QUANTIFICATION OF VALVE STICTION

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Abstract: Oscillations in control loops lead to poor controller performance. Stiction in control valves is one of the major causes of such oscillations. Therefore, the correct diagnosis of stiction is important. There are several methods for detecting stiction, but quantification of stiction still remains a challenge. Two parameters are used to model the stiction phenomenon successfully, namely, deadband plus stickband, $'S'$, and slip-jump,$'J'$. It has been observed that the main cause of valve deterioration is the presence of slip-jump, $'J'$. The higher the value of $'J'$, the more severe is the level of deterioration of controller performance. Thus, in addition to the estimation of $'S'$, an estimate of $'J'$ is the main challenge in monitoring the condition of a control valve. In this work a method is proposed to estimate both $'S'$ and $'J'$ simultaneously unlike existing quantification methods where stiction is quantified as a single parameter.

Keywords: Control loops, Control valves, Process control, Nonlinearity, Stiction.

1. INTRODUCTION

Non-linear effects are often encountered in process plants. These non-linearities can be due to: (1) Valve non-linearity, for example due to stiction, deadband and hysteresis; (2) the presence of non-linear external oscillations, and/or (3) non-linearity in the process.

The presence of a non-linearity in a control loop often leads to oscillations in a control loop and hence poor performance. About 30% of the oscillations in control loops are due to valve problems (e.g. the presence of static friction or stiction). Therefore, detection and quantification of stiction in control valves is an important issue in the process industry. There are several stiction detection methods (Choudhury *et al.*, 2004*b*; Choudhury *et al.*, 2004*c*; Horch, 1999; Singhal and Salsbury, 2005; Stenman *et al.*, 2003; Srinivasan *et al.*, 2005*a*; Srinivasan *et al.*, 2005*b*). But quantifying stiction still remains a challenge.

Earlier work by (Choudhury *et al.*, 2004*c*) quantifies stiction by fitting an ellipse to the pv-op plot and the maximum width of the ellipse is reported as 'apparent stiction'. Recently, Srinivasan *et al.* (2005*a*) introduced another approach where they exploited the fact that the presence of stiction has distinct qualitative shapes or pattern in the controller output, op and the controller variable, pv signals. They have applied a Pattern Recognition technique using Dynamic Time Warping (DTW) on the pv and op data. First, the test patterns (for both op and pv) are generated using the zero crossing data from the raw signals. Then these test patterns are compared to the actual signal. If stiction is confirmed then the maximum peak-to-peak amplitude is reported as stiction. However, the maximum peak-to-peak amplitude is just the magnitude of limit cycle and cannot be attributed to real stiction. Another disadvantage with this approach is the apriori knowledge of the patterns in the op and pv due to stiction. The patterns described therein may not be always due to stiction. Some of those patterns in the pv and op signals may arise simply due to the presence of a tightly tuned controller or an oscillatory disturbance. In addition to these, asymmetric stiction, which is not uncommon, cannot be detected and quantified using this approach.

In another method proposed by (Srinivasan *et al.*, 2005*b*), a Hammerstein model identification approach

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is explored. A general structure of a Hammerstein model is shown in figure 1. The non-linear part of the Hammerstein model is described by a single parameter stiction model ((Stenman *et al.*, 2003)).

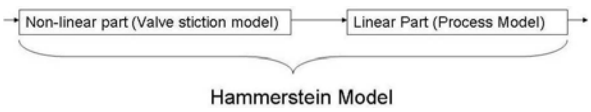

Fig. 1. *General Structure of a Hammerstein Model*

It has been observed that the single parameter stiction model does not depict the true stiction behavior (Choudhury *et al.*, 2004*a*), as discussed in section 2.

In this study, the proposed approach uses a two parameter stiction model proposed by (Choudhury *et al.*, 2004*a*) to model the non-linear component of the Hammerstein model.

The rest of the paper is organized as follows: In Section 2 a brief discussion of the two parameter stiction model is provided. This is followed by an example demonstrating the importance of slip-jump, J, in loop dynamics. Section 4 describes the proposed method. Sections 5 and 6 summarize simulation and experimental results respectively, followed by concluding remarks in Section 7.

2. WHY USE A TWO PARAMETER MODEL OF STICTION?

This section briefly discusses the adequacy of a two parameter stiction model for closed loop simulation of stiction. Also, the limitations of the one parameter stiction model proposed by (Stenman *et al.*, 2003) and used in (Srinivasan *et al.*, 2005*b*) are briefly discussed. Before discussing the data-driven stiction models, a case of an industrial example where a valve was sticky is presented in order to find the right pattern of stiction present in a valve operating under closed loop control configuration.

2.1 An industrial control loop with a sticky valve

Consider a level control loop which controls the level of condensate in the outlet of a turbine by manipulating the flow rate of the liquid condensate. The control valve of this loop is confirmed to have stiction. In total 8640 samples for each tag were collected at a sampling rate of 5 s. Figure 2 shows a portion of the time domain data. The left panel shows time trends for level (pv), the controller output (op) which is also the valve demand, and valve position (mv) which can be taken to be the same as the condensate flow rate. The plots in the right panel show the characteristics pv-op and mv-op plots. The bottom figure clearly indicates both the stickband plus deadband and the slip jump effects. The slip jump is large and visible from the bottom figure especially when the valve is moving in a downward direction. It is marked as 'A' in the figure. The pv-op plot does not show the jump behavior clearly because the process dynamics (i.e., the transfer function between mv and pv) destroys the pattern. The pattern shown in the actual valve position (mv) vs. controller output (op) can be taken as a typical signature of valve stiction because it clearly shows the deadband plus stickband and the slip-jump. Similar patterns can be found in many industrial control valves suffering from stiction.

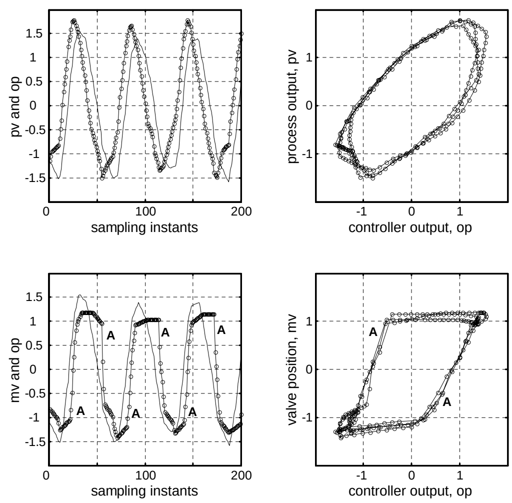

Fig. 2. *Flow control cascaded to level control in an industrial setting, the line with circles is* pv *and* mv*, the thin line is* op

2.2 One-parameter stiction model

A simple one parameter stiction model was proposed by (Stenman *et al.*, 2003). The model can be mathematically expressed by the following equation

$$x(t) = \begin{cases} x(t-1) & ,if \mid x(t) - d \mid < d \\ u(t) & \text{otherwise} \end{cases}$$

Where, *x(t)* and *x(t-1)* are the valve output (stem position) at time *'t'* and *'t-1'* respectively, *u(t)* is the controller output at time *'t'* and *'d'* is the valve stiction band. For details of this stiction model, interested readers are referred to (Stenman *et al.*, 2003).

2.3 Two-parameter stiction model

A two parameter model proposed by (Choudhury *et al.*, 2004*a*) captures the stiction phenomenon successfully. The two parameters are: S (Stickband + Deadband) and J (Slip-jump). For details on this stiction model interested readers are referred to (Choudhury *et al.*, 2004*a*).

2.4 Comparison between one-parameter and two parameter stiction model

Figure 3(a) shows a typical valve output (mv), vs. controller output (op) plot for the one parameter stiction model described in (Stenman *et al.*, 2003; Srinivasan *et al.*, 2005*b*) while Figure 3(b) shows the same plot for the two parameter stiction model proposed in (Choudhury *et al.*, 2004*a*). Figure 3(a) is clearly different from the pattern of stiction shown in Figure 2. It suffices to say that the one parameter stiction model does not capture the true characteristic of stiction. Indeed it should not be called a stiction model, rather it should be defined as a quantization or a staircase function. On the other hand, the plot for two parameter stiction model (Figure 3(b)) clearly matches with the pattern in Figure 2. Thus the two parameter stiction model is able to adequately capture the characteristic of valve stiction (Choudhury *et al.*, 2004*a*).

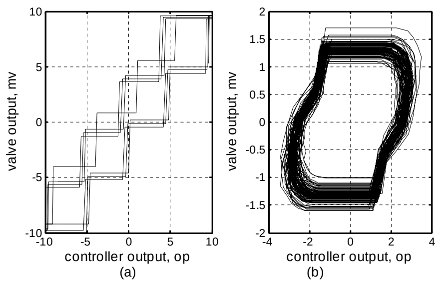

Fig. 3. *(a) mv-op for one parameter model ('d') (b)mv-op for two parameter model (S, J)*

3. ISSUES IN QUANTIFYING STICTION

3.1 *Effect of controller dynamics and process dynamics on apparent stiction*

Earlier work by (Choudhury *et al.*, 2004*c*; Choudhury *et al.*, 2005) quantifies stiction by fitting an ellipse to the *pv-op* plot and the maximum width of the ellipse is reported as 'apparent stiction'. Stiction is reported as 'apparent' because the estimate includes the effect of the process and controller dynamics. The following simulation example demonstrates the effect of the controller tuning on the estimation of apparent stiction.

Figure 4 shows the simulink block diagram used for generating stiction data. The process model is

$$G(z) = \frac{1.45z - 1}{z^4 - 0.8z^3} \quad (1)$$

The controller is implemented in the following form:

$$C(s) = K_c\left(1 + \frac{1}{\tau_i\ s}\right) \quad (2)$$

The reset time, τ_I, is fixed at 1 sec and the gain,K_c, is varied.The Stiction parameters 'stickband+deadband', S and 'slip jump', J are fixed at 3 and 1, respectively. Three cases, K_c = 0.05, 0.10 and 0.15, are considered and 1024 samples are generated for each case.

Figure 5 shows the *pv-op* plot and the fitted ellipse for the three cases. The apparent stiction reported are: for K_c = 0.05, 0.10 and 0.15, the estimated apparent stiction are 5.79, 3.06 and 1.62, respectively. Ideally,

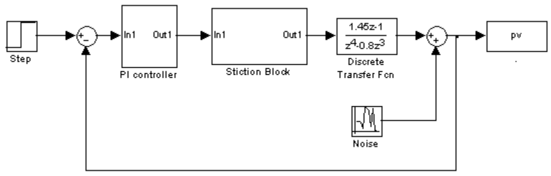

Fig. 4. *Simulink block diagram used for generating stiction data*

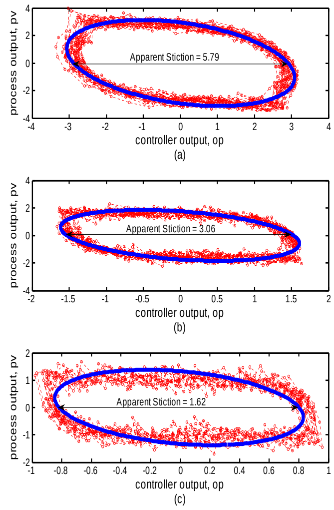

Fig. 5. *$mv - op$ plot and fitted ellipse (a)K_c = 0.05 (b)K_c = 0.10 (c)K_c = 0.15*

it should be same because the same amount of stiction was used for all cases (S=3 and J=1). A similar effect of the process dynamics can also be observed on the value of apparent stiction. Hence the width of the ellipse in the *pv-op* plot termed as 'apparent stiction' cannot be taken as an accurate estimate of stiction.

3.2 *The importance of quantifying Slip-Jump (J)*

Describing function analysis performed in (Choudhury *et al.*, 2004*a*) suggests that for processes without any integrator, limit cycles in a control loop may occur only in the presence of slip-jump (J) for the case of a sticky valve. Moreover, the amplitude and frequency of the limit cycles depend significantly on the slip-jump (J). The following simulation results show the effect of J on the amplitudes and frequencies of the limit cycles.

The system considered here is the same as in Section 3.1. In order to observe the impact of J clearly, the controller parameters are chosen as K_c = 0.15 and τ_I = 0.15 sec. Figure 6 shows the variation of the frequency and amplitude of limit cycles with slip jump (J) keeping S constant ($S = 6$). For each case, 1024 points were collected. No oscillations are observed for the case when there is no slip-jump, i.e. J=0. Periods of oscillation (T_p) are 250 s, 111 s and 72 s for values of $J = 1$, 3 and 6, respectively. From this simulation study, it is clear that both amplitude and frequency of limit cycles increase with the increase of

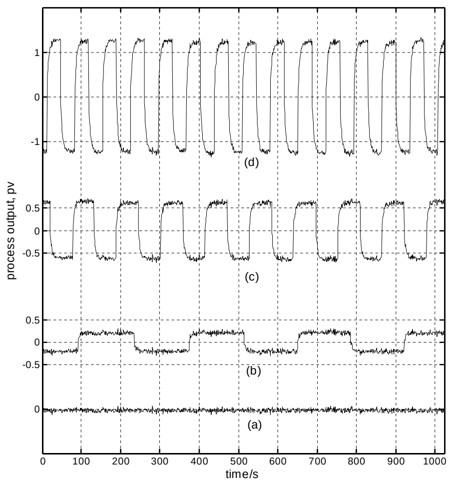

Fig. 6. *(a) J=0, no oscillations detected (b) J=1, T_p=250, amplitude=0.20 (c) J=3, T_p=111, amplitude=0.60 (d) J=6, T_p=72, amplitude=1.20.*

J. Therefore, the estimation of J is as important as the estimation of S.

4. METHODOLOGY FOR SIMULTANEOUS ESTIMATION OF S AND J

Figure 7 shows the detailed flow chart of the procedure for estimating $'S'$ and $'J'$. This is an iterative optimization procedure to identify both the stiction model parameters and the process model simultaneously. The controller output data (*op*) is supplied to the two parameter stiction model to obtain the actual valve output or valve-postion data, (vo), for a fixed value of S and J. Then, the predicted valve output, vo, and the process output data, (pv), are used to identify the process model using Akaike's Information Criteria (AIC). The procedure is repeated for various values of S and J obtained from a two dimensional grid search. The value of S and J that gives minimum mean square error for the controlled process variable (pv) is reported as stiction. The details of the algorithm are as follows:

- Import process ouput, pv and the controller output, *op*.
- Check for non-linearity in the system. In this work the bicoherence based method proposed by (Choudhury *et al.*, 2002) is used for non-linearity detection.
- Choose a value for (S_i,J_i) from a two dimensional grid of S and J.
- Use the controller output, *op*, data and the two-parameter stiction model with chosen (S_i, J_i) to compute the valve output, vo. This is the non-linear part of the Hammerstein model.
- Identify the process model (linear part of the Hammerstein model) using the valve output, vo, and the process output, pv.
- Then the process output is predicted $(pv^{'})$ using the identified process model and the computed valve output, vo.
- Compute the Mean Squared Error between the predicted and the actual process output

$$MSE(S_i, J_i) = \sum_{i=1}^{N} (pv_i - pv_i^{'})^2 \qquad (3)$$

- MSE is computed for all the points in the grid of S and J. The value (S_m, J_m), for which MSE is minimum, is reported as stiction.

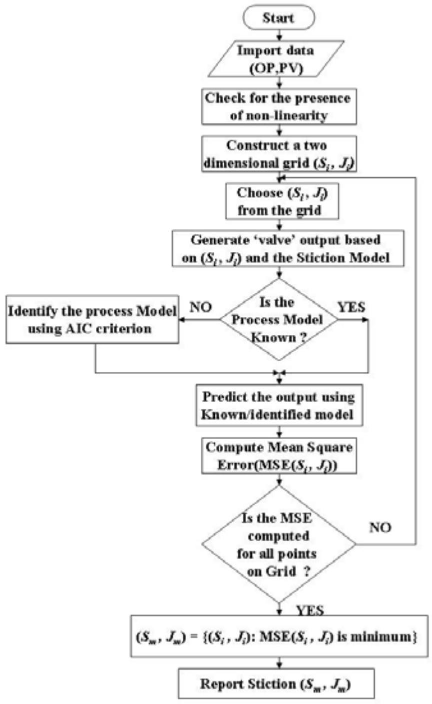

Fig. 7. *Logic flow diagram of the proposed method*

The following important points should be considered in the implementation of the method:

- The prediction, using the identified or known model and the valve output, is done using a one-step-ahead predictor. The purpose of using one-step-ahead predictor is that this makes the overall procedure less dependent on the process model, estimation of which is of less interest for this case.
- There is a possibility that for a particular value of (S, J) the computed valve output may be saturated. In this case the identification of the linear part of the Hammerstein model would be difficult because the input signal would not be persistently exciting. This may result in erroneous results. Therefore, before using the valve output (vo) for the identification of the process model, the signal should be should be examined for possible saturation.

5. RESULTS FROM SIMULATION STUDIES

All simulations were performed using the same system described in Section 3.1. The controller gain, K_c = 0.15 and τ_I = 1 are fixed.

Two scenarios are considered here. First, when the process model is known i.e. the linear component of the Hammerstein model is known. Second, when the linear part of the Hammerstein model is unknown and estimated along with the nonlinear part.

Table 1 shows the estimation results using the proposed method. It is assumed that the process model is known. The estimated values are close to the actual values.

Table 1. *Comparison of actual and estimated S and J (known model case)*

S		J	
Actual	Estimated	Actual	Estimated
1	1	0	0
1	1	1	1
4	4	2	2
6	6	4	3.5
8	8	8	8
8	8	10	10
10	8	2	0

Table 2 shows the estimation results when an external disturbance is added to the system with sticky valve. A sinusoidal input with a frequency of 1 rad/sec and amplitude of 1 is used as external disturbance. The process model is assumed to be known. The estimation is exact in most cases. This indicates that the proposed method is able to quantify stiction even in presence of external oscillations.

Table 2. *Comparison of actual and estimated S and J in the presence of external oscillations (known model)*

S		J	
Actual	Estimated	Actual	Estimated
1	1	1	1
4	4	2	2
6	6	4	4.5
10	10	5	5
12	12	4	4
12	13	0	1

In Table 3 estimation results are shown when the data is corrupted by noise (random noise with zero mean). Signal to noise ratio (SNR) is computed as the ratio of the variance of the noise free signal to variance of the noise. For this the value of S and J are fixed to 6 and 4 respectively and the data is simulated with different noise levels in the system. The results show that the method is relatively insensitive to the presence of noise, and therefore it should work well when applied to real process data.

Table 3. *Prediction in presence of noise (S = 6 and J = 4) (known model)*

SNR	Estimated (S)	Estimated (J)
100	6	3.5
50	6	4
25	6	4
12.5	6	4
10	6	3.5

Table 4 shows the results for the case when it is assumed that the process model is not known. The algorithm was not supplied with the process model. For all cases, S has been estimated correctly except when $S < J$ $(S = 4, J = 8)$. But such cases, where $J > S$, are rarely encountered in real life. Slip-jump is also estimated correctly for most cases.

Table 4. *Comparison of actual and estimated S and J, unknown model case*

S		J	
Actual	Estimated	Actual	Estimated
1	1	0	0.5
4	4	2	2
6	6	4	4
10	10	10	7.5
10	10	8	8
10	10	2	2
4	2	8	8

6. RESULTS FROM PILOT PLANT EXPERIMENTS

For the verification of the proposed method, data was generated using a laboratory scale setup of a tank system in the Computer Process Control Laboratory in the Department of Chemical and Materials Engineering at the University of Alberta. Data is generated for two control loops: flow and level(cascade) control.

6.1 Flow Control Loop:

The schematic of the process is shown in Figure 8. First of all, the control valve was checked for possible presence of stiction using the so called bump test or the valve travel test and it was found to be stiction free. Then the two-parameter stiction model was used to introduce valve stiction within the software as shown in Figure 8. The signal from the flow controller (FC) is supplied to the stiction model (with already known S and J). The output of the stiction model is then provided to the flow control valve (FV).

Figure 9 show the process output (pv) and the controller output (op) for the system for $(S, J) = (2, 1)$. Clearly, stiction introduces limit cycle behaviour in the loop. The results of stiction estimation are provided in Table 5. Two cases are considered for this loop. For both cases, estimated S and J are in good agreement with the actual S and J.

6.2 Level Control Loop:

The schematic of the control loop is shown in figure 10. This is a cascaded loop. The level controller (LC) signal acts like a set point for the flow controller (FC).Process output (pv, the level) and the controller output (op) for $(S, J) = (1, 1)$ are shown in Figure 11.Results of stiction estimation are summarized in Table 5. The method successfully quantifies S and J.

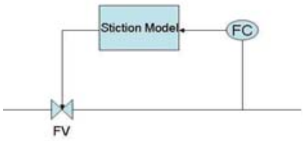

Fig. 8. *Schematic for the Flow loop*

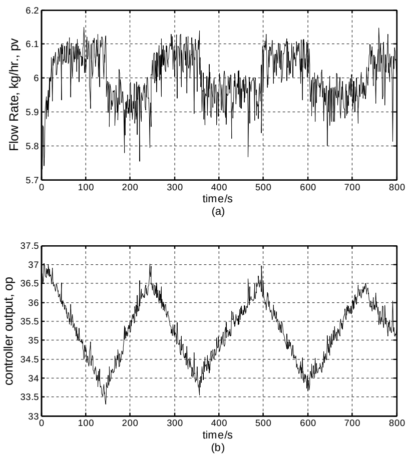

Fig. 9. *Process output (flow rate, PV) and controller output (OP) for the flow control loop*

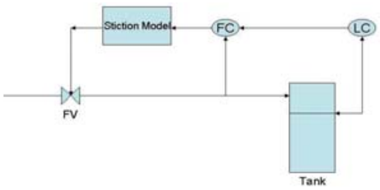

Fig. 10. *Schematic of the cascaded level loop control*

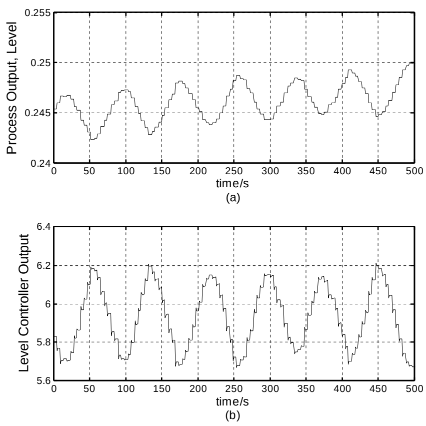

Fig. 11. *(a)Process output (Level, PV) (b)Level controller output (OP)*

7. CONCLUSIONS

In this work, the effect of controller dynamics on the apparent stiction and the impact of J on the frequency and amplitude of limit cycles due to stiction have been demonstrated using simulation examples. A method is proposed to simultaneously estimate both S (stickband+deadband) and J (slip-jump). The stiction model parameters and the process model are jointly identified using an optimization approach. The proposed method has been tested successfully on simulated and experimental data. The method needs only routine operating data from a control loop. The stiction model used in this method in its slightly modified form can also handle asymmetric stiction. Therefore it is possible to extend the method to estimate parameters of asymmetric stiction model.

Table 5. *Estimated S and J from experimental data*

	S		J	
Data	Actual	Estimated	Actual	Estimated
Flow Loop	1	1	1	1
	2	2	1	1.5
Level Loop	1	1	1	1
	2	1.5	1	0.5

The proposed method can also be extended to cases when the plant model is non-linear in itself. In such cases, to correctly estimate S and J, knowledge of the presence and structure of the non-linearity is required.

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