DETECTION AND QUANTIFICATION OF CONTROL VALVE STICTION

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Abstract: Stiction is one of the most common problems in the spring-diaphragm type control valves, which are widely used in the process industry. Although there have been many attempts to understand and detect stiction in control valves, none of the current methods can simultaneously detect and quantify stiction. There is thus a clear need in the process industry for a non-invasive method that can not only detect but also quantify stiction so that the valves that need repair or maintenance can be identified, isolated and repaired. This work describes a method that can detect and quantify stiction that may present in control valves using routine closed loop operating data obtained from the process. No additional excitation or experimentation with the plant is required. Over a dozen industrial case studies have demonstrated the wide applicability and practicality of this method as an useful diagnostic aid in control-loop performance monitoring.

Keywords: stiction, stickband, deadband, hysteresis, actuator, control valve, process control, nonlinearity, slip jump, clustering, ellipse, control loop, condition monitoring

1. INTRODUCTION

A typical chemical plant has hundreds of control loops. The presence of oscillation in a control loop increases the variability of the process variables thus causing inferior quality products, larger rejection rates, increased energy consumption, reduced average throughput and profitability. Bialkowski (1992) reported that about 30% of the loops are oscillatory due to control valve problems. In a recent study, Desborough and Miller (2002) reported that control valve problems account for about a third of the 32% of controllers classified as “poor” or “fair” in an industrial survey. If the control valve contains nonlinearities such as stiction, backlash, and deadband, the valve output may be oscillatory which in turn can cause oscillations in the process output. Among the many types of nonlinearities in control valves, stiction is one of the most common and long-standing problems in process industry. Stiction can easily be detected using invasive methods such as the valve travel or bump test. But to apply an invasive method across an entire plant site is neither feasible nor cost-effective because of the manpower, cost and time intensive nature of the method. Although there have been many studies (Taha *et al.*, 1996; Wallén, 1997; Sharif and Grosvenor, 1998; Gerry and Ruel, 2001) carried out for invasive analysis of control valve performance, only a few non-invasive methods ((Horch, 1999; Rengaswamy *et al.*, 2001; Stenman *et al.*, 2003) have appeared in literature. Horch’s method (Horch, 1999; Horch, 2000) detects stic-

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tion with the use of the cross-correlation function between *pv* and *op*. Horch's method is successful mainly in detecting valve stiction in flow control loops. It can not be applied for loops involving an integrator or those carrying compressible fluids. The method described in Rengaswamy *et. al.* (2001) depends on the qualitative shape of the time trends of the data which is often distorted by the presence of noise and disturbance. Also, in real life the shape of the time trends of the data is heavily affected by the process and controller dynamics. Stenman *et. al.* (2003) described a model based segmentation method to detect stiction in control valves. This method requires the model of the process with a lot of tuning parameters. To obtain the closed loop model of the process from the routine operation data is very difficult. Moreover, all these methods can only detect stiction but can not quantify it. As pointed out rightly in (Desborough and Miller, 2002), a passive or non-invasive method that can reliably and automatically classify valve performance in closed loop is "*desperately needed in process industry*". An effective non-intrusive data-based monitoring method could reduce the cost of control loop performance maintenance by screening and short-listing those loops and/or valves that need maintenance. This work describes a data-based non-invasive method that can detect and quantify stiction present in control valves.

2. WHAT IS STICTION?

Different people or organizations have defined stiction in different ways. Some of these definitions have been presented in Choudhury *et al.* (2003*a*) . Based on a careful investigation of real process data a new definition of stiction was also proposed by the authors (Choudhury *et al.*, 2004) and is summarized as following. It is observed that

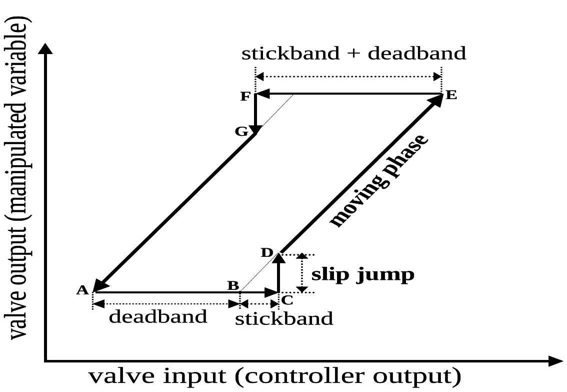


Fig. 1. *Typical input-output behavior of a sticky valve*

the phase plot of the input-output behavior of a valve "suffering from stiction" can be described by figure 1. It consists of four components: deadband, stickband, slip jump and the moving phase. When the valve comes to a rest or changes the direction at point A in figure 1, the valve sticks. After the controller output overcomes the deadband (AB) plus the stickband (BC) of the valve, the valve jumps to a new position (point D) and continues to move. Due to very low or zero velocity, the valve may stick again in between points D and E in figure 1 while travelling in the same direction (EnTech, 1998). In such a case the magnitude of deadband is zero and only stickband is present. This can be overcome if the controller output signal is larger than the stickband only. It is usually uncommon in industrial practice. The deadband and stickband represent the behavior of the valve when it is not moving though the input to the valve keeps changing. Slip jump represents the abrupt release of potential energy stored in the actuator chamber due to high static friction into kinetic energy as the valve starts to move. The magnitude of the slip jump is very crucial in determining the limit cyclic behavior introduced by stiction (Piipponen, 1996). Once the valve slips, it continues to move until it sticks again (point E in figure 1). In this moving phase dynamic friction is present which may be much lower than the static friction. Therefore, *"stiction is a property of an element such that its smooth movement in response to a varying input is preceded by a static part followed by a sudden abrupt jump called the slip-jump. Slip-jump is expressed as a percentage of the output span. Its origin in a mechanical system is static friction which exceeds the dynamic friction during smooth movement"*. This definition has been exploited in the next and subsequent sections for quantifying stiction in control valves. In the process industry, stiction is generally measured as a % of the valve travel or the span of the control signal (Gerry and Ruel, 2001). For example, a 2 % stiction means that when the valve gets stuck it will start moving only after the cumulative change of its control signal is greater than or equal to 2%. If the range of the control signal is 4 to 20 mA then a 2% stiction means that a change of the control signal less than 0.32 mA in magnitude will not be able to move the valve.

Note that it is difficult to estimate slip jump ('j') from the controlled output (*pv*) and the controller output (*op*) data because the slip jump in the valve output is destroyed by the process dynamics. This work will only quantify the parameter 's' (deadband plus stickband) which will be termed as the amount of stiction from this point forward.

3. DETECTION OF VALVE STICTION

In a control loop, nonlinearity may be present either in the process itself or in the control valve.

For our current analysis, we are assuming that the process nonlinearity is negligible in the steady state operating region during which the data has been collected. This is a reasonable assumption because the method works with the routine operating data of a control loop under regulatory control. For a particular operating region of a chemical plant, the plant is assumed to be locally linear under its feedback configuration. This is what makes linear controllers perform so well in the chemical process industries.

This method first examines the presence of a nonlinearity in a control loop. If a nonlinearity is detected then the process variable (*pv*), set point (*sp*) and controller output (*op*) signals are used to diagnose the possible causes of nonlinearity. The following section describes the method in brief.

3.1 *Detection of Loop Nonlinearity*

A control loop containing valve nonlinearities often produces non-Gaussian (e.g., a signal with asymmetric distribution) and nonlinear time series, namely process output (*pv*) and controller output (*op*). Higher order statistics based nonlinearity assessment can be used as a diagnostic tool for troubleshooting of hardware faults that may be present in control loop (Choudhury *et al.*, 2002; Choudhury *et al.*, 2003). As described in (Choudhury *et al.*, 2003), the test of Gaussianity and nonlinearity of the control error signal (*sp-pv*) is a useful diagnostic aid towards determining the poor performance of a control loop. The test described in Choudhury *et al.* (2003*c*) uses the sensitivity of the normalized bispectrum or bicoherence to detect the presence of nonlinear interactions in a time series signal. A distinctive characteristic of a non-linear time series is the presence of phase coupling such that the phase of one frequency component is determined by the phases of others. Phase coupling leads to higher order spectral features which can be detected in the bicoherence of a signal. Bicoherence is defined as:

$$bic^2(f_1, f_2) \triangleq \frac{|B(f_1, f_2)|^2}{E[|X(f_1)X(f_2)|^2]E[|X(f_1+f_2)|^2]} \tag{1}$$

where $B(f_1, f_2)$ is the bispectrum at frequencies (f_1,f_2) and is given by

$$B(f_1, f_2) \triangleq E[X(f_1)X(f_2)X^*(f_1+f_2)], \tag{2}$$

$X(f_1)$ is the discrete Fourier transform of the time series $x(k)$ at the frequency f_1, $X^*(f_1)$ is the complex conjugate and E is the expectation operator. A key feature of the bispectrum is that it has a non-zero value if there is significant phase coupling in the signal x between frequency components at f_1 and f_2. The bicoherence gives the same information but is normalized as a value between 0 and 1.

In (Choudhury *et al.*, 2003), two indices - the Non-Gaussianity Index (NGI) and the Non-Linearity Index (NLI) - have been defined as

$$NGI \triangleq \overline{\hat{bic}^2} - \overline{bic^2}_{crit} \tag{3}$$

$$NLI \triangleq |\ \hat{bic}^2_{max} - (\overline{\hat{bic}^2} + 2\sigma_{\hat{bic}^2})\ | \tag{4}$$

where, $\overline{\hat{bic}^2}$ is the average squared bicoherence and $\hat{bic}^2_{max}$ is the maximum squared bicoherence, $\sigma_{\hat{bic}^2}$ is the standard deviation of the squared bicoherence and $\overline{bic^2}_{crit}$ is the statistical threshold/critical value obtained from the central chi-square distribution of squared bicoherence. As outlined in (Choudhury *et al.*, 2003), if both indices, NGI and NLI, are greater than zero, the signal is described as non-Gaussian and nonlinear. The details of the procedure are shown in figure 2. The test can be applied on any time series to check its non-Gaussianity and non-linearity. For a control loop, this test is applied on the error signal (*sp-pv*) to the controller because the error signal is more stationary than *pv* or *op* signal. If the error signal is found to be non-Gaussian and nonlinear, it is inferred that the loop in question exhibits significant non-linearity. The nonlinearity can be attributed to the control valve under the following assumptions:

- The process is assumed to be locally linear.
- No nonlinear disturbance is entering the loop.

3.2 *Use of pv-op Plot*

The long time practice in industrial studies has been the use of *pv-op* plots for the detection of valve problems, especially stiction. But experience shows that this type of method is successful only for a handful cases of flow control loops. The use of *pv-op* plot for detecting valve problems was not successful because it only takes into account the qualitative trend information of the time series which can be destroyed due to the presence of process dynamics, noise dynamics, disturbances and tightly tuned controllers. In our method, the *pv-op* plot is used as a second step to diagnose the valve nonlinearity problem. The detection of valve or process nonlinearity is first carried out using higher statistical method-based NGI and NLI indices. Once a nonlinearity is detected, only then the *pv-op* plot is used to isolate its cause. Because of the contamination of real life data with noise/disturbance, a *pv- op* plot is often unclear and ambiguous, and it is difficult to find any information from it. This necessitates the use of a filter to clean the data.

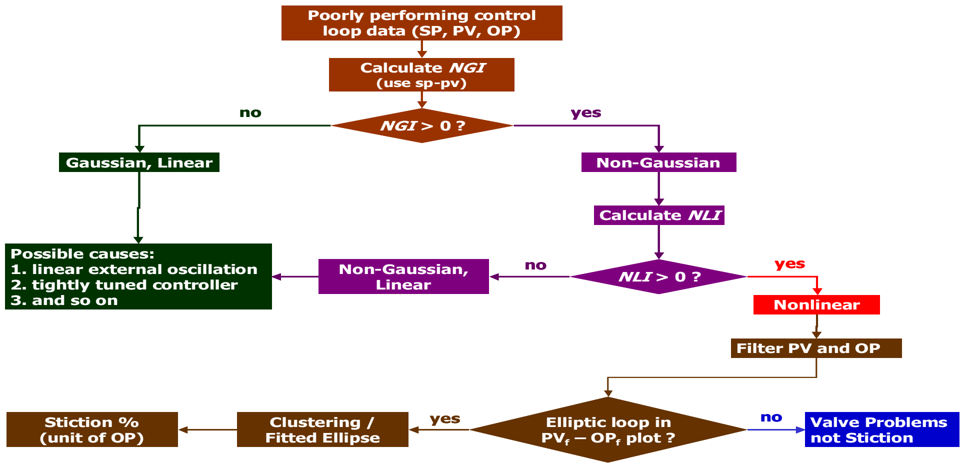


Fig. 2. *Decision Flow Diagram of the methodology for the detection and diagnosis of valve problems*

3.2.1. *Data Filtering or Pre-processing* Upon detection of a nonlinearity, the frequencies responsible for the significant nonlinear interactions can be determined from the significant peaks in the squared bicoherence plot. Then, a frequency domain Wiener filter is used to obtain the part(s) of the signal which contributes significantly to the signal nonlinearity. Both *pv* and *op* are filtered using a frequency domain Wiener filter. The detailed filter design algorithm is given in Thornhill *et. al.* (2003) . The frequency ranges for the filters are selected from the inspection of the peaks in the bicoherence plot. A segment of the data that has regular oscillations is then used for the construction of the pv_f-op_f plot (the pv_f and op_f are the filtered *pv* and *op*). If the pv_f-op_f plot shows an elliptical pattern, it is diagnosed as a signature of valve stiction, otherwise there is a valve problem which is not due to stiction. In this work, stiction is estimated as the maximum width of the cycles of the pv_f-op_f plot along the op_f axis. The quantified stiction is termed as "apparent stiction" because the actual amount of stiction to be obtained from the *mv*-*op* plot may differ from the estimated quantity because of the role of the controller in attempting to regulate the process variable.

4. QUANTIFYING STICTION

It is important to be able to quantify stiction so that a list of sticky valves in order of their maintenance priority can be prepared. The pv_f-op_f plot along with any of the following two methods can be used to quantify stiction in the unit of *op* signal. Note that there is no need to scale the data.

4.1 *Using a fitted ellipse*

An ellipse in the least square sense can be fitted to the pv_f-op_f plot and can be used for quantifying stiction. Since apparent stiction is defined as the maximum width of the ellipse along the *op* axis, the distance between two points lying on the intersections of the ellipse and a line parallel to the *op* axis and passing through the center of the ellipse will be the amount of stiction present in the loop. If m and n are the length of the major and minor axes of the fitted ellipse respectively, and α is the angle of rotation of the ellipse, the amount of stiction (length of AP in figure 3(e)) can be obtained using the following expression

$$stiction = AP = \frac{2mn}{\sqrt{(m^2\ sin^2\alpha + n^2\ cos^2\alpha)}} \qquad (5)$$

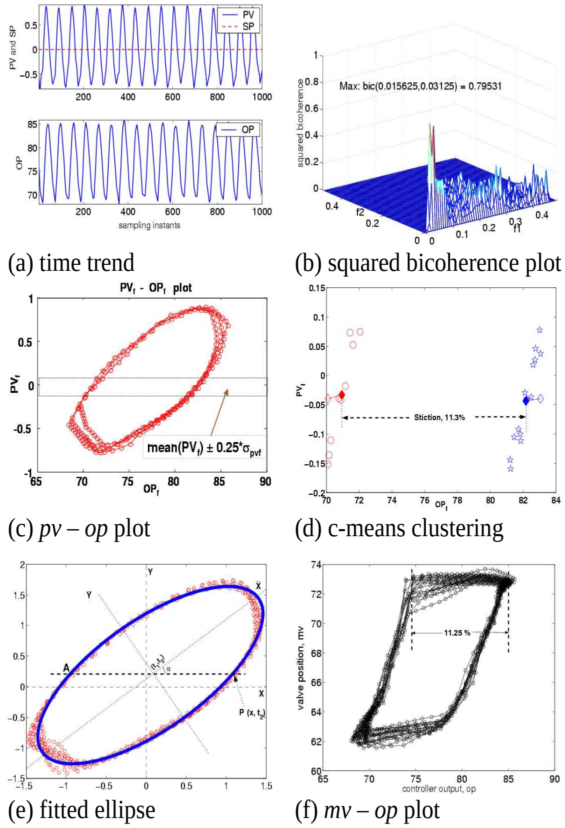
4.2 *Clustering Technique*

Clustering is a method for dividing scattered groups of data into several groups. Since the *pv*-*op* plot for a control loop with a sticky valve exhibits elliptic patterns, the data corresponding to a narrow strip along the mean of *pv* and parallel to the *op* axis can be collected (see figure 3(d)) and used for quantifying stiction with the help of c-means clustering technique (Johnson and Wichern, 1998). The amount of stiction can be estimated from the absolute value of the difference between x co-ordinates of the centers of the two clusters. If the final centers of the clusters are (op_1, pv_1) and (op_2, pv_2), then the amount of stiction is obtained using the following expression:

$$stiction = |op_1 - op_2| \qquad (6)$$

5. AN ILLUSTRATIVE EXAMPLE

The objective of this section is to explain the various steps of the proposed method with a detailed



(a) time trend (b) squared bicoherence plot

(c) $pv-op$ plot (d) c-means clustering

(e) fitted ellipse (f) $mv-op$ plot

Fig. 3. *Results of a level control loop data analysis*

presentation of an industrial example. This example represents a level control loop in a power plant, which controls the level in a condenser located at the outlet of a turbine by manipulating the flow rate of the liquid condensate from the condenser. Figure 3(a) shows the time trends for level (pv), set point (sp) and the controller output (op). The loop shows oscillatory behavior. 4096 data points were used for the bicoherence calculation and figure 3(b) shows the squared bicoherence plot corresponding to the controller error signal (sp-pv). The values of NGI and NLI were found to be 0.04 and 0.61, respectively, indicating the presence of significant loop nonlinearity. To isolate the nonlinearity, the pv-op plot is found to be useful. Figure 3(c) demonstrates the c-means clustering technique used in quantification of the stiction. The points denoted with empty and filled diamonds are the initial and final centers of the clusters, respectively. This method quantifies the amount of stiction in this loop as 11.3%. Figure 3(e) shows the ellipse fitting technique and the amount of stiction estimated using this method is 11.40%. Both methods have produced identical results with practically tolerable limits of deviation from each other.

Validation of the Results of the Illustrative Example: Once the results of our analysis was sent to the plant people, plant engineers confirmed that this loop was suffering from stiction. For this

Table 1. Results for Industrial Loops

Loop No.	Loop Type	NGI	NLI	Apparent Stiction %	
				c-means	ellipse
1	Level	0.08	0.44	9.3	8.7
2	Level	0.10	0.40	4.2	4.3
3	Level	-0.02	—	—	—
4	Flow	0.01	0.55	0.35	0.33
5	Flow	0.05	0.59	0.42	0.42
6	Temp	0.003	0.19	1.00	1.14

loop, the valve positioner data was made available. Figure 3(f) shows the actual valve position (mv) vs. controller output (op) plot. This plot clearly shows that the valve was sticking during the change of its direction. From this plot, the amount of stiction can be estimated as 11.25% which is in agreement with the results obtained from the proposed methods.

6. INDUSTRIAL CASE STUDIES

The objective of this section is to evaluate the proposed method on a number of selected control loop data obtained from different types of process industries. For each loop, the set point (sp), controlled output (pv) and controller output (op) data were available. Unless otherwise stated, a data length of 4096 was used for the squared bicoherence calculation for each case. The numerical results for all loops are provided in table 1. Due to space limitations, it is not possible to include figures for these examples. These data were analyzed before the prior knowledge of the control valve problems and the results of the analysis were confirmed later by the plant personnel.

- **Loops 1 and 2:** These loops are also level control loops in the same power plant described in the illustrative example. They also control the level of condensers located at the outlet of two different turbines by manipulating the flow rate of the liquid condensate. Both c-means clustering and fitted ellipse techniques provide the amount of stiction approximately as 9% for loop 1 and 4% for loop 2.
- **Loop 3:** This is another level control loop in the same power plant described in the illustrative example. It also controls the level of a condenser located at the outlet of a different turbine by manipulating the flow rate of the liquid condensate. The magnitude of NGI was -0.02, clearly indicating that nonlinearity is not a problem for this loop. From the valve positioner (mv) vs. controller output (op) plot (figure 4) it is obvious that the valve shows a linear response.
- **Loops 4 and 5:** These are flow control loops obtained from a refinery. The results of the analysis of these loops are given in

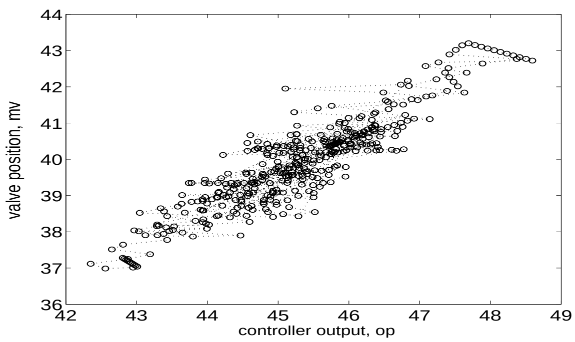


Fig. 4. *Valve positioner vs. controller output plot for loop 3*

the fourth and fifth rows of the table 1. The presence of small amount of stiction (0.35% for loop 3 and 0.4% for loop4) was causing large oscillations in these loops.

- **Loop 6:** It describes a temperature control loop on a furnace feed dryer system at the Tek-Cominco mine plant, BC, Canada. The temperature of the dryer combustion chamber is controlled by manipulating the flow rate of natural gas to the combustion chamber. The results are presented in the sixth row of table 1. The amount of stiction found in this loop was approximately 1%.

7. CONCLUSIONS

A non-invasive method for detecting and quantifying stiction in control valve has been presented in this paper. The method first detects nonlinearity in a control loop by the use of the sensitivity of the normalized bispectrum or bicoherence to the nonlinear interactions among various frequency components of the control error signal. If nonlinearity is detected, *pv* and *op* signals are filtered using a frequency domain Wiener filter to obtain filtered pv_f and op_f signals. If an ellipse can be fitted suitably to the pv_f-op_f plot, then it indicates a signature of valve stiction. C-means clustering or fitted ellipse techniques can be used for automatic quantification of stiction. The method has been extensively evaluated on simulated as well as industrial data sets.

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