likely to be spiky than sinusoidal, then it is concluded that valve stiction occurs.

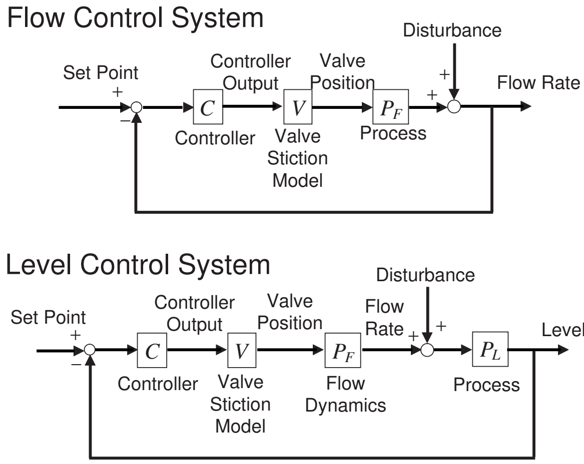

Fig. 5 Block diagram of control systems

Table 1 Controller tuning

	Proportional Gain	Integral Time [min]
Flow Control	0.5	0.3
Level Control	3	30

Table 2 Parameters of valve stiction model

	S[%]	J[%]
Case 1 (No Stiction)	0	0
Case 2 (Weak Stiction)	1	0.3
Case 3 (Strong Stiction)	5	1

4. Applications

In this section, the proposed valve stiction detection methods, A and B, as well as conventional methods are applied to simulation data generated by using the proposed stiction model and also operation data obtained from several chemical processes.

4.1 Validation with Simulation Data

A flow control system and a level control system are investigated here. Block diagrams of both control systems are shown in **Fig. 5**. Process transfer functions of flow $P_F(s)$ and level $P_L(s)$ are given by

$$P_F(s) = \frac{1}{0.2s+1} \tag{17}$$

$$P_L(s) = \frac{1}{15s}e^{-s} \tag{18}$$

where the unit of time is min. In the level control system, a flow meter is installed for monitoring and the dynamics from valve opening to flow rate is given by Eq. (17).

PI controllers are used for both control systems. Disturbances are added into flow rate. Control parameters and valve stiction model parameters are summarized in **Table 1** and **Table 2**, respectively. Under these conditions, simulations were executed and data of 1500 min length were obtained. The sampling interval is three sec.

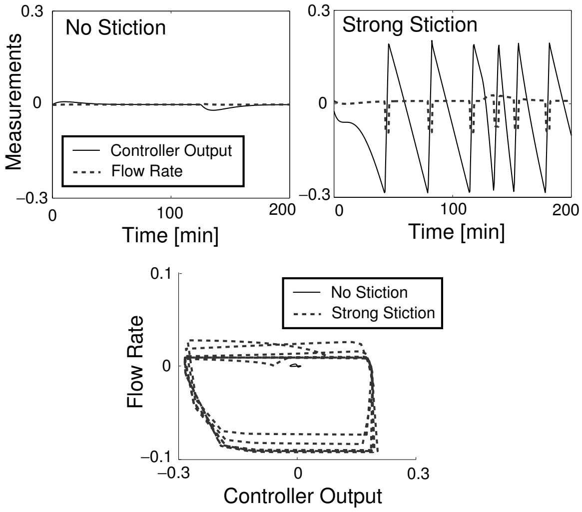

Fig. 6 Simulation results of flow control system

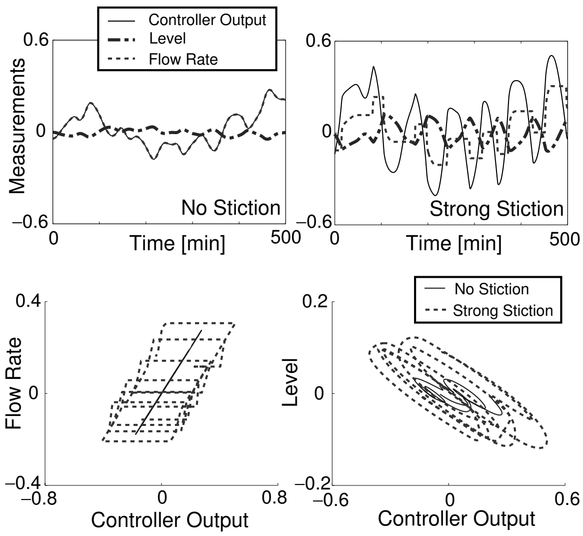

Fig. 7 Simulation results of level control system

Simulation results are shown in **Fig. 6** and **Fig. 7**.

Each stiction detection method was applied to resampled data. The sampling interval for flow control and level control is 0.5 min and 2.5 min, respectively. The number of sampling points used for analysis is 300. In all methods, data were mean-centered and scaled to have unit variance. In method A, $\varepsilon = 0.1$ and $\varepsilon_u = \varepsilon_y = 0.5$ in all cases. In Horch's method, $\varepsilon_H = 0.1$.

The results are summarized in **Table 3**. LC-F is the case where controller output and flow rate are used for detection. On the other hand, LC-L is the case where controller output and level are used. Average computational times of methods A, B, Kaseda, and Horch are 0.07 sec, 1.12 sec, 0.06 sec, and 79 sec, respectively. The computational load of Horch's method is excessively heavy, because it requires solving two optimization problems to fit data into two predefined probability distributions.

Table 3 Application results of four detection methods (300 samples of simulation data)

	A		B		Kaseda	Horch
	ρ	σ	F_{max}	r	ξ	Stiction
Flow Control (FC)						
Case 1	0.00	0.00	0.00	0.03	3.99	Yes
Case 2	0.77	0.60	0.00	0.18	2.03	Yes
Case 3	0.83	3.50	0.00	0.11	3.68	Yes
Level Control - F (LC-F)						
Case 1	0.00	0.00	0.00	1.00	1.19	Yes
Case 2	0.56	0.83	0.74	1.00	1.79	Yes
Case 3	0.79	4.54	4.20	0.99	2.99	Yes
Level Control - L (LC-L)						
Case 1	0.05	0.54	0.00	0.53	1.17	Yes
Case 2	0.02	0.68	0.00	0.65	1.25	Yes
Case 3	0.00	0.00	0.00	0.82	1.18	Yes

In case FC, only method A can detect stiction successfully. The index ρ of method A becomes zero under no valve stiction, and it becomes non-zero when stiction occurs. In addition, the index σ corresponds roughly with S in Table 2. That means method A can quantify the degree of valve stiction. Small σ is derived because its mean is adopted. In fact, $\sigma = 0.00, 0.92, 4.66$ when its maximum value is adopted. On the other hand, method B fails to detect stiction because the relationship between the controller output and the flow rate does not take the shape of a parallelogram. The small correlation coefficient r indicates that the assumption of method B is not satisfied. The index ξ of Kaseda's method is larger when valve stiction does not occur than when stiction occurs, because the valve opening is constant for a long period of time if the process is operated stably. Kaseda's method, which uses only flow rate or valve opening for analysis, thus cannot distinguish between stable operation and valve stiction. Horch's method concludes that stiction occurs in all cases. Of course, this is not true. Horch's method does not function well in this case study because flow rate does not fluctuate persistently. In all cases, $\mathrm{MSE}_1 = 0.02 \sim 0.04$ and $\mathrm{MSE}_2 = 0.22 \sim 0.24$.

In case LC-F, method A can detect stiction successfully, and σ is coincident with S in Table 2. Method B can be used in this case because r is almost one. The index F_{max} becomes larger as stiction becomes stronger; thus stiction is successfully detected. In addition, $S - J$ in Table 2 is accurately estimated by F_{max}. That is, methods A and B can detect valve stiction and also quantify the degree of stiction. In Kaseda's method, the index ξ becomes larger as stiction becomes stronger. Thus, stiction is successfully detected, but Kaseda's method cannot quantify the degree of stiction. On the other hand, Horch's method does not function well. It concludes that stiction occurs in all cases.

In case LC-L, no method can detect stiction successfully. Methods A and B and also Kaseda's method do not function well in such a case where the controlled variable is delayed. These methods should be used only when flow rate or valve position is measured. Horch's method is not applicable because persistent fluctuation is not found in a controlled variable.

4.2 Validation with Data from Chemical Plants

The results of applying stiction detection methods to actual plant data are described here. Normalized operation data obtained from four chemical processes are shown in **Fig. 8**. In case 1, a level control loop is investigated, in which valve stiction occurs. In case 2, a flow control loop is investigated, in which valve stiction occurs. In case 3, a level control loop is investigated, and the controlled variable fluctuates due to bad tuning. Finally, in case 4, a flow control loop is investigated, and significant disturbances affect the controlled variable. In each case, operation data are stored in the database with the sampling period of 1 min. Operation data of 24 hours are used for analysis. The results of applying four methods to the normalized data are summarized in **Table 4**. The settings are the same as before.

In cases 1 and 2, all methods can detect stiction successfully. In case 3, where there is no stiction but bad controller tuning causes fluctuation, Horch's method incorrectly concludes that there is stiction. However, methods A and B give small indexes ρ and F_{max}, respectively, that is, methods A and B correctly conclude that there is no stiction. Kaseda's method also concludes that there is no stiction. In case 4, where no stiction occurs, Horch's method reaches a wrong conclusion again because the plant is in stable operation when disturbance does not enter. The index ξ of Kaseda's method is larger than that in case 3, and it is difficult to conclude that there is no stiction. This difficulty is caused by stable operation. On the other hand, method A does reach the right conclusion. Although method B reaches the right conclusion, the correlation coefficient r is too small and thus the result is not reliable.

The influence of the number of samples on the stiction detection performance is investigated. A stiction method can be used on-line if it functions well with a small number of samples. The results of applying four methods to the normalized data of 100 samples are summarized in **Table 5**. In cases 1, 3, and 4, the stiction detection performance of all methods is similar to that using 1440 samples. However, in case 2, method B fails to detect stiction because the relationship between the controller output and the flow rate does not take the shape of a parallelogram due to the small sample number. That is, method B requires more data than the other methods.

5. Conclusions

In the present work, a valve stiction model is developed and new stiction detection algorithms are proposed. The validity of this model is demonstrated by comparing simulation results generated by using the model with operation data of a chemical process that suffers from valve stiction. Using only two parameters, the model can describe stiction phenomena with sufficient accuracy. In addition, the usefulness of the proposed detection methods is demonstrated by comparing them with conventional methods.

Conventional stiction detection methods including Horch's method that assume periodical fluctuation are not applicable when the assumption is not satisfied. In practice, another method that does not assume periodical fluctuation is preferable because periodical fluctuation does not necessarily occur when valve stiction occurs. Although Kaseda's method is simple and achieves high performance, it cannot distinguish between stable operation and valve stiction, and it is difficult to determine an appropriate threshold of the index ξ. In addition, conventional methods cannot quantify the degree of stiction.

The proposed methods solve these problems. They are shown to successfully detect valve stiction, distinguish it from bad tuning or disturbances, and quantify the degree of stiction, with applications to simulation data sets and real operation data sets obtained from several chemical processes.

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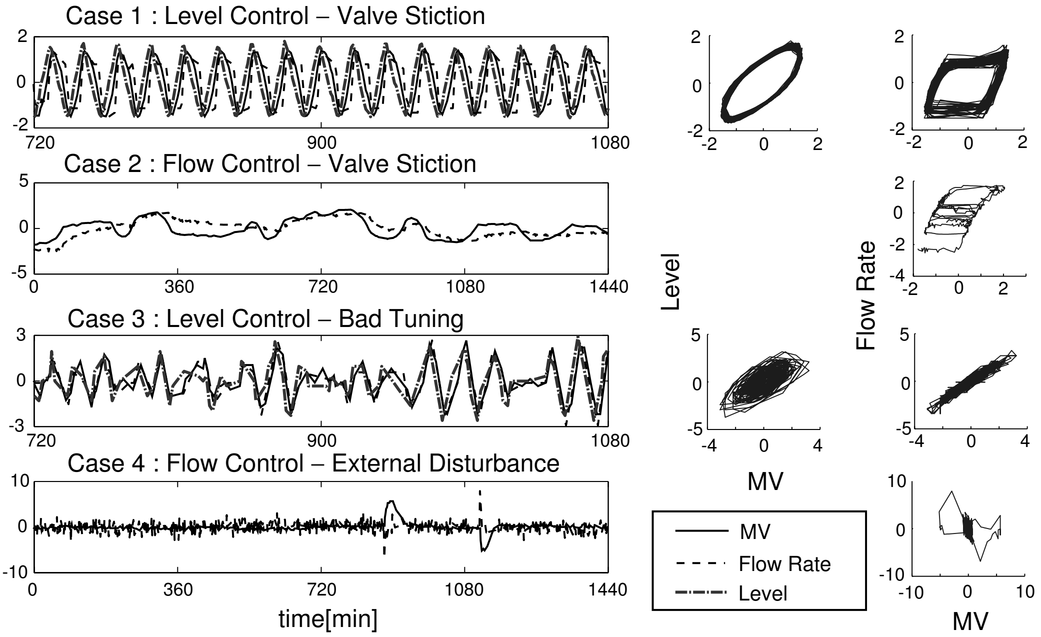

Fig. 8 Real operation data of four control systems

Table 4 Application results of four detection methods (1440 samples of operation data)

	A		B		Kaseda		Horch	
Case	ρ	σ	F_{max}	r	ξ	MSE_1	MSE_2	Stiction
1 LC, stiction	0.50	1.72	2.12	0.98	1.80	0.24	0.56	Yes
2 FC, stiction	0.31	1.21	1.92	0.97	1.81	33	194	Yes
3 LC, bad tuning	0.13	0.89	0.17	0.95	1.32	0.03	0.78	Yes
4 FC, disturbance	0.03	0.80	0.00	0.13	1.55	0.00	0.03	Yes

Table 5 Application results of four detection methods (100 samples of operation data)

	A		B		Kaseda		Horch	
Case	ρ	σ	F_{max}	r	ξ	MSE_1	MSE_2	Stiction
1 LC, stiction	0.55	1.77	2.06	0.98	1.80	0.20	0.52	Yes
2 FC, stiction	0.28	1.02	0.00	0.31	1.81	2.01×10^3	1.70×10^4	Yes
3 LC, bad tuning	0.00	0.00	0.00	0.98	1.19	0.45	0.79	Yes
4 FC, disturbance	0.00	0.00	0.00	0.34	1.41	0.00	0.04	Yes

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