# Modelling and Quantification of Valve Stiction by Unknown Input Estimation

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***Abstract:*** *Presence of nonlinearities, e.g., stiction, and deadband in a control valve limits the control loop performance. Valve stiction is one of the most common causes of oscillations in industrial process control loops. In this work, we propose a novel approach to estimate the valve position using unknown input estimation. The estimation algorithm is a numerical method based on maximum likelihood. With estimated valve position, we can detect and also quantify the amount of stiction. The main advantages of the proposed method are numerical stability, computational efficiency. The efficiency of the method has been demonstrated through simulation examples.*

**Keywords:** Stiction, hysteresis, maximum likelihood, unknown input.

## 1. Introduction

The presence of oscillations in a control loop enhances the variability of the process variables hence creating inferior quality products, higher rejection rates, increased energy consumption and reduced average throughput. Surveys in the process industry have revealed that almost 30% of control loops are oscillating [1]. Among the many types of nonlinearities in control valves, stiction is the most commonly encountered in the process industry. The detection and quantification of valve stiction in industrial process control loops is thus important. Conventional invasive methods such as the valve travel test can easily detect stiction, but are expensive and tedious to apply to hundreds of valves to detect stiction. Thus there is 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 [1], [2].

A number of researchers have studied the valve stiction problem and suggested methods for detecting it. Horch presented two more methods for detecting stiction in oscillating loops [3]. The first method detected valve stiction by analyzing the cross-correlation function (CCF) between the controller output and the plant output. This method cannot be applied to integrating processes, for which in a later work Horch and Isaksson [4] have presented another method based on the distribution of the second derivative of the pv signal. [5], [6] and [7] have presented data based methods based on the qualitative shapes in the time trends of the op and pv signals. In another study, Choudhury et al. [8] presents a method for detecting and quantifying stiction for linear processes using the pv and op data. This method is based on the fact that for a linear process under closed loop control, a sticky valve would induce nonlinearity in the pv and op signals and hence stiction can be detected based on the nonlinearity in the control error signal. The disadvantage of this quantification methodology is that the width of the ellipse will be dependent on the effect of loop dynamics on the pv.

Several authors have proposed model-based approaches for stiction detection and quantification. Stenman et al. [9] has presented a model-based approach based on ideas from the field of change detection and multi-model mode estimation. Stiction detection was performed through a combined identification of the process model parameters and the mode sequence. [8], [10] and [11] have proposed model-based methods where a linear process with a sticky valve is considered to be a Hammerstein system, the sticky valve being the nonlinear element in the system. Chitralekha et al. [12] consider the problem of estimating the valve position as an unknown input estimation problem. But, standard Kalman filter limits process dynamic and reduces flexibility of this method.

In this paper, a model-based approach to estimate unknown input is proposed. An extended Kalman filter is used to estimate the state and unknown input from a noisy measurement set.

The stiction model of Choudhury et al. [8] is discussed in Section 2. In Section 3, we explain the formulation of the stiction detection problem as an unknown input estimation problem for suitable estimate of valve position mv–op data plot and how stiction quantification can be carried out using the plot. In Section 4, we emonstrate the application of the method on simulated examples. We show through simulation how the quantification is not significantly affected by model plant, external disturbances and controller tuning.

## 2. Modeling Valve Stiction

Fig.1 shows the schematic operation diagram of a sticky valve, where S denotes the deadband plus stickband, and J the stick band. Some of definitions of stiction can be found in [1], [13].

### 2.1 Physics-based Stiction Model

For a pneumatic sliding stem valve, the force-balance equation based on Newton's second law can be written as:

$$M\frac{d^2x}{dt^2} = \sum forces = F_a + F_r + F_f + F_p + F_i \qquad (1)$$

where $M$ is the mass of the moving parts, $x$ is the relative stem position, $F_a = Au$ is the force applied by pneumatic actuator, where $A$ is the area of the diaphragm and $u$ is the actuator air pressure or the valve input signal, $F_r = -kx$ is the spring force, where $k$ is the spring constant, $F_p = -A_p \Delta p$ is the force due to fluid pressure drop, where $A_p$ is the plug unbalance area and $\Delta p$ is the fluid pressure drop across the valve, $F_i$ is the extra force required to force the valve to be into the seat and $F_f$ is the friction force. One of the commonly used friction models is the Karnopp model. It includes static and moving friction. The disadvantage when applying the friction model to a generic valve is the need to specify a large set of parameters. In order to overcome this disadvantage many researchers developed different kinds of empirical data-driven stiction models.

### 2.2 Data-driven Stiction Modeling

For a dynamic stiction model, the challenges are (i) to model the tendency of the valve to stay moving once it has started until the input changes direction or the velocity goes to zero, and (ii) to include the effects of deadband and the slip jump.

A valve stiction model was proposed by Kano et al. [14]. The input and output of this valve stiction model are the controller output and the valve position, respectively. The controller output is transformed to the range corresponding to the valve position in advance. This valve stiction model has several advantages: (i) It can cope with the stochastic input as well as the deterministic input. (ii) $u_s(t)$, which is the controller output at the moment the valve state changes from moving to resting, can be updated at appropriate timings by introducing the valve state. (iii) It can change the degree of stiction according to the direction of the valve movement.

Based on the typical input-output behavior of a sticky valve, He et al. proposed a new valve stiction model [15] which is simpler and more straightforward in logic. If desired, the saturation constraint can be easily added to $u_v(t)$ after the model calculation.

Choudhury et al. proposed a valve stiction model in [13], where the control signal is translated to the percentage of valve travel with the help of a linear look-up table. The model consists of two parameters, namely, deadband plus stickband S, which is specified in the input axis, and slip jump J, which is specified in the output axis. Two-parameter data-driven Choudhury's stiction model algorithm can be described as:

• The controller output (mA) is converted to valve travel percentage using a look-up table.

• The first two branches in the model flow chart check if the upper and the lower bounds of the controller output are satisfied.

• If the signal is within the 0 to 100% range, the algorithm calculates the slope of the controller output signal.

• Next, the change of the direction of the slope of the input signal is taken into consideration. If the *sign* of the slope changes or remains zero for two consecutive instants, the valve is assumed to be stuck and does not move.

• For the case where the input signal changes direction, if the cumulative change of the input signal is more than the amount of the deadband plus stickband ($S$), then the valve slips and starts moving.

• For the case when the input signal does not change direction, if the cumulative change of the input signal is more than the amount of the stickband ($J$), then the valve slips and starts moving. This takes care of the case when the valve sticks again while travelling in the same direction.

• The output is calculated using the equation:

$$y(k) = x(k) - sign(v-new)(S-J)/2 \qquad (2)$$

• The parameter $J$ is an output quantity measured on the vertical axis. It signifies the slip-jump start of the control valve immediately after it overcomes the deadband plus stickband. It accounts for the offset or deviation between the valve input and output signals.

• Finally, the output is converted back to a mA signal using a look-up table based on characteristics of the valve such as linear, equal percentage or square root, and the new valve position is reported.

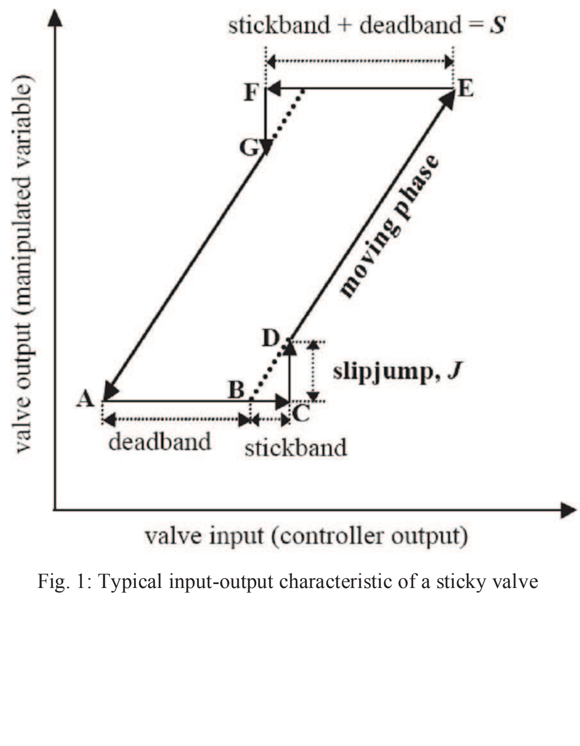


Fig. 1: Typical input-output characteristic of a sticky valve

## 3. Problem Formulation

Consider the closed loop block diagram as shown in Fig. 2, where a sticky valve is included between the process and the controller block. Typically, the controller will be P or PI. For a normal valve, the mv and op signal will be equal at all times [12]. But if the valve is sticky, then there will be a clear difference between the two signals. In such a situation the valve acts like a nonlinear element transforming the op signal. If we model this transformation of the op by adding an additive, nonlinear, external signal which enters the loop just after the controller output, we get an equivalent representation as shown in Fig. 3 with the valve block replaced by an external unknown input signal [12], [16].

In order to estimate unknown input (MV signal) with the help of extended Kalman filter, assume that the process can be described as a singular linear discrete time system with the following state-space representation

$$e(k+1)x(k+1) = a(k)x(k) + b_1(k)u(k) + b_2(k)\tilde{u}(k) + b_3(k)w(k) \quad (3)$$

$$y(k+1) = c(k+1)x(k+1) + d_1(k+1)u(k+1) + d_2(k+1)\tilde{u}(k+1) + d_3(k)v(k) \quad (4)$$

Where x(k) is the process state, $u(k)$ is the output controller, and y(k) is the measurement available from the process. The process noise $w(k)$ and measurement noise $v(k)$ are assumed to be Gaussian with variance Q and R, respectively. With the above system, we can use the method of unknown input estimation proposed by [17] and [18] in order to obtain an estimate of $\tilde{u}(k)$. This system can be written as a singular system without unknown input:

$$\begin{bmatrix} e(k+1) & 0 \end{bmatrix} \begin{bmatrix} x(k+1) \\ \tilde{u}(k+1) \end{bmatrix} = \begin{bmatrix} a(k) & b_2(k) \end{bmatrix} \begin{bmatrix} x(k) \\ \tilde{u}(k) \end{bmatrix} + b_1(k)u(k) + b_3(k)w(k) \quad (5)$$

$$y(k+1) = \begin{bmatrix} c(k+1) & d_2(k+1) \end{bmatrix} \begin{bmatrix} x(k+1) \\ \tilde{u}(k+1) \end{bmatrix} + d_1(k+1)\tilde{u}(k+1) + d_3(k)v(k) \quad (6)$$

Being full column rated of the following matrix, is estimability condition of the unknown input

$$\begin{bmatrix} e(k+1) & 0 \\ c(k+1) & \mathrm{d}_2(k+1) \end{bmatrix} \quad (7)$$

Unknown input can be estimated using the following numerical algorithm

$$\hat{X}(k+1) = M(k+1) \begin{bmatrix} A(k)\hat{X}(k) + b_1(k)u(k) \\ y(k+1) - d_1(k+1)u(k+1) \end{bmatrix}$$
$$A(k) = \begin{bmatrix} a(k) & \mathrm{b}_2(k) \end{bmatrix} \quad (8)$$
$$X(k+1) = \begin{bmatrix} x(k+1) \\ \tilde{u}(k+1) \end{bmatrix}$$

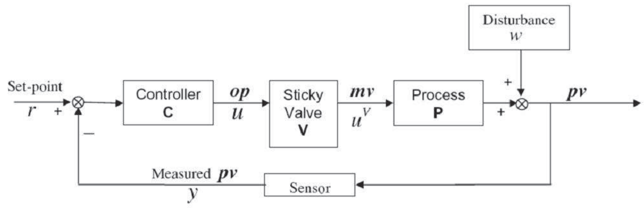


Fig. 2. Close loop with sticky valve

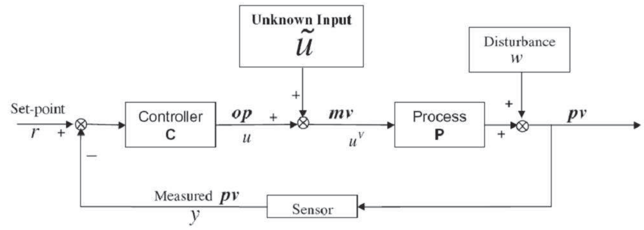


Fig. 3. Equivalent loop of sticky valve and unknown input

Where

$$M(k+1) = \begin{bmatrix} R_a^{-1}(k+1) & 0 \end{bmatrix} Q_a^T(k+1) \begin{bmatrix} R_b^{-1}(k) & 0 \\ 0 & d_3^{-1}(k) \end{bmatrix}$$

In this equation $R_a$, $Q_a$ and $R_b$, $Q_b$ are QR decomposition given by

$$\begin{bmatrix} R_b^{-1}(k)E(k+1) \\ d_3^{-1}(k)C(k+1) \end{bmatrix} = Q_a(k+1) \begin{bmatrix} R_a(k+1) \\ 0 \end{bmatrix}$$
$$\begin{bmatrix} A(k)S(k) & -b_3(k) \end{bmatrix} = \begin{bmatrix} R_b(k) & 0 \end{bmatrix} Q_b(k) \quad (9)$$
$$E(k+1) = \begin{bmatrix} e(k+1) & 0 \end{bmatrix}$$
$$C(k) = \begin{bmatrix} c(k) & d_2(k) \end{bmatrix}$$

Where covariance matrix square S(k) can be obtained from the following equation

$$S(k+1) = R_a^{-1}(k+1) \quad (10)$$

Therefore, state $(\hat{x}(k))$ and unknown input $(\hat{\tilde{u}}(k))$ estimations can be derived. The process in valve stiction problem is non-singular; so, e(k)=1.

## 4. Simulation Study

In this section, we demonstrate the efficacy of the proposed stiction detection and quantification algorithm through simulation examples, where the stiction is introduced in the closed loop simulation studies using the stiction model proposed in [13].

### 4.1 Detection and Quantification of Stiction

We consider a simple integrating process with the process gain being unity $(i.e., G(s) = 1/s)$, controlled by a discrete PI controller by the transfer function $K_C(1 + \frac{1}{\tau_I(1 - z^{-1})})$, where $K_C = 0.1$ and $\tau_I = 0.01$,

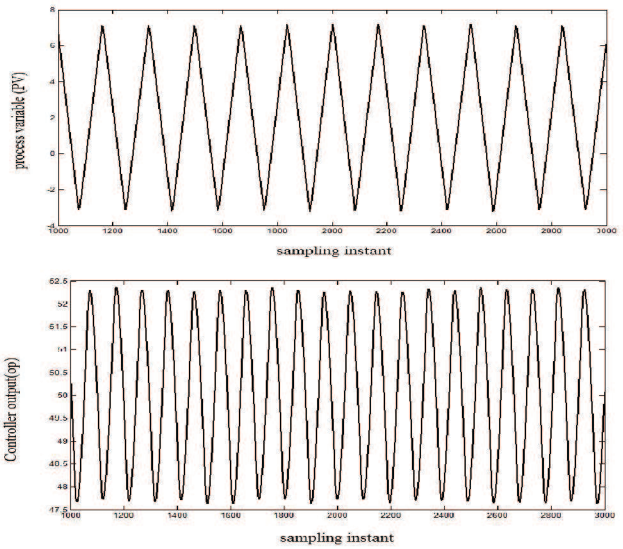


Fig. 4. Simulated data set with stiction

was used in the simulation. A sampling time of 1s was used in all the simulation studies.

The two parameter stiction model was included in between the process and the controller in closed loop simulation. We use the parameter values of $S = 4$ and $J = 2$ in the stiction simulation block. Fig. 4 shows the time trend of the pv and op signals, after the close loop system has attained steady state. A Gaussian white noise with a variance of 0.01 was introduced as disturbance in the simulation. The state noise variance (Q) and measurement noise variance (R) values of 1e-5 and 1e-3, respectively, were used in the estimator. In Fig. 5 we plot the true mv–op plot. Note that in this simulation the true mv is naturally available.

In Fig. 6 we plot estimated mv-op plot patternand hence we can detect stiction visually from this figure. As mentioned earlier, the width of the mv–op plot quantifies stiction. We denote the estimated width as $\hat{S}$ . For the quantification part it is only the width of the mv–op plot that is of interest and in the proposed scheme, if the model is fairly precise, then $\hat{S}$ will be close to S. In the simulated example, the estimated width matches the parameter S exactly and thus we can conclude that the quantification is accurate.

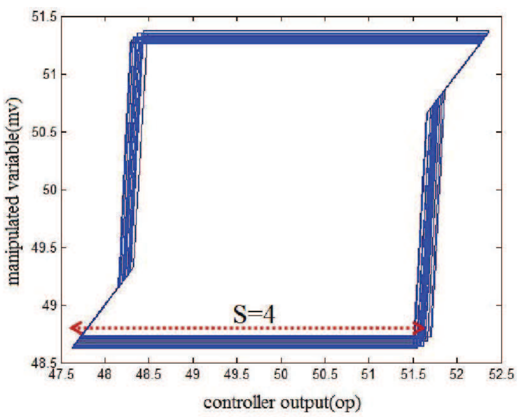


Fig. 5. mv-op Plot for S=4 and J=2

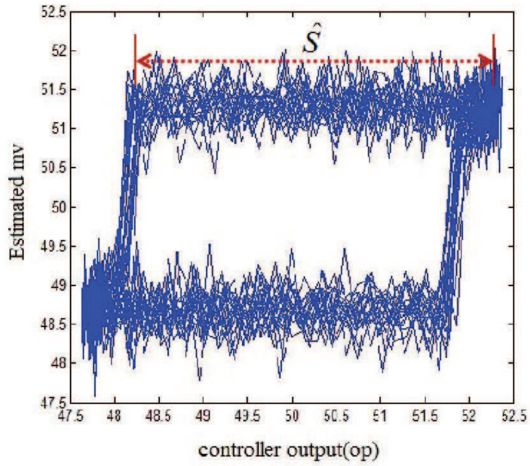


Fig. 6. Estimated mv-op plot for S=4 and J=2

To investigate further, a first order plus time delay (FOPTD) system is considered to be simulated using the proposed method. The transfer function of the process is

$$G_p(s) = \frac{3e^{-10s}}{10s+1} \tag{11}$$

This system is controlled by a PI controller whose transfer function can be written in the continues state as

$$G_c(s) = 0.2\left(1 + \frac{1}{10s}\right) \tag{12}$$

In this case, we use the parameter values of S=5 and J=2 in the stiction simulation block. Sampling time, state noise and measurement noise variance values are the same as before.

Fig. 7 shows input-output behavior of a sticky valve with FOPTD process. mv-op is depicted in Fig. 7a and Fig. 7b estimates mv-op plot.

Simulation results demonstrate the ability of this method in estimating stiction parameters with delay in the process.

### 3.3 Oscilation Occur Due to Reasons Other Than Stiction

This method can also detect oscillation other than stiction. A very common scenario is when an external oscillatory disturbance enters the closed loop. In this section, we demonstrate through a simulation example how the proposed algorithm will be able to correctly identify that the valve in a closed loop is normal when an external disturbance is causing persistent oscillations in the loop. If the algorithm had lacked this aspect, there would be false alarms whereby a normal valve will be wrongly reported as a sticky valve.

We removed the stiction block from the Simulink model to emulate the case of a normal valve. Then, we consider the same integrating process discussed earlier. In order to introduce an external oscillatory disturbance, we add a sinusoidal disturbance with amplitude 1 and frequency 0.05 rad/s along with a random noise disturbance in the closed loop simulation. The controller

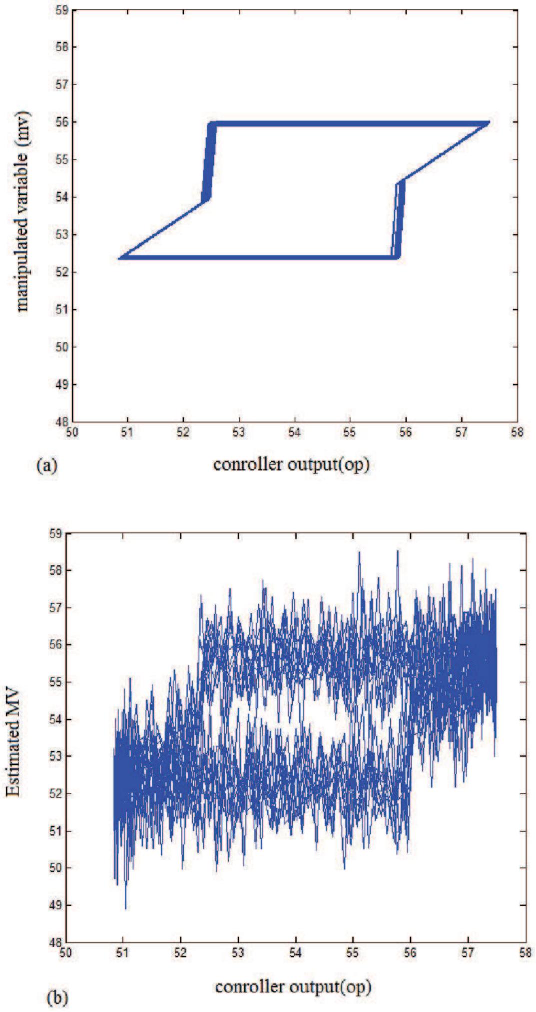


Fig. 7. a) mv-op plot b) estimated mv-op plot for FOPTD process

tuning settings are the same as before. Due to the oscillatory disturbance, the pv and op variables oscillate.

The plot of the estimated mv vs. op is shown in Fig. 8. This pattern is clearly an ellipse and is very different from that of a sticky valve. Hence, we can diagnose that the oscillations are not due to stiction, but are caused by some oscillatory external disturbance.

An aggressively tuned PID controller can be a cause for oscillations in many industrial control loops. In such a case a good valve stiction detection algorithm should confirm that the root cause of the oscillations is not valve stiction. We will demonstrate here the efficacy of the current methodology by deliberately introducing aggressive tuning specifications into the simulated control loops considered earlier. The controller tuning parameters and the process model transfer functions used to generate oscillatory closed loop data are given in TABLE I.

TABLE I. Aggressive Controller Tuning Parameters

| Process | $K_C$ | $1/\tau_I$ |
|---|---|---|
| $\frac{1}{s}$ | 0.5 | 0.1 |

The stiction block was removed from the simulation so that the valve can be considered to be a normal one. Also for this case the external oscillatory disturbance is removed. With a normal linear valve without oscillatory disturbance in closed loop, we would expect the mv–op plot to be a straight line without any stiction pattern being depicted. Fig. 9 shows the estimated and the true mv–op plots for the two processes. From the figure, we can observe that the estimated mv vs. op line coincides with the actual one and is clearly showing a linear dependence between the two. Thus, the absence of any stiction pattern in the estimated mv–op plot clearly shows that the valve is normal.

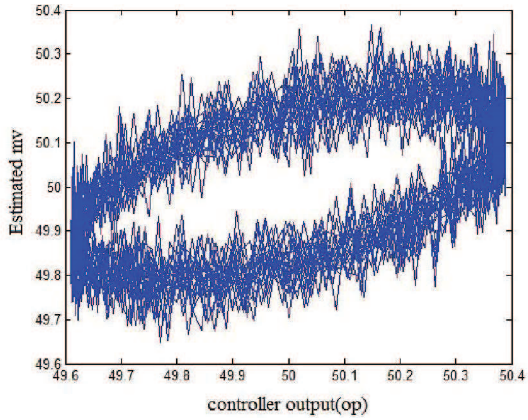


Fig. 8. Diagnosis of external oscillatory disturbance

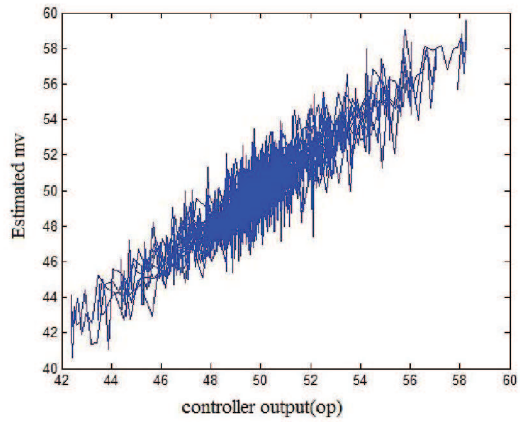


Fig. 9. Diagnosis of oscillations due to aggressive controller tuning

## Conclusions

In this paper, a novel method for detection and quantification of valve stiction has been proposed. According to the numerical algorithm of the extended Kalman filter, a suitable estimation of the valve position signal is acquired. Hence, stiction parameters are calculated simply and accurately through mv-op plot. A square root numerical algorithm obtained for implementation of unknown input estimation. In addition, the proposed method has the ability of differentiating between stiction and other cause of oscillation. The validity of the proposed method has been demonstrated by several simulation results.

## References


[1] M. Jelali, B. Huang (Eds.), Detection and Diagnosis of Stiction in Control Loops – State of the Art and Advanced Methods, Springer, 2009.

[2] M.A.A.S. Choudhury, S.L. Shah, N.F. Thornhill, Diagnosis of Process Nonlinearities and Valve Stiction – Data Driven Approaches, Advances in Industrial Control, Springer, 2008.

[3] A. Horch, A simple method for detection of stiction in control valves, Control Engineering Practice 7 (1999)1221–1231.

[4] A. Horch, A. Isaksson, Detection of stiction in integrating processes, in: European Control Conference, Porto, Portugal, pp. 1327–1332, 2001.

[5] Y. Yamashita, An automatic method for detection of valve stiction in process control loops, Control Engineering Practice 14 (2006) 503–510.

[6] A. Singhal and T. I. Salsbury, A simple method for detecting valve stiction in oscillating control loops, *Journal of Process Control*, vol. 15, p. 371382, 2005.

[7] M.A.A.S. Choudhury, S.L. Shah, N.F. Thornhill, D.S. Shook, Automatic detection and quantification of stiction in control valves, Control Engineering Practice 14 (2006) 1395–1412.

[8] M.A.A.S. Choudhury, M. Jain, S.L. Shah, Stiction – definition, modelling, detection and quantification, Journal of Process Control 18 (2008) 232–243.

[9] A. Stenman, F. Gustafsson, K. Forsman, A segmentation-based method for detection of stiction in control valves, International Journal of Adaptive Control and Signal Processing 17 (2003) 625–634.

[10] R. Srinivasan, R. Rengaswamy, S. Narasimhan, R. Miller, Control loop performance assessment. 2. Hammerstein model approach for stiction diagnosis, Industrial & Engineering Chemistry Research 44 (17) (2005) 6719–6728.

[11] M. Jelali, Estimation of valve stiction in control loops using separable least squares and global search algorithms, Journal of Process Control 18 (2008) 632–642.

[12] S.B. Chitralekha, S.L. Shah, J. Prakash, Detection and quantification of valve stiction by the method of unknown input estimation, Journal of Process Control 20 (2010) 206–216.

[13] M.A.A.S. Choudhury, N.F. Thornhill, S.L. Shah, Modelling valve stiction, Control Engineering Practice 13 (2005) 641–658.

[14] K. Kano, H. Maruta, H. Kugemoto, and K. Shimizu, Practical model and detection algorithm for valve stiction, in Proceedings of the IFAC Symposium on Dynamics and Control of Process Systems, (Cambridge, MA), 2004.

[15] Q. He, J. Wang, M. Pottmann, and S. J. Qin, A curve fitting method for detecting valve stiction in oscillating control loops, *Ind. Eng.Chem. Res.*, vol. 46, no. 13, pp. 4549 –4560, 2007.

[16] S. Gillijns, B. De Moor, Unbiased minimum variance input and state estimation for linear discrete-time systems, Automatica 43 (2007) 111 116.

[17] B.C. Levy, A. Benveniste and R. Nikoukhah, High-level primitives for recursive maximum likelihood estimation. Automat. Control, 1996.

[18] G.J. Beirman, Factorization methods for dicrete sequential estimation, New York: Academic, 1977.