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Valve Stiction Quantification: a Robust Methodology to Face Most Common Causes of Loop Perturbations

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Valve stiction is one of the most common causes of poor performance in control loops. Quantification of valve stiction is of crucial importance for maintenance scheduling, but can be heavily affected by the presence of unavoidable perturbations in loop variables. A procedure which allows stiction modelling and quantification is proposed. The technique requires only data normally registered in industrial plants - controller output and controller variable - and permits to reproduce the unknown real stem position. The method describes the system by means of a Hammerstein model: a non-linear block for valve stiction followed by a linear block for process dynamic. A two-parameters empirical model is used to reproduce accurately the valve behaviour and a linear least square identification is performed. A grid search method allows to estimate process and stiction parameters. The paper analyses how several loop perturbations as setpoint variations, controller tuning and external disturbances, could affect the stiction estimation obtained by this inherently robust technique. A general methodology is proposed to discard data for which quantification is very likely to give wrong indications and to restrict the application to appropriate cases. Simulations show that several sources of perturbations can be eliminated, thus improving the reliability of stiction evaluation. Results are confirmed by the application of the method to industrial data.

1. Introduction

The performance of control system plays an important role in process industry because poor performance considerably reduces the profits of the plants (Jelali and Huang, 2010). The control loop performance monitoring detects poor performance loops, understands sources of malfunction and suggests ways of correction. Control valves are said to be source of oscillations and poor performance in 30 % of control loops (Jelali and Huang, 2010). In particular, the most common problem is stiction (static-friction). An accurate definition of this phenomenon has been proposed by Choudhury et al. (2005). To describe valve stiction, different models have been developed: physical models (Karnopp, 1985) and data-driven models. In addition, many stiction detection techniques have been proposed. These techniques distinguish two common causes of oscillations: external disturbance and valve stiction. They can be broadly classified into four categories: cross-correlation function based (Horch, 1999), shape based (Rossi and Scali, 2005; He et al., 2007), nonlinearity detection based (Choudhury et al., 2004) and model based algorithms (Karra and Karim, 2009). A performance comparison of the most recent techniques, on a large benchmark (93 loops) of industrial data, is reported in Jelali and Huang (2010). In stiction data-driven models (Choudhury et al., 2005; Kano et al., 2004) the relation between controller output (desired valve position) OP and flow rate (real valve position) MV is described in three phases (Figure 1, left):

1. Sticking: MV is steady and the valve is still due to static friction force (deadband + stickband, S).
2. Jump: MV changes abruptly because the active force unblocks the valve, J.
3. Motion: MV changes gradually, only dynamic friction force can possibly fight against the active force.

Diagram MV(OP) shows a parallelogram shaped limit cycle. Valve stiction produces an offset between control variable PV and setpoint SP and causes loop oscillation because the valve does not move and the integral action of the controller acts increasing the pressure on valve diaphragm over the necessary value. MV(OP) would be perfectly linear without valve stiction. It is worth to say that S is easy recognizable, but J is hard to detect in industrial data because is small and covered by field noise (Figure 1, right).

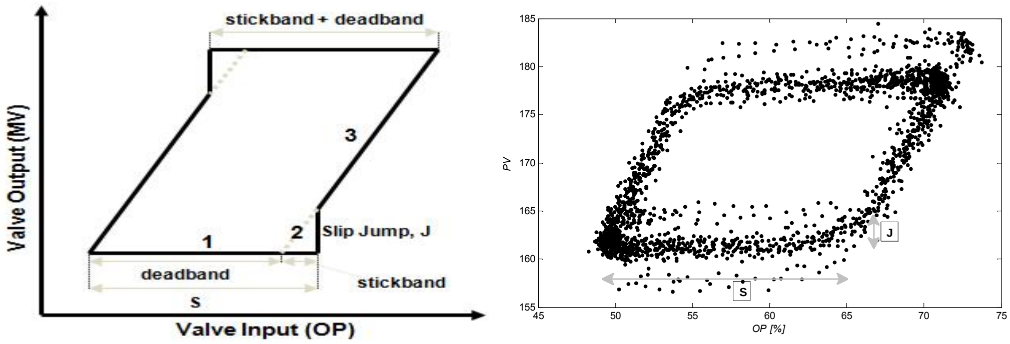

Figure 1: MV(OP) diagram; left) valve stiction modelling; right) typical industrial limit cycle

However the size of J is critical to originate limit cycles (Choudhury et al., 2008). Usually, in industrial plants only PV and OP are registered and MV and MV(OP) are not available. In case of stiction, especially for loop with slow dynamics (PC, LC, TC), PV(OP) diagrams have elliptic shapes. Similar paths are obtained for other types of oscillating loops, due to external stationary disturbance or aggressive controller tuning. Valve stiction quantification allows to estimate the amount of this malfunction and is remarkably important because permits to monitor and schedule valve maintenance. The real problem of quantification is connected to its reliability in presence of other sources of oscillations in loop variables. The aim of this work is to develop a method to eliminate cases of poor reliability. The paper is organized as follows: in Section 2 a brief review of stiction quantification techniques is presented, in Section 3 the proposed method is illustrated, in Section 4 and Section 5 respectively results on simulated and industrial data are presented, in Section 6 conclusions are drawn.

2. Review of stiction quantification techniques

Stiction quantification techniques do not use invasive procedures for plants, but only algorithms based on normal data trends used for performances monitoring. If MV is registered, stiction can be detected and quantified directly on MV(OP) diagram. This is possible when smart equipments (valve positioners) and advanced communication systems (Field Bus) are available (Scali et al., 2011). Choudhury et al. (2006) fitted the limit cycle on PV(OP) with a geometrical ellipse in least square sense. A stiction index is evaluated as the ellipse length in OP direction. This technique gives a relative value of stiction, called apparent, which represents only an indication of stiction severity. This index is influenced by the other loop parameters, that is: controller (firstly the gain) and process; therefore cannot be consider effective to follow stiction evolution in time. Techniques which estimate the parameters of a data-driven stiction model and recreate MV signal are much more effective. In this problem, the objective function does not have generally a concave shape, but shows many flat regions where the gradient is zero or close to. A global search algorithm for the minimum is necessary; a gradient method would be too much influenced by the initial guess and would stop in a local minimum. In many techniques the loop control is modeled by a Hammerstein system: a non-linear block for valve stiction, followed by a linear block for process. Srinivasan et al. (2005) used an one parameter stiction model and linear dynamic was identified by ARMAX (AutoRegressive Moving Average with eXternal input) model. Choudhury et al. (2008) performed a grid search of the two stiction parameters of Choudhury model. The S/J combination and the corresponding process parameters vector which minimize mean squared error on PV are evaluated. Jelali (2008) used a stochastic optimization approach for the non-linear part. A two-stage quantification is performed: stiction parameters are obtained with genetic algorithms or patterns search methods, then linear part is identified using ARX or ARMAX models and a time delay estimation algorithm. The method of Farenzena and Trierweiler (2012) is said to be an improvement with respect to Jelali method. It performs a simultaneous identification of stiction and process parameters by means of a deterministic algorithm of global optimization, which is no more dependent on initial guess. Lee et al. (2010) describe valve stiction with He et al. (2007) model and identify linear process model of first or second order plus time delay. A triangular search grid represents a remarkable improvement, because it constrains the search space of stiction parameters and fastens the method. Romano and Garcia (2011) model control loop with Hammerstein - Weiner structure: the valve non linear block precedes the process, represented by a linear block and a non-linear static block. Process identification is performed with ARMA or ARMAX models for linear part and third grade spline functions for non-linear part. This approach avoids possible process nonlinearity be wrongly included in the stiction model. Karra and Karim (2009) describe control loop with Kano stiction model and a specific linear model (E(xtended)-ARMAX type), which accounts also for the presence of non stationary disturbances entering the process. Recently methods to evaluate the reliability of stiction detection and quantification techniques have been performed. Qi and Huang (2011) propose a bootstrap method to obtain the statistical distribution of stiction quantification. The authors define a values region for stiction parameters with a 95 % confidence. Srinivasan et al. (2012) perform a frequency domain analysis of loop oscillation and determine a confidence function for the estimated stiction parameters. It is clear that stiction quantification reliability is still an open issue. Different quantification techniques can strongly disagree when applied on the same benchmark of industrial data (Jelali and Huang, 2010). The objective of our work is to show how most common causes of control loop perturbation influence stiction estimation. The proposed method is inherently robust in order to avoid accuracy problems connected to many solution algorithms and is simpler than similar methods, recently proposed in literature; by the way, validations presented up to date cannot be considered satisfactory.

3. The proposed method

The proposed stiction quantification technique uses a grid search. This method is very solid but needs a quite long computational time, in some cases minutes. This is not a disadvantage for three reasons: the technique is oriented to an offline application which requires data registered for hours, valves wear phenomena occur slowly (after weeks or months) and valves maintenance usually occurs annually for plant shutdown. Control loop is modeled by a Hammerstein system (Figure 2, left). Kano stiction model describes the non-linear valve dynamic and an ARX model describes the linear process dynamic.

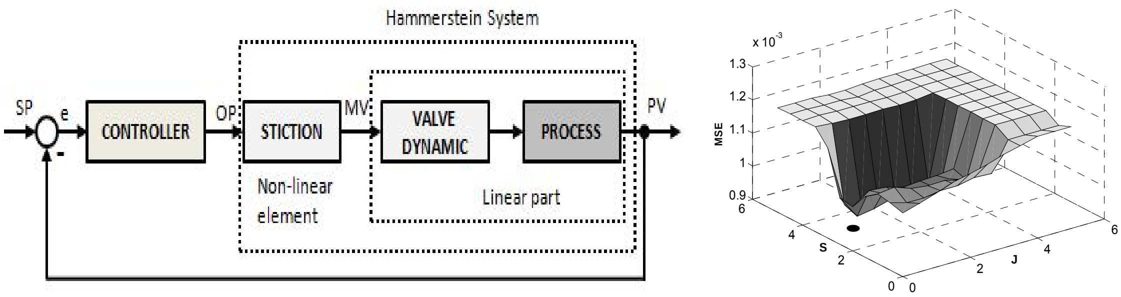

Figure 2: left) Hammerstein system: control loop with valve stiction; right) grid search

The method goes as follows: a grid of stiction parameters S/J is built (Figure 2, right); for each possible combination MV signal is generated from OP; another grid of possible process time delay units *L* is performed. For every triad S/J/L the coefficient vector *θ* of the ARX model is identified in linear least square sense, based on MV and industrial PV. The following minimization problem is stated:

$$(\bar{S},\bar{J},\bar{\vartheta},\bar{L}) = \min_{S,J,\vartheta}(\min_{L}(F_2))$$

$$F_2 = 1 - \frac{|PV_{ric} - PV|_2}{|PV - PV_m|_2} \tag{1}$$

F_2 is a fitting index connected to the mean squared error between industrial registered signal PV and recreated one PV_{ric}; PV_m is the mean signal. The stiction parameters grid has a triangular shape to restrict the search space. Overshoot stiction cases (J>S) are excluded and the greatest value of S (and J) is the OP oscillation span; so at boundary conditions (S=J and S=OP span) the valve jumps between two extreme positions producing an exactly squared MV wave. Srinivasan et al. (2005) have demonstrated that non linear identification accuracy is not affected by the complexity of linear model structure. This statement justifies the use of a simple model to describe linear dynamic. For this reason, we use a simple ARX model which allows an exact solution for least square problem and which, differently from ARMAX, implies only an iterative estimation of non-linear parameters. Our simulation has shown that an ARX(2,2) model is adequate to quantify stiction with good precision even for complex process dynamics, with sustainable computational times. In addition, for this type of problems, a good time delay estimation is necessary. This is guaranteed using the time delay grid which makes the method heavier but represents a particularly reliable and solid approach. In our simulations, the proposed technique shows the stiction parameters grid step as the key element. A small step size guarantees an accurate quantification and avoids local minimum solution. We believe that step equal to 0.05 is adequate, because the minimal accuracy on parameters estimation is set to 0.01, which is 1/1000 part of valve steam stroke (0 - 100 %). Our technique shows also robustness to noise; the errors become significant only in case of SNR = 2. To conclude, the proposed technique guarantees a correct mathematical solution of the problem, when stiction is the unique cause of oscillation.

On the contrary, in the perspective of application on industrial data, there are some practical issues which might alter results of stiction quantification. They are mainly correlated to the presence of oscillations with or without valve stiction: irregular oscillations, variable set point loops, incorrect controller tuning, periodic external disturbances can be seen as unavoidable phenomena in industrial situations. To reduce the impact of these practical issues on the reliability of stiction estimation, a systematic filtering procedure is proposed, as described in the sequel.

Firstly two appropriate techniques to detect significant loop oscillations are applied. Regularity factor r (Thornhill et al., 2003) and decay ratio R_{acf} (Miao and Seborg, 1999) of autocorrelation function (ACF) of control error (e = PV - SP) are calculated. If these two indexes exceed threshold values, set respectively to 1 and 0.5 as suggested by the authors, the control loop is considered to oscillate significantly: regularly and steadily. In this condition the quantification goes on, otherwise no significant oscillation is detected and the analysis is stopped. Secondly, a stiction diagnostics technique (Rossi and Scali, 2005) is applied in order to avoid cases of periodic disturbances, as unique source of oscillation. Finally, as these techniques may give wrong indications in the simultaneous presence of disturbances and stiction, a further check on the two identified models (linear and non linear) is performed by dividing the data in two sets and applying the method separately. The comparison of the two data windows is performed using two specific indexes (model deviations) defined below.

$$MD^{NL} = 1 - \frac{\left| MV_1^{OL} - MV_2^{OL} \right|_2}{\left| \underline{MV}_{12}^{OL} \right|_2} \quad MD^{LIN} = 1 - \frac{\left| y_1^{sr} - y_2^{sr} \right|_2}{\left| \underline{y}_{12}^{sr} \right|_2} \tag{2}$$

MD^{NL} is a non-linear model deviation index. MV_1^{OL} and MV_{2OL} are respectively output signal of the first and the second couple of estimated stiction parameters in response to a specific OP input signal. $\underline{MV}_{12}^{OL}$ is the mean signal. MD^{LIN} is a linear model deviation index. The output signal of the first (y_1^{sr}) and the second (y_2^{sr}) model in response to a unitary step are compared. $\underline{y}_{12}^{sr}$ is the mean signal. These two indexes are equal to 1 when the responses are exactly the same, that is when the two couples of stiction parameters and the two linear models perfectly correspond. Indexes tend to -∞ when differences increase. We have verified that, to obtain reliable results in our method, these three following conditions have to be satisfied: $MD^{NL} > 0.95$, $MD^{LIN} > 0.8$ and $\min(F_2) > 0.8$. In this case the identified stiction and linear model parameters are connected to the best data set, that is the one with the highest F_2 index.

4. Simulation results

We simulate an industrial control loop. The process P is described by a First Order Plus Time Delay (FOPTD) transfer function and controller C has PI algorithm with Ziegler-Nichols tuning. Valve stiction is described with Kano model. Sample time is set to 1 s. This loop is a specific case study, but the results have absolutely general validity.

$$P = \frac{1}{15s+1} \cdot e^{-5s} \quad C = 2.44\left(1 + \frac{1}{14.9s}\right) \tag{3}$$

Our methodology is applied to different sources of oscillation, as described above (9 typologies). In case 1 and 2 low and high valve stiction is present. In case 3 the loop oscillates due to SP sinusoidal variation and the valve has no stiction. Case 4 is equal to case 3, but the valve has low stiction. In case 5 the loop oscillates due to aggressive controller tuning (Kc = 4.15), which causes marginal stability condition. In case 6 an aggressive tuning (Kc = 3.66) acts with high valve stiction. In case 7 an external sinusoidal disturbance is the unique cause of loop oscillation. In case 8 and 9 an external sinusoidal disturbance acts respectively with low and high valve stiction.

Results are reported in Table 1. In the columns, from left to right: simulated stiction parameters ($S°$,$J°$), regularity and decay ratio factors (r, R_{acf}), diagnostic verdicts of Relay technique, estimated stiction parameters (S, J), model deviation indexes (MD^{NL}, MD^{LIN}) and F_2 index. It can be seen that the oscillation is regular and steady for all cases, as indicated by values of r and Racf above thresholds. In cases from 1 to 6, the procedure perfectly succeeds and gives good stiction estimations, both in the presence of stiction or not. In the case of pure disturbance (7), stiction quantification could fail (non zero S and J estimation), but the Relay technique indicates the presence of disturbance, so these data should not be examined by the stiction estimation algorithm. In cases of simultaneous stiction and disturbance (8 and 9), Relay technique detects stiction but the estimated stiction parameters are always wrong. In case 8, the low value of MD^{LIN} (< 0.80) gives an indication of scarce accuracy, while in case 9 both indexes are above thresholds, then wrong stiction estimation is obtained.

Simulation results confirm that the proposed methodology is able to give a correct stiction estimation when stiction is the only source of oscillation. The procedure continues to be correct also in case of oscillations caused by setpoint variations and incorrect tuning, with or without stiction presence. On the contrary, in the presence of external disturbances, the methodology may give wrong stiction estimations. The screening by means of Relay diagnosis technique and the check on the windows model deviations indexes are not sufficient to eliminate the problem completely, but can reduce the number of wrong evaluations.

Table 1: Simulation examples: different sources of loop oscillation.

case		$S°$	$J°$	r	R_{acf}	*Verdict*	S	J	MD^{NL}	MD^{LIN}	F_2
1	low stiction	0.5	0.5	9.8	0.98	Stiction	0.5	0.46	0.99	0.83	0.97
2	high stiction	4	1	2.32	0.96	Stiction	4.02	1.08	0.98	0.89	0.96
3	SP variation	0	0	21.4	0.97	No stiction	0	0	0.99	0.82	0.95
4	SP variation + low stiction	0.5	0.5	21.2	0.97	Stiction	0.46	0.42	0.99	0.83	0.95
5	aggressive tuning (marginal stability)	0	0	12.1	0.99	No stiction	0.04	0.04	0.99	0.84	0.97
6	aggressive tuning + high stiction	4	1	14.4	0.97	Stiction	3.84	0.88	0.99	0.89	0.97
7	sinusoidal disturbance	0	0	8.6	0.99	No stiction	0.36	0.14	0.99	0.87	0.97
8	disturbance + low stiction	0.5	0.5	6.92	0.93	Stiction	0	0	0.99	0.46	0.94
9	disturbance + high stiction	6	4	12.9	0.98	Stiction	4.98	4.98	0.97	0.91	0.95

5. Application to industrial data

The significance of the proposed filtering procedure in the analysis of industrial data has been checked by application on a wide number (70) of refinery valves. Data consist in about 800 acquisitions before and after plant shutdown for periodic maintenance. The whole procedure has allowed to issue reliable results for 43 out of 70 valves. The reliability criterion was the repeatability and homogeneity of stiction values estimation in different acquisitions for the same valve. This result can be considered encouraging, taking into account different perturbations which may be present in an industrial environment.

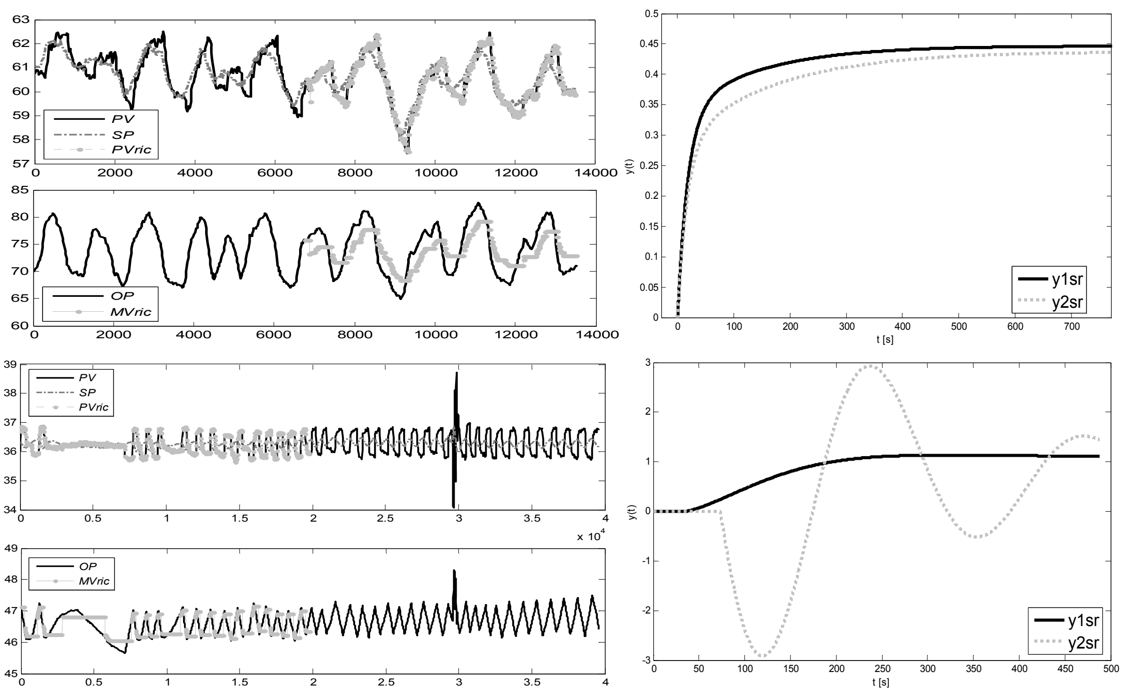

Figure 3: Application of the procedure: (top) successful; (bottom) unsuccessful.

Causes of unreliable results might be assigned to the presence of perturbations and stiction acting simultaneously, as shown in simulations. Figure 3 (top) shows a case of success (MD^{NL} = 0.99, MD^{LIN} = 0.95, F_2 = 0.90) and Figure 3 (bottom) a case of failure (MD^{NL} = 0.95, MD^{LIN} = -0.45, F_2 = 0.85), which might belong to simulation typology 8. On the left of the figures, time trends of SP, PV, PVric, OP and MV are reported, while on the right the step responses of the two linear models identified are reported. In the second case, the two responses are quite different and this explains a low value of MD^{LIN} index.

6. Conclusions

The proposed technique, which models loop control as a Hammerstein system allows quantification of valve stiction in a very reliable way when stiction is the only cause of oscillations. The key problem in stiction quantification is given by the presence of different sources of oscillations. The filtering procedure suggested to discard data for which stiction quantification is very likely to fail. The procedure gives reliable stiction estimations in the case of incorrect tuning and setpoint variation, but, in general, not in the case of simultaneous presence of disturbances and stiction. However, even though not sufficient to eliminate the problem completely, the methodology is able to reduce the number of wrong evaluations.

References

Choudhury M.A.A.S., Shah S.L., Thornhill N.F., 2004, Diagnosis of poor control loop performance using higher order statistics, Automatica 40, 1719-1728.

Choudhury M.A.A.S., Shah S.L., Thornhill N.F., 2005, Modelling valve stiction, Con. Eng. Pr. 13, 641-658.

Choudhury M.A.A.S., Shah S.L., Thornhill N.F., Shook D.S., 2006, Automatic detection and quantification of stiction in control valves, Control Engineering Practice 16, 1395-1412.

Choudhury M.A.A.S., Jain M., Shah S.L., Shook D.S., 2008, Stiction - definition, modelling, detection and quantification, Journal of Process Control 18, 232-243.

Farenzena M., Trierweiler J.O., 2012, Valve stiction evaluation using global optimization, Control Engineering Practice 20, 379-385.

He Q., Wang J., Pottmann M., Qin S. J., 2007, A curve fitting method for detecting valve stiction in oscillating control loops, Industrial and Engineering Chemistry Research 46, 4549-4560.

Horch A., 1999, A simple method for detection of stiction in control valves, Cont. Eng. Prac. 7, 1221-1231.

Jelali M. 2008, Estimation of valve stiction in control loops using separable last square and global search algorithms, Journal of Process Control 18, 632-642.

Jelali M., Huang B., Editors, 2010, Detection and Diagnosis of Stiction in Control Loops: State of the Art and Advanced Methods, Springer-Verlag, London, UK.

Kano M., Hiroshi M., Kugemoto H., Shimizu K., 2004, Practical model and detection algorithm for valve stiction, In Proceedings of 7th IFAC DYCOPS, Boston, USA.

Karnopp D., 1985, Computer simulations of stick-slip friction in mechanical dynamics systems, Journal of Dynamics Systems, Measurement and Control, Trans ASME 107, 100-103.

Karra S., Karim M. N., 2009, Comprehensive methodology for detection and diagnosis of oscillatory control loops. Control Engineering Practice 17, 939-956.

Lee K.H., Ren Z., Huang B. 2010, Stiction estimation using constrained optimisation and contour map, in M. Jelali, B. Huang (Eds.), Detection and Diagnosis of Stiction in Control Loops, 225-256 (Chapter 11).

Miao T., Seborg D.E, 1999, Automatic detection of excessively oscillatory feedback control loops, In Proceedings of IEEE International Conference on Control Applications, Hawaii, USA, 359-364.

Qi F., Huang B., 2011, Estimation of distribution function for control valve stiction estimation, Journal of Process Control 21, 1208-1216.

Romano R.A., Garcia C., 2011, Valve friction and nonlinear process model closed-loop identification, Journal of Process Control 21, 667-677.

Rossi M., Scali C., 2005, A comparison of techniques for automatic detection of stiction: simulation and application to industrial data, Journal of Process Control 15, 505-514.

Scali C., Matteucci E., Pestonesi D., Zizzo A., Bartaloni E., 2011, Experimental Characterization and Diagnosis of Different Problems in Control Valves, Prep. XVII IFAC W.C. Milano (Italy), 7334-7339.

Srinivasan R., Rengaswamy R., Narasimhan S., Miller R., 2005, Control loop performance assessment. 2. Hammerstein model approach for stiction diagnosis, Ind. and Eng. Chem. Res. 44, 6719-6728.

Srinivasan B., Spinner T., Rengaswamy R., 2012, A reliability measure for model based stiction detection approaches, In Proceedings of the 8th IFAC Symp. on Adv. Con. of Chem. Proc. Singapore, 750-755.

Thornhill N.F., Huang B., Zhang H., 2003, Detection of multiple oscillations in control loops, Journal of Process Control 13, 91-100.