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A Curve Fitting Method for Detecting Valve Stiction in Oscillating Control Loops

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Many control loops in process plants perform poorly because of valve stiction as one of the most common equipment problems. Valve stiction may cause oscillation in control loops, which increases variability in product quality, accelerates equipment wear, or leads to control system instability and other issues that potentially disrupt the operation. In this work, data-driven valve stiction models are first reviewed and a simplified model is presented. Next, a stiction detection method is proposed based on curve fitting of the output signal of the first integrating component after the valve, i.e., the controller output for self-regulating processes or the process output for integrating processes. A metric that is called the stiction index (SI) is introduced, based on the proposed method to facilitate the automatic detection of valve stiction. The effectiveness of the proposed method is demonstrated using both simulated data sets based on the proposed valve stiction model and real industrial data sets.

1. Introduction

Studies in controller performance monitoring show that many control loops in the process industry perform poorly because of bad tuning or equipment problems,[1−5] and it has been witnessed in some facilities that as many as one-third of all control loops are oscillating.[6] Oscillations in control loops raise particular concerns because they increase variability in product quality, accelerate equipment wear, and may cause other issues that could potentially disrupt the operation. Therefore, detecting and diagnosing oscillations yield commercial benefits and are important activities in control loop supervision and maintenance.

Generally, oscillations are caused by any one or a combination of the following reasons: (i) limit cycles caused by valve stiction or other process nonlinearities, (ii) poor controller tuning, (iii) poor process and control system design, and (iv) external oscillatory disturbances.[2,7,8] Simple and efficient methods have been developed to detect oscillating control loops automatically.[3,8,9] In this work, we focus on diagnosing valve stiction from other causes, given that oscillation has been detected.

Several methods[10−13] have been developed to detect valve stiction during the past decade. However, all of these methods require either detailed process knowledge or user interaction, which are not desirable for automated monitoring systems.[14] To address this problem, Horch[14] presents the first automatic detection method based on the cross-correlation function (CCF) between the controller output (OP) and the process variable (PV), which is applicable to nonintegrating processes. Later, Horch[15] proposed another method to detect valve stiction in integrating processes by considering the probability distribution of the second-order derivative of the controlled variable. Singhal and Salsbury[16] proposed a valve stiction detection method based on the comparison of areas before and after the peak of an oscillating control error signal, i.e., the difference between the setpoint and the controlled variable. Kano et al.[17] proposed two valve stiction detection methods: one method requires knowledge of the valve position (VP), and the other method is based on detecting characteristic parallelogram shapes within the PV vs OP plots. He and Pottmann[18] developed a stiction detection technique for self-regulating processes in which the OP is fitted, in a piecewise fashion, to both triangular and sinusoidal waves, using least-squares estimation. A better fit to a triangular wave indicates valve stiction, whereas a better fit to a sinusoidal wave indicates non-stiction. Rossi and Scali[19] proposed a similar technique independently, in which the PV signal is fitted using three different models: a relay wave, a triangular wave, and a sinusoidal wave. More recently, Srinivasan and co-workers[21,22] presented a qualitative pattern matching approach for simultaneous oscillation detection and valve stiction detection using dynamic time warping (DTW), as well as a Hammerstein model identification approach for the diagnosis and quantification of valve stiction. Yamashita[23] proposed another pattern matching method based on the typical patterns from valve input and valve output in a control loop. Choudhury et al.[24] proposed a method for detecting and quantifying stiction in the control valve. The method consists of three steps. First, it detects nonlinearity in a control loop. Next, if nonlinearity is detected, an ellipse is fitted to the filtered PV and OP signals to detect valve stiction. Finally, the stiction is quantified by clustering or fitted ellipse techniques.

In this work, we extend our work in He and Pottmann[18] to cover both self-regulating and integrating processes, based on

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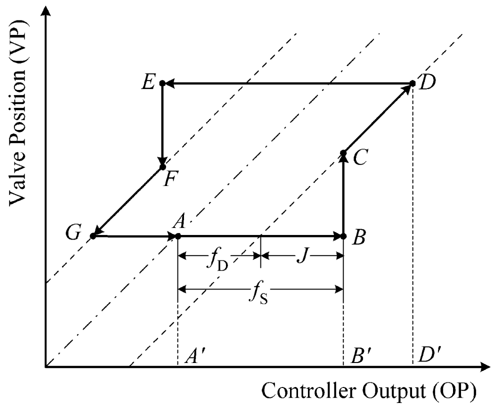

Figure 1. Schematic operation diagram of a sticky valve.

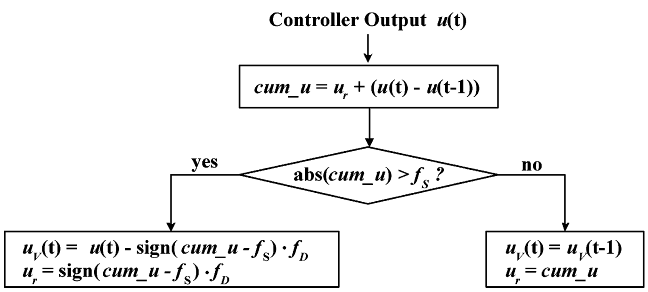

Figure 2. Flowchart of the proposed valve stiction model.

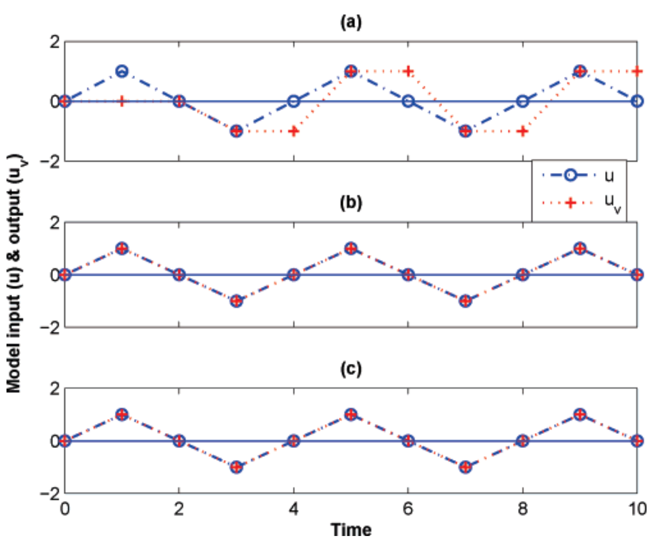

Figure 3. Ideal valve stiction model input (u, denoted by open circles (○)) and output (u_v, denoted by crosses (+)) in the case of no stiction ($f_S = f_D = 0$): (a) Choudhury et al.[26] model, (b) Kano et al.[17] model, and (c) proposed model.

the following qualitative analysis of the control signals: In the case of control-loop oscillations caused by controller tuning or external oscillating disturbances, the OP and PV typically follow sinusoidal waves for both self-regulating and integrating processes. In the case of stiction, the valve position signal usually takes the form of a rectangular wave[3,14] and the reason is explained later in section 2. Because the valve position signal usually is not measured, instead of looking at the valve position signal, we examine the measured output of the first integrating element after the valve, which is either OP or PV. The integrating element converts the rectangular valve position moves into a triangular wave. For self-regulating processes, the proportional−integral (PI) controller acts as the first integrator and the OP's move follows a triangular wave, whereas for integrating processes such as level control, the integrator in the process integrates the rectangular waves and the PV signal follows a triangular wave. The aforementioned analysis answers the questions of which signal to look after and why it takes a triangular shape in the presence of valve stiction. The basic idea of the new detection method is to fit two different functions—triangular wave and sinusoidal wave—to the measured oscillating signal of the first control-loop component containing an integrator after valve (i.e., OP for self-regulating processes or PV for integrating processes). A better fit to a triangular wave indicates valve stiction, whereas a better fit to a sinusoidal wave indicates non-stiction.

The remainder of this paper is organized as follows. Section 2 reviews existing valve stiction models and proposes a new valve stiction model. In section 3, several existing stiction detection methods are reviewed; Horch's first method is analyzed in detail, and a new valve stiction detection method is proposed. The application of the proposed method to simulated and industrial examples is presented in section 4. Conclusions and discussions are given in section 5.

2. A Simple Valve Stiction Model

The purpose of this section is to review the main characteristics of valve stiction and mathematically model its behavior. Literally, valve stiction can be viewed as the necessary force applied to the valve stem to make it move.[27] Because of stiction, the valve will not move if the amount of force corresponding to the controller output is too small to overcome the static friction. If the OP adjustment is not implemented by the actuator (i.e., the valve) because of stiction, integral action in the controller or process will cause the OP to continue to increase in the same direction until the valve overcomes the stiction band. After stiction has been overcome, the valve moves suddenly and potentially causes the process variable to exhibit an overshoot. If this is the case, the OP then changes in the opposite direction in an effort to get the process back to the setpoint until the valve overcomes the stiction band, which causes the process variable to overshoot again in the opposite direction, thus introducing process oscillations. During this process, the valve shifts back and forth in the form of a rectangular wave.

Both detailed physical models and purely empirical models have been used to simulate valve stiction. Physical models[26] describe the stiction phenomenon using force balances based on Newton's second law of motion. The main disadvantage of these models is that they require knowledge of several parameters such as the mass of the moving parts and different types of friction forces that cannot be easily measured and are dependent on the type of fluid and valve wear. On the other hand, empirical or data-driven models[17,25,26] use simple empirical relationships between OP and VP to describe valve stiction, with just a few parameters that can be determined from operating data. Because of their simplicity and easy implementation, in this work, we focus on empirical or data-driven models. Choudhury et al.[25,26] have discussed the definition of stiction thoroughly, distinguished it from other valve nonlinearities, and proposed a data-driven model of stiction. Compared to physical models, this data-driven model significantly simplifies the simulation of a sticky valve and has been wildly used in the study of valve stiction. Kano et al.[17] extended Choudhury's model to cope with both deterministic and stochastic signals. In this work, we reduce the complexity of Kano's model and propose another data-driven model with a straightforward logic flow.

Figure 1 shows the typical input−output behavior of a sticky valve. Without stiction, the valve would move along the dash-

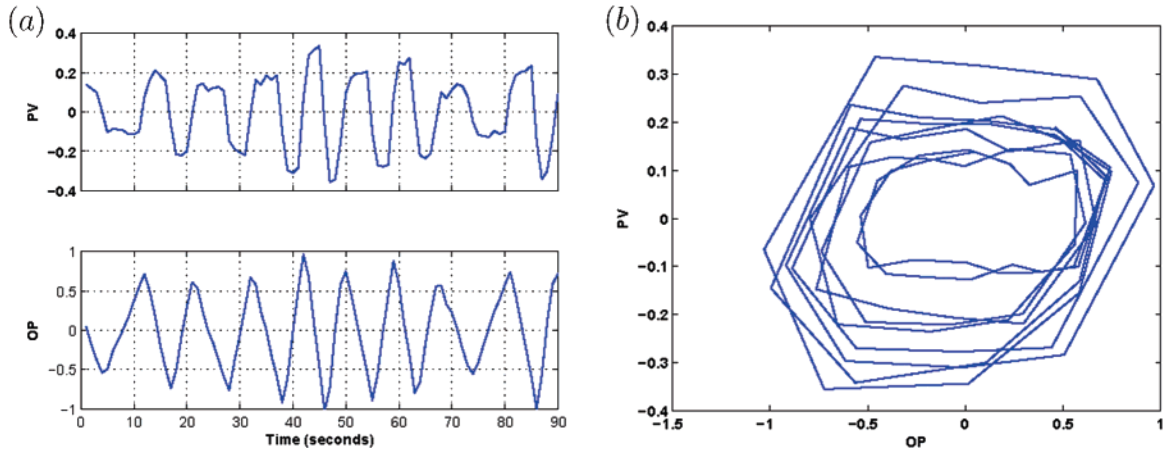

Figure 4. Simulation results of the flow control loop based on the Choudhury et al.[26] model.

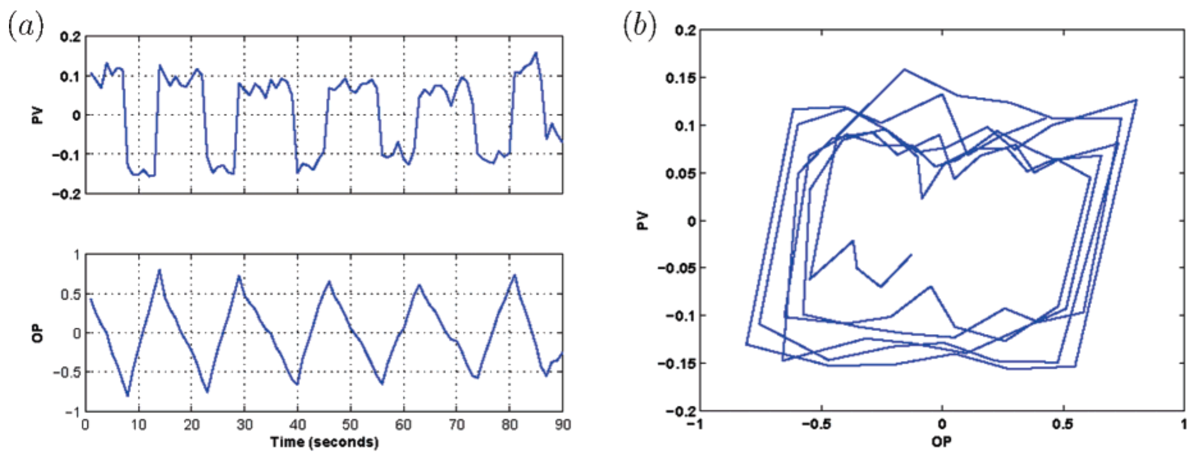

Figure 5. Simulation results of the flow control loop based on the proposed model.

dotted line crossing the origin (i.e., any amount of OP adjustment would result in the same amount of VP change). However, for a sticky valve, static and kinetic frictions must be taken into account. In Figure 1, the parameters f_S, f_D, and J denote the static friction band, the kinetic friction band, and the stick band, respectively, where J is defined as $f_S - f_D$. Because stiction is generally measured as a percentage of the valve travel range, for simplicity, as in Choudhury et al.[25,26] and Kano et al.,[17] all variables such as f_S, f_D, J, controller output u, process output y, and valve position u_V are translated into a percentage of the valve range, so that algebra can be performed among them directly. [In this work, both OP and u are used to represent controller output. OP is used in descriptions, tables, and figures; u is used in mathematical derivations. Similarly, both PV and y denote the process variable, and both VP and u_V are used to denote valve position or valve output.]

Based on the sticky-valve behavior, we propose a new valve stiction model and Figure 2 shows the flowchart of the proposed model. The variable u_r is the residual force acting on the valve which has not materialized a valve move. The variable cum_u is a temporary variable, which is the current net force acting on the valve. If cum_u is large enough in magnitude to overcome the static friction f_S, the valve position $u_V(t)$ will be the controller output $u(t)$ offset by the dynamic stiction f_D. Otherwise, the valve position will not change and cum_u is the residual force on the valve to be used in the next control instant. The proposed model is flexible and works well for several special cases, as listed in Choudhury et al.[26] For example, for valve hysteresis only, we can set $f_S = f_D$. For the case of pure static friction, f_D is set to zero. The saturation constraint can be added on $u_V(t)$ to restrict its value to vary between 0% and 100%.

There is arguably a gray area for static stiction, in terms whether it happens at every control move. If the valve is sluggish, relative to the control interval, the valve may still be moving when the next control move is executed, and, hence, static stiction would not be in effect. If the valve is fast and stops moving before the next control move, it would be affected by static friction. However, even in the case of slow valve, if the controller output does not change for several intervals such that the valve indeed stops moving before the next control move, static friction would be in effect again. In this paper, we choose to include static friction in every valve move.

To compare the behavior of different stiction models, we give two examples. In the first simulation example, we assume that there is no stiction, so that $f_S = f_D = 0$, where the output of the valve stiction model should be exactly the same as the model input. In this simulation, model input is given by

$$u(t) = \sin\left[\left(\frac{\pi}{2}\right)t\right] \tag{1}$$

Figure 3 shows inputs and outputs of three different models, including Choudhury et al.,[26] Kano et al.,[17] and the proposed new model. Figure 3a shows that Choudhury's model output does not match its input in the absence of valve stiction, whereas Figures 3b and 3c show that Kano's model and the proposed model do not suffer from this shortfall.

The second simulation example is designed to examine different model assumptions, regarding whether static friction

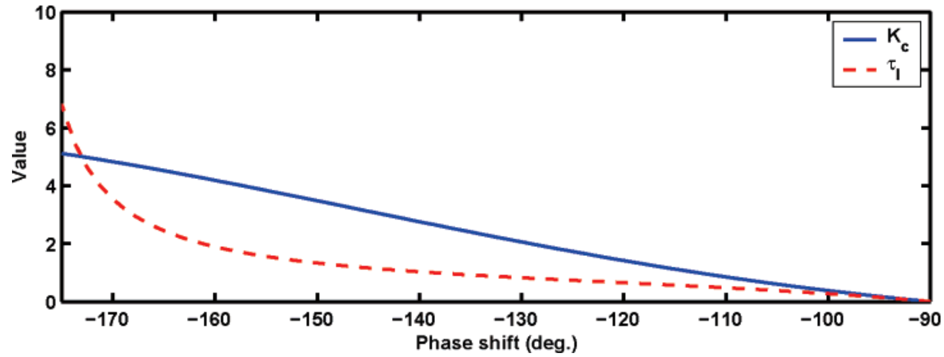

Figure 6. Relationship between (K_c, τ_I) and the phase shift at the marginal stable condition.

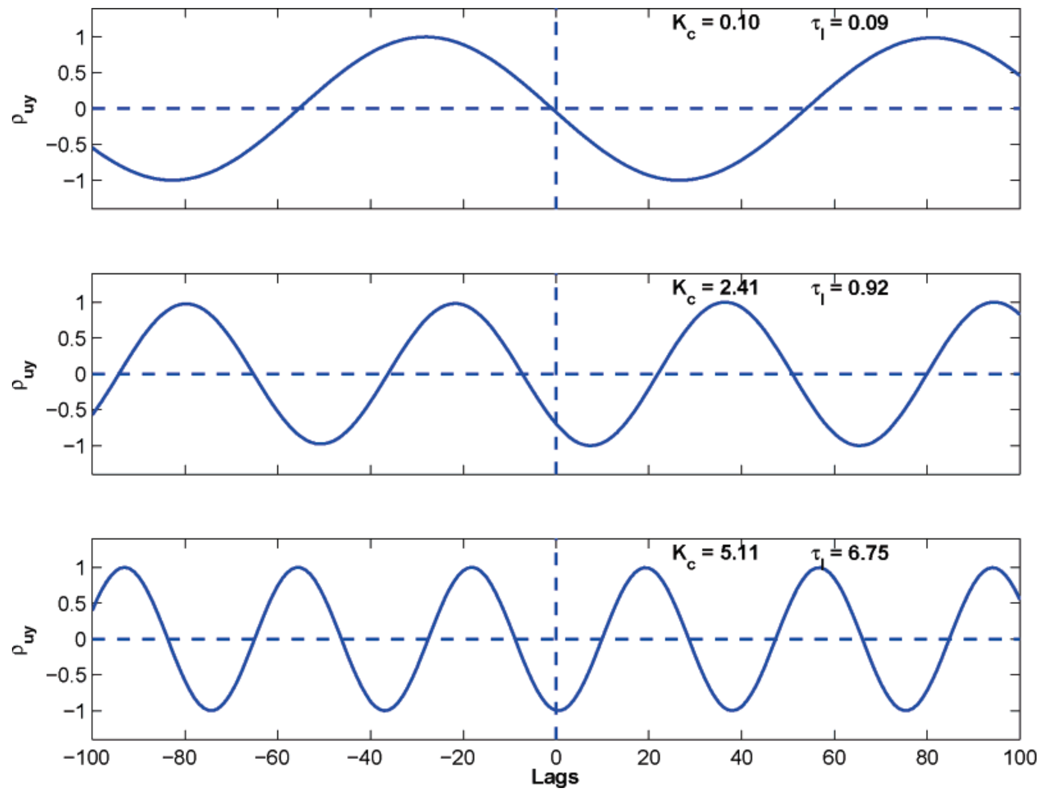

Figure 7. Different controller tuning results in different types of cross-correlation function (CCF) between the controller output (OP) and the process variable (PV).

is in effect in every control move. In this example, a flow control loop with weak stiction ($f_S = 0.65$ and $f_D = 0.35$) is used and details can be found in section 4.1. Model outputs from the Choudhury et al.[26] model and the Kano et al.[17] model are exactly the same, which are shown in Figure 4. The model output from the proposed model is shown in Figure 5. By comparing these two figures, we see that, in the proposed model, the relationship between the controller output and flow rate, representing valve position, takes the shape of a parallelogram, whereas this is not the case in the Choudhury et al.[26] model and the Kano et al.[17] model. The simulation results, based on the proposed method, share the same characteristic parallelogram shape with many industrial cases in this work (see section 4.2) and others.[14,17,28] However, the reality in practice probably lies between the two cases. If the stick-slip effect is not significant, the two assumptions essentially make no difference, although the proposed model has a simpler logic.

3. A New Valve Stiction Detection Method

In this section, we briefly review several published stiction detection methods. We then examine Horch's first method[14] in detail and propose a new stiction detection method.

3.1. Existing Stiction Detection Methods. In Horch's pioneering work on valve stiction detection that was published in 1999, Horch proposed the first automatic valve stiction detection method for self-regulating processes based on the CCF between OP and PV. Given the assumptions that (i) the process does not have an integral action, (ii) the process is controlled by a PI controller, and (iii) the process is oscillating with a significantly large amplitude, it is concluded that the valve stiction would result in an odd CCF (i.e., the phase shift between OP and PV is $\pi/2$), while an external oscillating disturbance or an aggressive controller would result in an even CCF (i.e., the phase shift between OP and PV is π). Because the method is easy to implement and does not require any process knowledge, it has been widely adopted in industry.

Later, Horch[15] proposed another method to address the valve stiction in integrating processes by considering the probability distribution of the second derivative of the controlled variable. In the stiction case, the distribution is close to Gaussian; otherwise, it will have two peaks. One drawback of this method is the differentiation of noisy signals.[16] A suitable filter and cutoff frequency must be carefully chosen to filter out noise. It

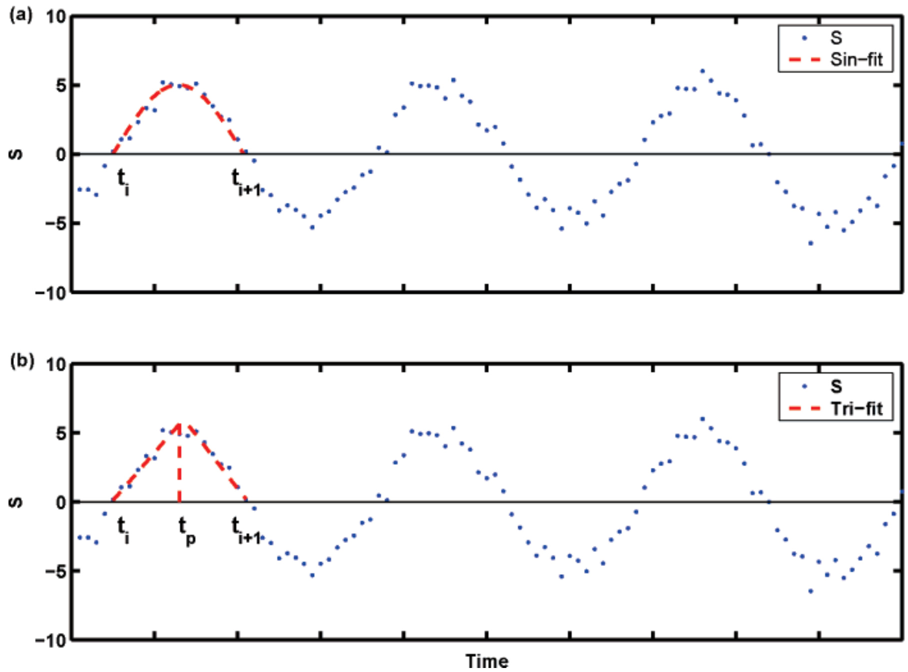

Figure 8. Schematic of the curve fittings: (a) sinusoidal fitting and (b) triangular fitting.

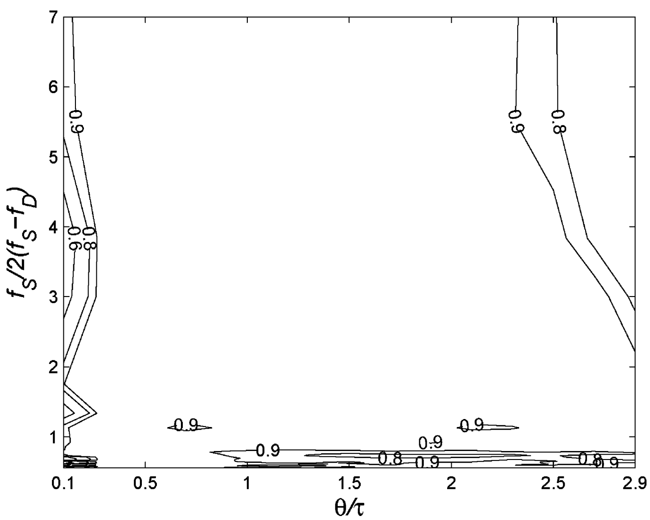

Figure 9. Proposed method applied to a first-order plus time delay (FOPTD) process with stiction, by varying process and stiction parameters.

has been observed that, even after filtering, the calculation of derivatives amplifies even a moderate amount of noise and diminishes the distinction between the shapes of the two probability distributions.[16]

Singhal and Salsbury[16] proposed a valve stiction detection method based on the comparison of areas before and after the peak of an oscillating control error signal (i.e., the difference between the set-point and the process variable being controlled). The idea is based on the observation that aggressive controller tuning usually results in a sinusoidal control error signal, whereas for a sticking valve, the oscillating signal typically increases slower than it decreases. The method requires little computation time and is easy to implement. However, the method is not developed for integrating processes and the effect of noise must be reduced for practical applications.[16]

Kano et al.[17] proposed two valve stiction detection methods. Method A is based on the percentage of time when VP does not change while OP changes. Method B is based on the observation that the plot of PV vs OP takes shape of a parallelogram. However, as noted by the authors, these methods should be used only when flow rate or valve position is measured. Method B is not always reliable even when the flow rate or valve position is measured as shown in one of their flow control examples.

Rossi and Scali[19] proposed a technique to fit the PV using three different models: relay wave, triangular wave, and sinusoidal wave. Relay and triangular waves are associated with the presence of stiction, whereas the sinusoidal shape was associated with the presence of external perturbations.

Srinivasan et al.[21] presented a qualitative pattern matching approach for simultaneous oscillation detection and valve stiction detection using DTW. They generated a reference shape template for each cycle to accommodate time-varying frequency and amplitude changes of oscillation, instead of using a single constant frequency square, triangular, or saw-tooth signals for shape matching in their earlier work.[29] The pattern matching results are compared with a shape library that lists different pattern shapes of OP and PV for different type of processes. This consideration is necessary to make consistent diagnosis for different type of processes. In our proposed approach, we make use of the process information by distinguishing self-regulating processes from integrating processes.

3.2. Analysis of Horch's First Method. Although Horch's first method has many successful applications, it has been discussed in the work of other researchers[16,19] that Horch's first method is not effective all the time. No formal analysis has been given to show why Horch's first method sometimes gives incorrect results. In this subsection, we show that, with no valve stiction, different controller tuning could result in either an odd CCF or an even CCF between OP and PV and thus demonstrate that controller tuning could be one of the reasons that cause Horch's first method to fail.

To illustrate this point, we consider a first-order plus time delay (FOPTD) process with a PI controller. The process transfer function is given as

$$G_p = \frac{K_p \exp^{-\theta s}}{\tau s + 1} \tag{2}$$

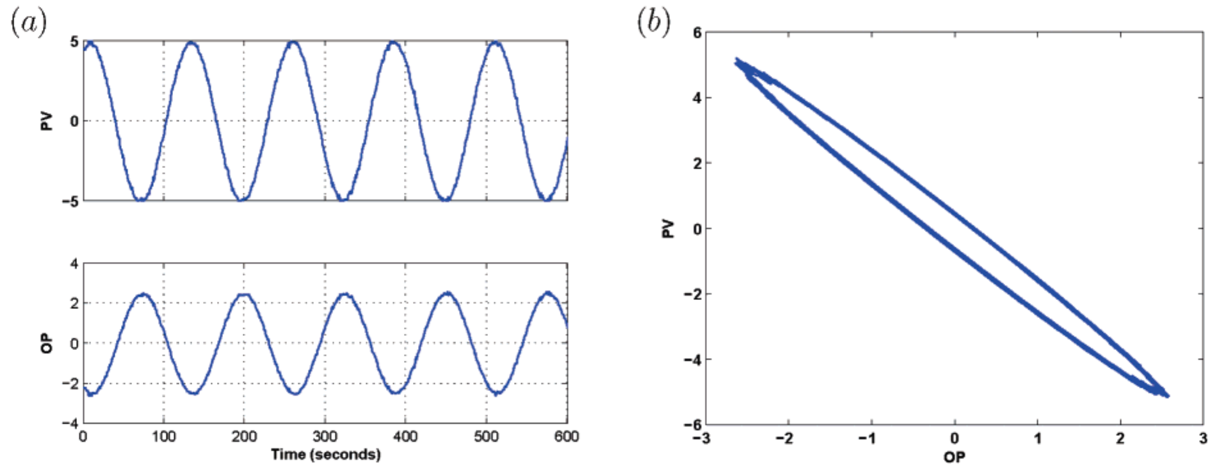

Figure 10. Flow control, case 1: no stiction, but external sinusoidal disturbance.

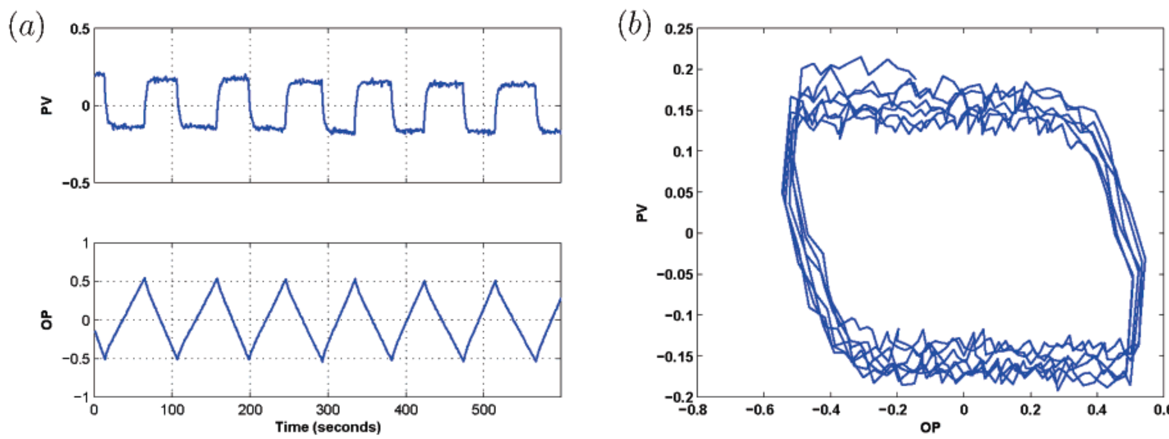

Figure 11. Flow control, case 2: weak stiction.

where K_p is the process gain, θ the process delay, and τ the process time constant. The controller transfer function is

$$G_c = K_c\left(1 + \frac{1}{\tau_I s}\right) \tag{3}$$

where K_c is the proportional gain and τ_I is the integral time constant. Because the purpose of this analysis is to show the inconsistency of Horch's first method, here, we only show that, under certain circumstances, it gives incorrect results. For the aforementioned FOPTD process with a PI controller, we show that different controller tunings can result in either an odd or even CCF between OP and PV with no valve stiction, thus demonstrating the inconsistency of this method.

In an oscillatory control loop without stiction, the oscillation frequency can be obtained by solving the characteristic equation with setting $s = j\omega$, i.e.,

$$1 + G_c(j\omega)G_p(j\omega) = 0 \tag{4}$$

Plugging eqs 2 and 3 into eq 4 and applying Euler's formula, we have

$$-\tau_I\tau\omega^2 + j\tau_I\omega + K_cK_p(\cos\omega\theta - j\sin\omega\theta)(1 + j\tau_I\omega) = 0 \tag{5}$$

which can be used to solve for oscillation frequencies, given different controller tuning parameters K_c and τ_I.

Meanwhile, it is straightforward to see that the phase shift ϕ between OP and PV is

$$\phi = \angle G_p(j\omega) = -\omega\theta - \arctan\omega\tau \tag{6}$$

Equations 5 and 6 show that different controller tunings will lead to different oscillation frequencies, which, in turn, will result in different phase shifts between OP and PV. To illustrate this point, we consider the following example with the plant model:

$$G_p = \frac{\exp^{-s}}{3s + 1} \tag{7}$$

The relationship between the phase shift ϕ and the controller tuning (K_c and τ_I) is shown in Figure 6, where different controller tuning settings result in different phase shifts, ranging from $-\pi$ to $-\pi/2$. More specifically, we pick three pairs of K_c and τ_I values at phase shifts of approximately $-\pi$, $-3\pi/4$, and $-\pi/2$ and the resulting CCF values are shown in Figure 7. For these three cases, Horch's first method would conclude that there is stiction for the first case, the existence of stiction is undetermined for the second case, and no stiction is present for the third case, although there is no stiction in all three cases.

3.3. Proposed Curve Fitting Method. In this subsection, a simple curve fitting method is proposed for valve stiction detection based on the original work of He and Pottmann.[18] The key idea of the proposed method is based on the following analysis of the control signal flow:

(i) In the case of stiction-induced oscillations, the valve position switches back and forth periodically, which results in a rectangular wave. The first integrator after the valve in the control loop (i.e., the PI controller, if it is a self-regulating

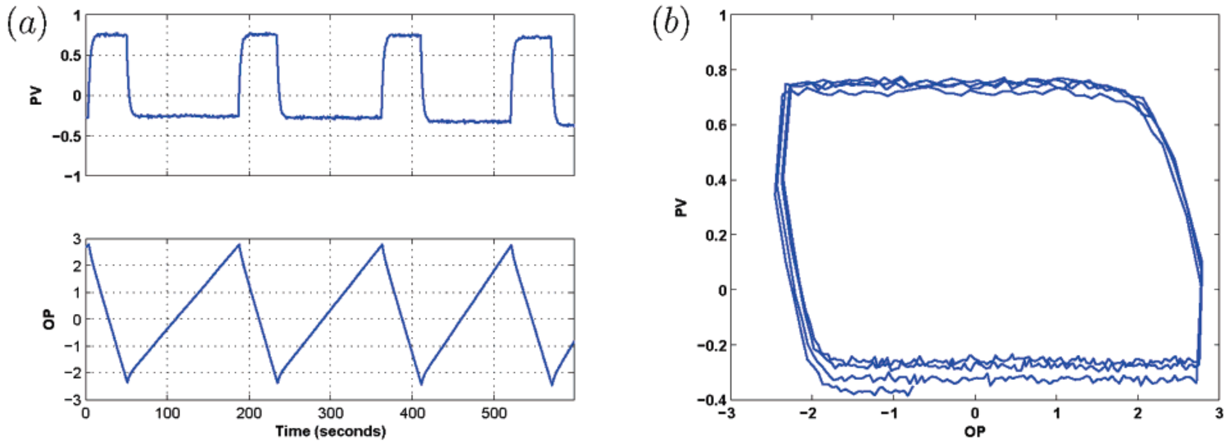

Figure 12. Flow control, case 3: strong stiction.

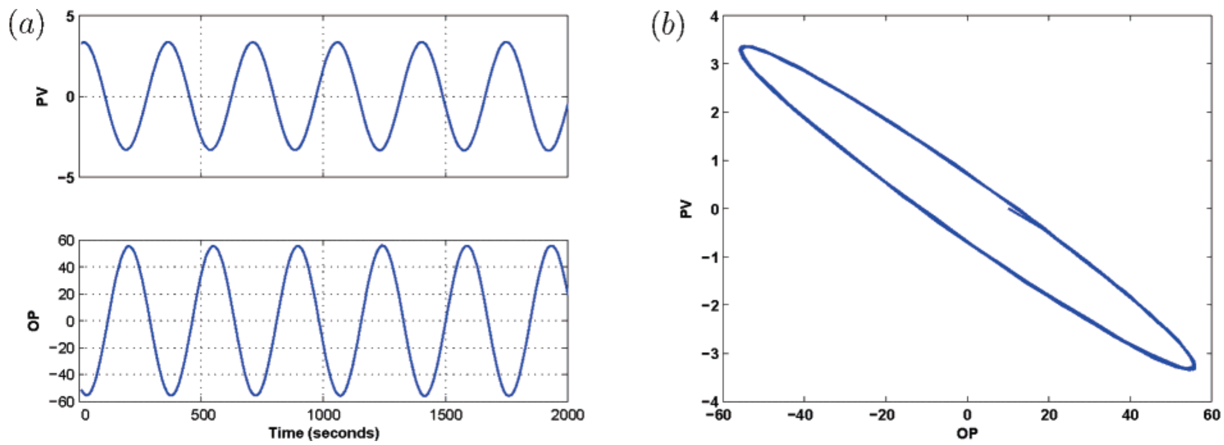

Figure 13. Level control, case 1: no stiction, but aggressive tuning.

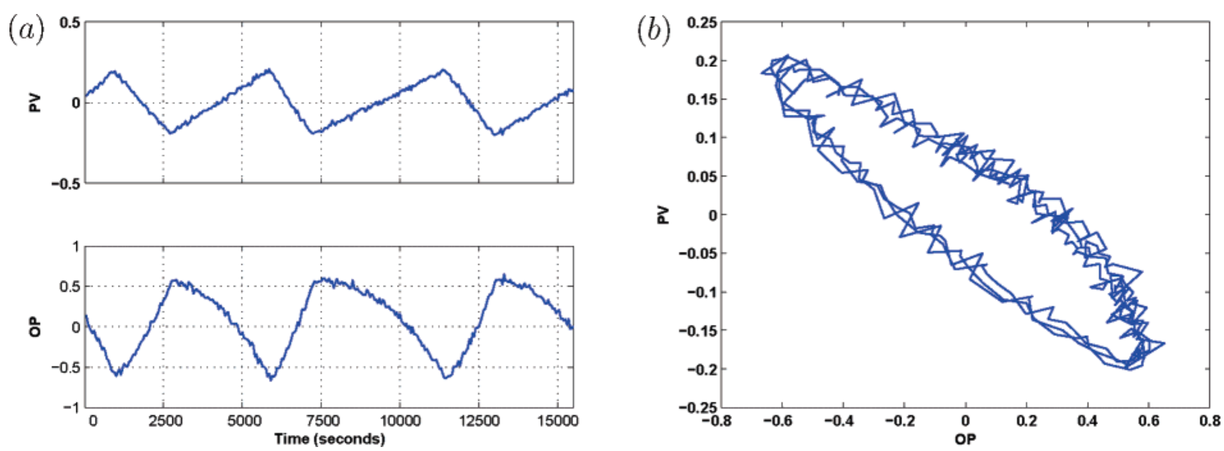

Figure 14. Level control, case 2: weak stiction.

process, or the process, if it is an integrating process) converts it to a triangular wave.

(ii) A sinusoidal external disturbance results in sinusoidal OP and PV signals, because the integration of a sinusoidal wave results in a sinusoidal wave with a phase shift. [Disturbances will eventually become more sinusoidal as they propagate away from the source, because of low-pass plant dynamics.[30,31]]

(iii) A marginally stable control loop also results in smooth sinusoidal shape OP and PV signals for the same reason as that given in step (ii).

To identify stiction-induced oscillations from others, we fit two different functions—triangular wave and sinusoidal wave—to the output signal of the first integrating component after the valve, i.e., OP for self-regulating processes or PV for integrating processes. A better fit to a triangular wave indicates valve stiction, whereas a better fit to a sinusoidal wave indicates no stiction.

It is assumed that the loop in question is known to be oscillating, using oscillation detection methods (see, e.g., Hagglund,[3] Miao and Seborg,[8] Forsman and Stattin[9]). After the detection of the oscillation, the signal is detrended and mean-centered. Time-varying set-point (SP) is subtracted from PV. The location of each zero crossing is automatically detected and determined by linear interpolation of two points on both sides of the axis. Detailed implementation of the method (see section 3.3.1 and 3.3.2) involves isolating half-periods of the oscillating signal and applying piecewise least-squares fitting with noisy data.

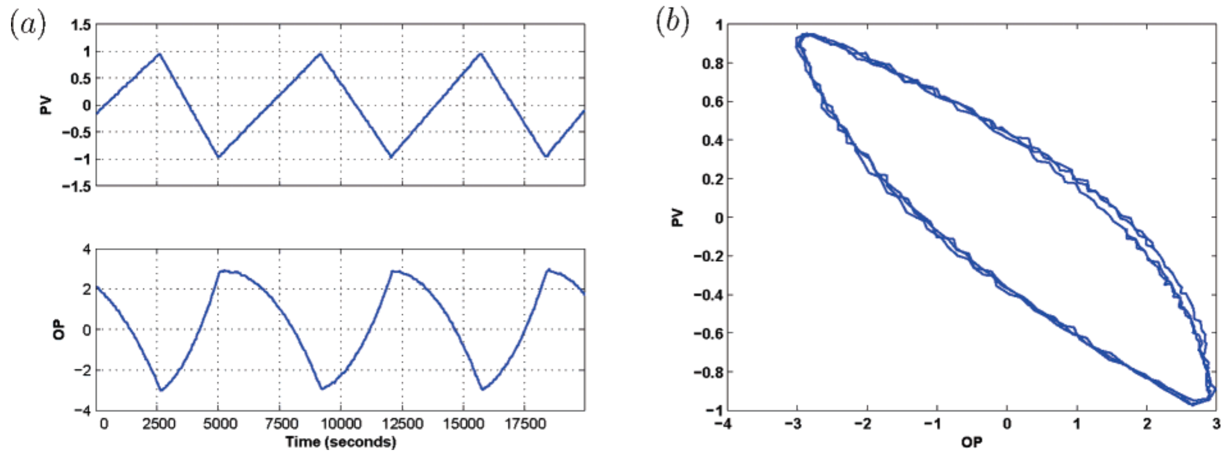

Figure 15. Level control, case 3: strong stiction.

3.3.1. Sinusoidal Fitting. The OP or PV signal is fitted in a piecewise manner for each half-period of oscillation (see Figure 8a), which means that each fitting piece may have a different amplitude and/or frequency. This consideration is reasonable, considering the presence of noise in the signal. Besides, in real processes, the oscillation magnitude may change from time to time and other factors (e.g., external disturbances) may result in an unsymmetrical signal, with respect to its mean.

Denoting the signal to be fitted as S, and defining two vectors,

$$a \equiv \sin(\omega(t_i{:}t_{i+1} - t_i) + \phi) \tag{8}$$

$$b \equiv S(t_i{:}t_{i+1}) \tag{9}$$

the objective function for the sinusoidal fitting is

$$J = \min_{x,\omega} || xa - b||^2 \tag{10}$$

where x is the amplitude, ω the frequency, and ϕ the phase shift of the sinusoid. The term $(t_i{:}t_{i+1})$ is the time range of fitting, as depicted in Figure 8a. In our case, because the curve is fitted in a piecewise manner, we have $\phi = 0$. For simplicity, we fix the value of ω to be

$$\omega = \frac{\pi}{t_i - t_{i+1}} \tag{11}$$

Using the least-squares method, we have

$$x = (a^{\mathrm{T}}a)^{-1}(a^{\mathrm{T}}b) \tag{12}$$

After the optimal value of x is determined, the mean squared error for the sinusoidal fitting during the time period $(t_i{:}t_{i+1})$, which is denoted as $\mathrm{MSE_{Sin}}(i)$, is calculated. The overall mean squared error for the sinusoidal fitting $\mathrm{MSE_{Sin}}$ is the average of $\mathrm{MSE_{Sin}}(i)$ over all time periods.

3.3.2. Triangular Fitting. Triangular fitting, as shown in Figure 8b, is not as straightforward as sinusoidal fitting, because it is a piecewise curve fitting with two degrees of freedom: the location and the magnitude of the maxima. Therefore, we use a numerical iterative method to find the best fitting. The algorithm is described below.

Step 1: For each half-period of signal S (e.g., t_i to t_{i+1}), set the minimum MSE: $\mathrm{MSE_{Tri}}(i) = \infty$.

Step 2: For a peak location t_p between t_i and t_{i+1}, first, determine the linear least-squares fitting for $(t_i{:}t_p)$, with the constraint that the line must pass through the first zero-crossing point at t_i, and then the linear least-squares fitting for $(t_{p+1}{:}t_{i+1})$, with the constraint that the line must pass through the second zero-crossing point at t_{i+1}. Finally, calculate MSE between t_i and t_{i+1}. If $\mathrm{MSE_{Tri}}(i) > \mathrm{MSE}$, set $\mathrm{MSE_{Tri}}(i) = \mathrm{MSE}$.

Step 3: Repeat step 2 for different t_p values.

Step 4: The overall $\mathrm{MSE_{Tri}}$ value is the average of the $\mathrm{MSE_{Tri}}(i)$ values.

3.3.3. Stiction Index (SI). The stiction index (SI) is defined as the ratio of the MSE value of the sinusoidal fitting to the summation of the MSE values of both the sinusoidal and triangular fittings:

$$\mathrm{SI} = \frac{\mathrm{MSE_{Sin}}}{\mathrm{MSE_{Sin}} + \mathrm{MSE_{Tri}}} \tag{13}$$

Note that the SI value is bounded to the interval [0, 1]. SI = 0 indicates non-stiction, where S fits a sinusoidal wave perfectly ($\mathrm{MSE_{Sin}} = 0$), whereas SI = 1 indicates stiction, where S fits a triangular wave perfectly ($\mathrm{MSE_{Tri}} = 0$). For real process data, an SI value close to zero would indicate non-stiction, whereas an SI value close to 1 would indicate stiction. When SI $\approx$ 0.5, which means $\mathrm{MSE_{Sin}} = \mathrm{MSE_{Tri}}$, the presence of stiction is undetermined. Based on our experience, we recommend the following rules:

$$\begin{aligned} \mathrm{SI} \le 0.4 &\Rightarrow \text{no stiction} \\ 0.4 < \mathrm{SI} < 0.6 &\Rightarrow \text{undetermined} \\ \mathrm{SI} \ge 0.6 &\Rightarrow \text{stiction} \end{aligned}$$

4. Application Examples

4.1. Simulation Examples. In this subsection, the proposed valve stiction detection method is applied to simulation examples in which stictions are simulated using the stiction model proposed in this work.

To test how the proposed method is affected by process dynamics, the method is applied to an FOPTD process with stiction and evaluated for different process conditions. As in Rossi et al.,[20] we have varied the ratio θ/τ, and the ratio $f_S/[2 \times (f_S - f_D)]$, which is equivalent to the ratio of $S/(2J)$ that was used by Rossi et al.[20] The result is shown in Figure 9 as a contour plot of the SI values with varying process and stiction parameters. It can be seen that the gray area of the proposed method is small and stiction is detected under almost all test conditions. As a comparison, the gray area of Rossi's method is larger when PV, instead of OP, is fitted to triangular, relay, and sinusoidal shapes, and the cross-correlation method has the largest gray area under the same conditions.[20]

Table 1. Valve Stiction Model Parameters[a]

case	degree of stiction	f_D	f_S
1	no stiction	0	0
2	weak stiction	0.35	0.65
3	strong stiction	2	3

[a] Data taken from Kano et al.[17]

Table 2. Flow Control Case Study

control system	case	SI_{OP}
flow control	1	0.06
flow control	2	0.94
flow control	3	1.00

To compare the proposed valve detection method with the methods of Kano et al., the same flow control and level control systems used in Kano et al.[17] are investigated. The transfer functions for the flow and level processes are given by

$$G_f(s) = \frac{1}{0.2s + 1} \tag{14}$$

$$G_l(s) = \frac{1}{15s} \exp^{-s} \tag{15}$$

PI controllers are used for both control systems, and their transfer functions are given by

$$\text{flow control:} \quad G_c = 0.5\left(1 + \frac{1}{0.3s}\right) \tag{16}$$

$$\text{level control:} \quad G_c = 3\left(1 + \frac{1}{30s}\right) \tag{17}$$

Three cases are examined for both systems: no stiction, weak stiction, and strong stiction. Valve-stiction model parameters are summarized in Table 1. In the case of no stiction, because both systems are closed-loop stable, there is no oscillation and the proposed method is not applicable. To test the capability of the proposed method on distinguishing valve stiction from external disturbances, for the case of no stiction in the flow control system, an external sinusoidal disturbance is introduced at the PV:

$$d = 5 \sin(30t) \tag{18}$$

Simulation results for the flow control are shown in Figures 10−12, and the detection results are listed in Table 2. As we can see, the stiction index based on the controller output (SI_{OP}) successfully detected valve stiction in the flow control and distinguished it from the external disturbance. Here, we use a sinusoidal disturbance because nonlinear disturbances will eventually become more sinusoidal and more linear as they propagate away from the source due to low-pass plant dynamics.[30,31] However, it is worthwhile to note that, if the external oscillatory disturbance is highly nonlinear, such as a triangular wave, the proposed curve fitting method may not be able to diagnose it correctly.

For the cases where there might be multiple causes of oscillation, the calculated SI value may not be able to exclusively indicate whether there is a valve stiction or not. However, the SI value can identify the dominant factor that causes the oscillation. In the flow control, the mixed case of the external disturbance and weak valve stiction (i.e., Case 1 coexisting with Case 2), as well as the mixed case of the external disturbance and strong valve stiction (i.e., Case 1 coexisting with Case 3), are studied, and the results are given in Table 3. As we can see, for the case where both external disturbance and weak

Table 3. Flow Control with Mixed Cases

control system	case	SI_{OP}
flow control	case 1 coexisting with case 2	0.17
flow control	case 1 coexisting with case 3	0.75

Table 4. Level Control Case Study

control system	case	SI_{PV}
level control	1	0.00
level control	2	0.93
level control	3	0.99

Table 5. Industrial Examples

control system	case	SI_{OP}	SI_{PV}
level control	1	–	0.34
flow control	2	0.77	–
flow control	3	0.75	–

stiction exist, the SI value indicates that the dominant factor is external disturbance whereas for the case where both external disturbance and strong stiction exist, the SI value indicates that the dominant factor is valve stiction.

To test the capability of this method, in regard to distinguishing valve stiction from bad tuning, for the case of no stiction in the level control system, the controller gain is increased from 3 to 8.4 to make the system marginally stable. Because it is an integrating process, PV is fitted. Simulation results are shown in Figures 13−15, and the detection results are listed in Table 4. The calculated SI value, based on the PV (SI_{PV}) detects stiction successfully and distinguishes it from the bad tuning.

As a comparison, in the case of flow control, method A from the work of Kano et al.[17] successfully detects the stiction, but method B from the work of Kano et al.[17] fails. In the case of level control, where level is used for detection, none of the methods of Kano et al.[17] can successfully detect stiction.

It is worthwhile to note that limit cycles can also be caused by nonlinearities other than valve stiction. This aspect has not been addressed by other curve fitting methods. In this work, limit cycles caused by valve saturation are tested using the proposed method. Figure 16a shows the PV and OP time series plots of an FOPTD process with valve saturation. Because it is a self-regulating process, OP is fitted to sinusoidal and triangular shapes, as shown in Figure 17. The SI value is 0.31, which indicates that the oscillation is not caused by valve stiction.

4.2. Industrial Examples. The proposed stiction detection method has been successfully used within Performance Surveyor, which is DuPont's web-based controller performance monitoring tool.[32] As referenced in section 3.3, the stiction index is only calculated if a control loop is known to be oscillating, as indicated by a normalized oscillation index that is determined from the extrema of the error autocorrelation function.[8] Because set-point excitation could result in OP patterns similar to those observed when stiction is present, therefore leading to incorrect diagnosis, data sets in which the oscillations are mainly due to set-point variability (as indicated by an oscillation index and the period of the SP signal) are also excluded from this analysis. Finally, sufficient data resolution is required for reliable diagnosis in practice. Because the proposed stiction detection method is essentially based on the shape detection of a signal, the results have a tendency to be biased toward stiction if the data resolution is low. A requirement of at least 15 points per cycle is used by the Performance Surveyor implementation. Note that we deliberately do not make any assumptions on sampling intervals, because stiction cycles can vary significantly in duration from case to case. The stiction index is reported along with oscillation index, oscillation period, and PV vs OP plots,

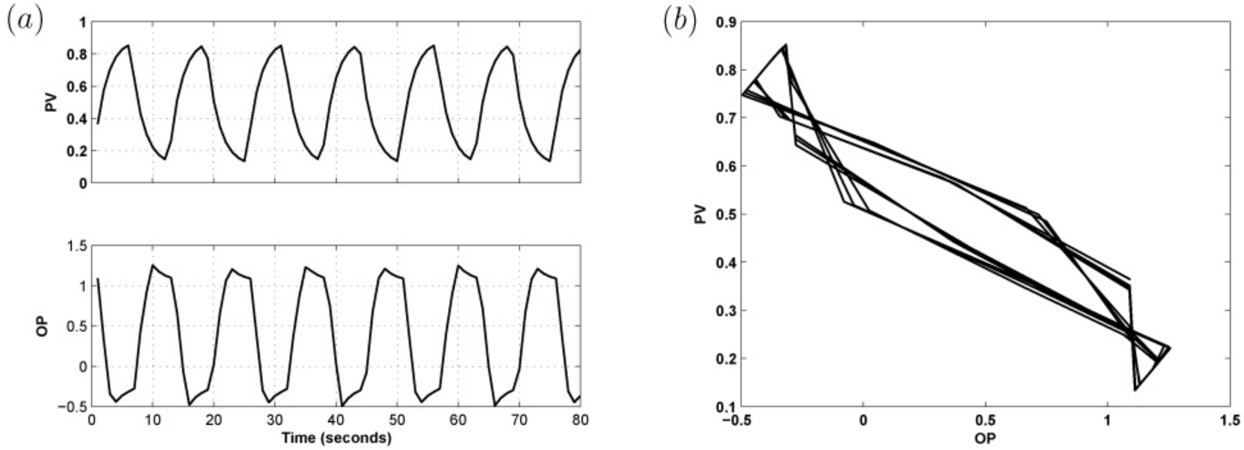

Figure 16. Valve saturation of an FOPTD process.

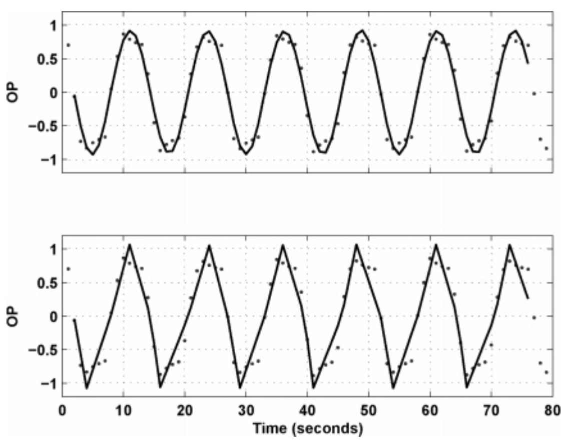

Figure 17. Curve fitting of OP for the valve saturation case.

to facilitate a final diagnosis by the user. Three cases from DuPont's chemical processes are given as examples in this subsection: case 1 is a level control loop that is overaggressively tuned; cases 2 and 3 are flow control loops, and these loops are known to have valve stiction problems. Figures 18–20 show normalized operation data, and Table 5 summarizes detection results by stiction indices. The proposed method successfully detects valve stiction in cases 2 and 3 and indicates that the level oscillation in case 1 is not caused by stiction.

5. Conclusions and Discussions

In this work, two existing data-driven valve stiction models are reviewed and a structurally simple and logically straightforward valve stiction model is proposed. The new model handles both deterministic and stochastic signals naturally and overcomes some of the disadvantages of existing models.

A new stiction detection method is proposed to fit two different functions—triangular wave and sinusoidal wave—to the measured output signal of the first integrating component after the valve, i.e., controller output for self-regulating processes or process output for integrating processes. A better fit to a triangular wave indicates valve stiction, and a better fit to a sinusoidal wave indicates non-stiction. The proposed stiction detection method is evaluated on simulated examples and industrial data sets where the actual oscillation causes are known, and the results show that the proposed method and metric successfully detect valve stiction in both self-regulating and integrating processes.

Another advantage of the proposed curve fitting method lie in its industrial practicability, including straightforward methodology, fully automatic execution with no user interaction, robustness to noise, flexibility in handling asymmetric or damped oscillations, and applicability to both self-regulating and integrating processes. On the other hand, the proposed method does not guarantee detection of valve stiction in all cases. The following remarks discuss some limitations and application-related issues of the proposed method:

(1) It is worthwhile to note that there is a gray area where neither sinusoidal nor triangular shapes fit the signal well. In this case, the proposed method cannot provide meaningful detection results.

(2) Limit cycle oscillations can also be caused by process nonlinearities other than valve stiction. In this work, we have shown that the proposed method can distinguish valve stiction from valve saturation in a first-order plus time delay (FOPTD) example. However, the capability of the proposed method in distinguishing valve stiction from other nonlinearities needs further investigation. Our research in this direction is underway.

(3) In the proposed method, we assume that the external disturbance is sinusoidal. This is true for most of the cases, because disturbances will eventually become more sinusoidal as they propagate away from the source, because of low-pass plant dynamics. However, if the disturbance source that leads to oscillation is close to the valve being diagnosed, the proposed method may fail or lead to an incorrect diagnosis.

(4) An exact triangular wave will be obtained only if there is a pure integrator in the controller or process. However, in the proposed method, a clear triangle is not required for the method to work. Therefore, the proposed method can handle most of the processes with weak integration action where clear triangular waves are not expected.

(5) When the setpoint is constant and there are no load disturbances or the load disturbances are stationary time series, detrending is not needed. For the case of varying load, such as step changes, the user has the choice to select the data segment to avoid the transient due to the step changes. Because we use piecewise sinusoidal or triangular fitting on half-periods, the impact of nonstationary disturbances or noise is minimized. In the Performance Surveyor implementation at DuPont, detrending and mean-centering are done automatically for incoming data.

(6) The low-pass filter associated with a proportional–integral (PI) controller has no significant impact on the proposed method. For valve stiction in integrating processes, although the triangular process variable (PV) signal can be smoothed by the filter, because PV is fitted, the smoothing effect does not matter. For valve stiction in self-regulating processes, the rectangular wave

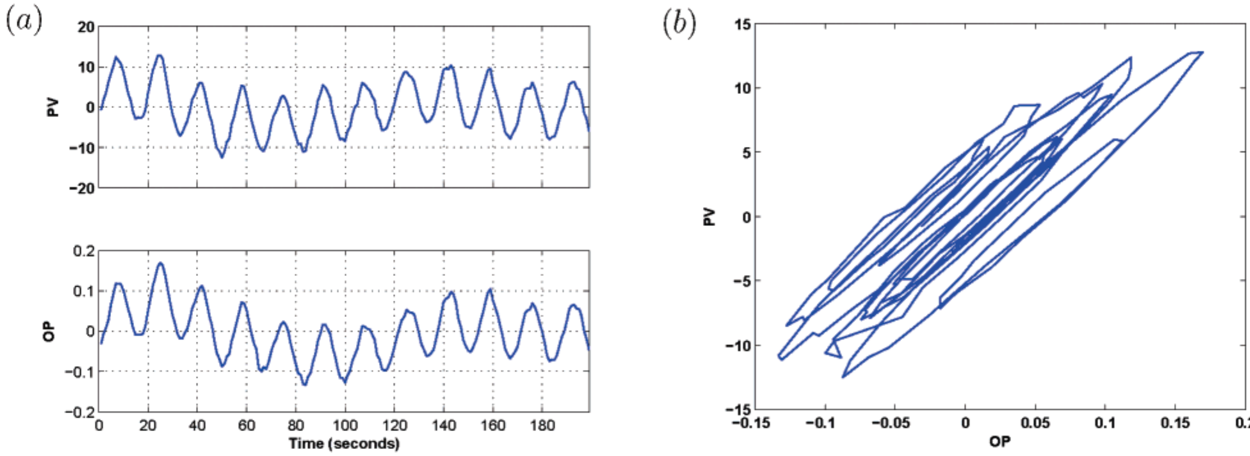

Figure 18. Industrial example, case 1: level control with aggressive tuning.

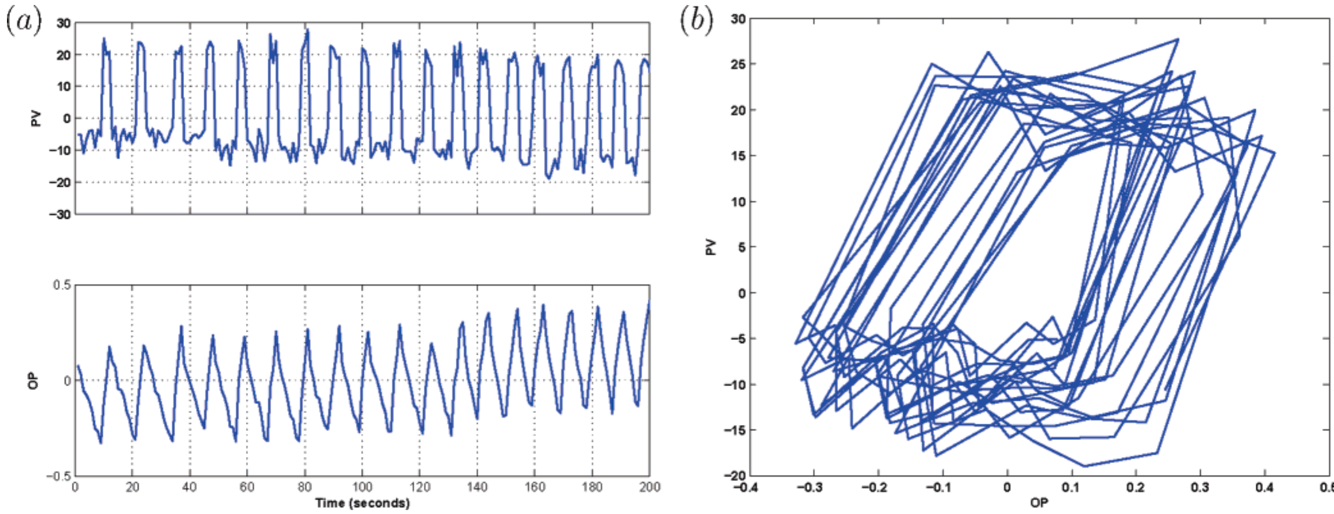

Figure 19. Industrial example, case 2: flow control with valve stiction.

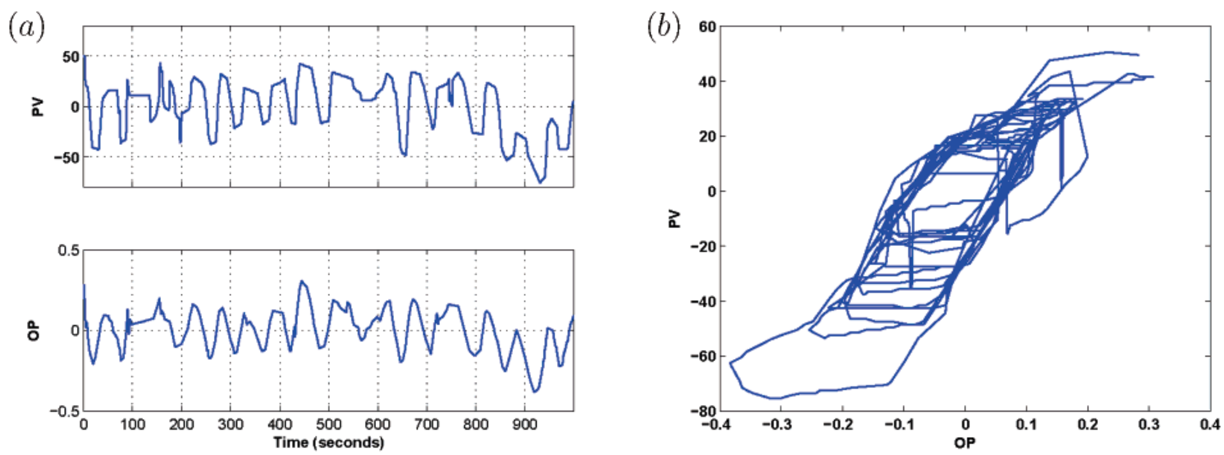

Figure 20. Industrial example, case 3: flow control with valve stiction.

will be smoothed by the filter, but after the integration action of the PI controller, the controller output (OP) fitting still favors the triangular wave if the stiction is not too weak, i.e., in the gray area.

While the proposed method works well for single-loop controllers, it is interesting to apply the method to interacting processes with multi-loop controllers where oscillations may be caused by one sticky valve and propagated to other loops through interaction. It is important, in this case, to identify correctly which valve among the oscillating loops is the cause and which are effects.

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Literature Cited

(1) Astrom, K. Assessment of achieviable performance of simple feedback loops. *Int. J. Adaptive Control Signal Process.* **1991**, *5*, 3−19.

(2) Ender, D. B. Process control performance: Not as good as you think. *Control Eng.* **1993**, (Sept.), 180−190.

(3) Hagglund, T. A control-loop performance monitor. *Control Eng. Pract.* **1995**, *3*, 1543−1551.

(4) Thornhill, N. F.; Hagglund, T. Detection and diagnosis of oscillation in control loops. *Control Eng. Pract*. **1997**, *5*, 1343−1354.

(5) Qin, S. Control performance monitoring—a review and assessment. *Comput. Chem. Eng.* **1998**, *23*, 178−186.

(6) Desborough, L.; Nordh, P.; Miller, R. Control system reliability: process out of control. *Ind. Comput.* **2001**, *2*, 52−55.

(7) Bialkowski, W. L. Dreams vs. reality: A view from both sides of the gap. *Pulp Pap. Can.* **1993**, *94*, 19−27.

(8) Miao, T.; Seborg, D. E. Automatic detection of excessively oscillatory feedback control loops. In *Proceedings of IEEE International Conference on Control Applications*, Kohala Coast, Island of Hawaii, August 22−27, 1999; IEEE: Piscataway, NJ, 1999; Vol. 1, pp 359−364.

(9) Forsman, K.; Stattin, A. A new criterion for detecting oscillations in control loops. Presented at the European Control Conference, Karlsruhe, Germany, 1999, Paper No. CP8-3.

(10) Taha, O.; Dumont, G. A.; Davies, M. S. Detection and diagnosis of oscillations in control loops. In *Proceedings of the 35th IEEE Conference on Decision and Control*, Kobe, Japan, December 1996; pp 2432−2437.

(11) Deibert, R. Model based fault detection of valves in flow control loops. In *IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes—SAFEPROCESS '94*, Espoo, Finland, 1994; pp 417−422.

(12) Horch, A.; Isaksson, A. J. A method for detection of stiction in control valves. In *IFAC Workshop on On-Line Fault Detection and Supervision in the Chemical Process Industries*, Lyon, France, 1998; pp 257−262.

(13) Wallen, A. Valve diagnostics and automatic tuning. In *Proceedings of the American Control Conference*, Albuquerque, NM, June 1997; pp 2930−2934.

(14) Horch, A. A simple method for detection of stiction in control valves. *Control Eng. Pract*. **1999**, *7*, 1221−1231.

(15) Horch, A. Condition monitoring of control loops, Thesis, Royal Institute of Technology, 2000.

(16) Singhal, A.; Salsbury, T. I. A simple method for detecting valve stiction in oscillating control loops. *J. Process Control* **2005**, *15*, 371−382.

(17) Kano, M.; Maruta, H.; Kugemoto, H.; Shimizu, K. Practical model and detection algorithm for valve stiction. In *Proceedings of the Seventh IFAC−DYCOPS Symposium*, Cambridge, MA, July 5−7, 2004. (CD-ROM.)

(18) He, Q. P.; Pottmann, M. Detection of Valve Stiction Using Curve Fitting, Internal Report, Process Dynamics and Control, DuPont Engineering, August 2003.

(19) Rossi, M.; Scali, C. Automatic Detection of Stiction in Actuators: A Technique to Reduce the Number of Uncertain Cases. In *Proceedings of the Seventh IFAC−DYCOPS Symposium*, Cambridge, MA, July 5−7, 2004; Paper 157. (CD-ROM.)

(20) Rossi, M.; Scali, C. A comparison of techniques for automatic detection of stiction: simulation and application to industrial data. *J. Process Control* **2005**, *15*, 505−514.

(21) Srinivasan, R.; Rengaswamy, R.; Miller, R. Control Loop Performance Assessment. 1. A Qualitative Approach for Stiction Diagnosis. *Ind. Eng. Chem. Res.* **2005**, *44*, 6708−6718.

(22) Srinivasan, R.; Rengaswamy, R.; Narasimhan, S.; Miller, R. Control Loop Performance Assessment. 2. Hammerstein Model Approach for Stiction Diagnosis. *Ind. Eng. Chem. Res.* **2005**, *44*, 6719−6728.

(23) Yamashita, Y. An automatic method for detection of valve stiction in process control loops. *Control Eng. Pract*. **2006**, *14*, 503−510.

(24) Choudhury, M. S.; Shah, S.; Thornhill, N.; Shook, D. Automatic detection and quantification of stiction in control valves. *Control Eng. Pract*. **2006**, *14*, 1395−1412.

(25) Choudhury, M. A. A. S.; Thornhill, N. F.; Shah, S. L. A Data-Driven Model for Valve Stiction. In *Proceedings of the Triennial ADCHEM (Advanced Control of Chemical Processes)*, 2003 Conference, Hong Kong, January 11−14, 2004.

(26) Choudhury, M. A. A. S.; Thornhill, N. F.; Shah, S. L. Modelling valve stiction. *Control Eng. Pract*. **2005**, *13*, 641−658.

(27) Gerry, J.; Ruel, M. How to measure and combat valve stiction online. Presented at the ISA International Fall Conference, Houston, TX, September 11, 2001. Available via the Internet at http://www.expertune.com/articles/isa2001/StictionMR.htm.

(28) Ruel, M. Stiction: the hidden menace. How to Recognize This Most Difficult Cause of Loop Cycling. *Control Mag.* **2000**, (Nov.), 69−75. Also available via the Internet at http://www.expertune.com/articles/RuelNov2000/stiction.html.

(29) Rengaswamy, R.; Hägglund, T.; Venkatasubramanian, V. A qualitative shape analysis formalism for monitoring control loop performance. *Eng. Appl. Artif. Intell.* **2001**, *14*, 23−33.

(30) Thornhill, N.; Cox, J.; Paulonis, M. Diagnosis of plant-wide oscillation through data-driven analysis and process understanding. *Control Eng. Pract.* **2003**, *11*, 1481−1490.

(31) Thornhill, N. Finding the source of nonlinearity in a process with plant-wide oscillation. *IEEE Trans. Control Syst. Technol.* **2005**, *13*, 434−443.

(32) Hoo, K.; Piovoso, M.; Schnelle, P.; Rowan, D. Process and controller performance monitoring: Overview with industrial applications. *Int. J. Adapt. Control Signal Process.* **2003**, *17*, 635−662.

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