Valve Stiction Evaluation Using Global Optimization

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Abstract: Valve stiction is a well known villain in process industry. Quantifying this valve damage is essential to ensure plant stability and profitability. The scope of this work is to propose a new method to compute valve stiction parameters, using a two parameter model, using only routine operating data. The proposed method uses global optimization to evaluate loop and plant parameters. Combining the proposed procedure with an efficient global optimization algorithm, the mean computation time for each valve was about 5 minutes. The method was applied in both simulation and industrial valves, providing reliable results, with relative errors smaller than 3% in all parameters.

Keywords: Performance Monitoring, Valve, Static Friction, Hysteresis, Global Optimization.

1 INTRODUCTION

In the last two decades, control loop performance monitoring has been a fruitful research field, providing automatic tools for process industry, which has great interest in evaluating loop performance in real time. Inside this scope, one topic that has been in focus is valve stiction, whose frequency in control loops is about 30% (Bialkowski, 1993). The effects of stiction are one explanation for these developments: it can cause plant-wide oscillations and increase the variability of the process and products.

Evaluating loop stiction is not a new issue. First studies were dated from 60's (Brown, 1958). However, in the last years, a big effort has been made to diagnose and solve this valve illness. A first group of works aimed at diagnosing stiction automatically, using only process variable (PV) and controller output (OP) (He *et al.*, 2007, Horch, 1999, Rossi and Scali, 2005, Ruel, 2000, Scali and Ghelardoni, 2008, Singhal and Salsbury, 2005, Stenman *et al.*, 2003, Yamashita, 2006). Some works have proposed specific stiction models for diaphragm type valves (Chen *et al.*, 2008, Choudhury *et al.*, 2005). A good survey about stiction models was recently written by Garcia (2008).

Also, some authors have proposed to compute stiction parameters in real time. Choudhury et al. (2006) proposed two methods to quantify stiction parameters, based on ellipse fitting and *c-clustering*, using a 1 parameter empirical model. Subsequently, some authors have proposed to quantify stiction parameters using a more reliable model, with two parameters. Choudhury *et al.* (2008) have proposed a method based on optimization and grid search.

Recently, Jelali (2008) has introduced one methodology to compute both stiction models, based on least-squares and global search algorithms. This method has two drawbacks: it is dependent of initial guess and it is computationally expensive. The scope of this work is to propose an alternative method based on global optimization to compute stiction parameters and linear plant model.

The main difference between our and Jelali's method is the optimization procedure, which is made in a single step, using global optimization. Both plant models and stiction parameters are computed in each optimization step. Combining the proposed procedure with an efficient global optimization algorithm, the computation time for each valve was less than 5 minutes.

The proposed methodology was applied in a set of 1000 simulation valves, with a relative error smaller than 3% in all cases, for all parameters. Then, the proposed method was applied in a group of industrial valves, showing reliable results.

The paper has been organized as follows: in section 2, the stiction definition, model and methodologies to evaluate valve stiction will be briefly discussed. Then, in section 3, the proposed methodology will be detailed. Several simulated and industrial case studies are shown in section 4, to corroborate the applicability of the proposed methodology. The paper ends with the concluding remarks.

2 STICTION: MODEL AND COMPUTATION

Stiction, or high static friction, can be defined as the valve damage that keeps the stem from moving, because the static friction exceeds the dynamic. As a consequence, the force to move the steam is generally larger than the desired new stem value, and the movement is jumpy (Ruel, 2000).

2.1 Stiction: model

A valve "suffering from stiction" has in the phase plot MV versus OP, shown in Fig. 1, four components: deadband (*DB*), stickband (*SB*), slip jump (*J*) and moving phase (*MP*). The method assumes that the process and controller have linear behaviour, while the sticky valve inserts in the loop nonlinear behaviour.

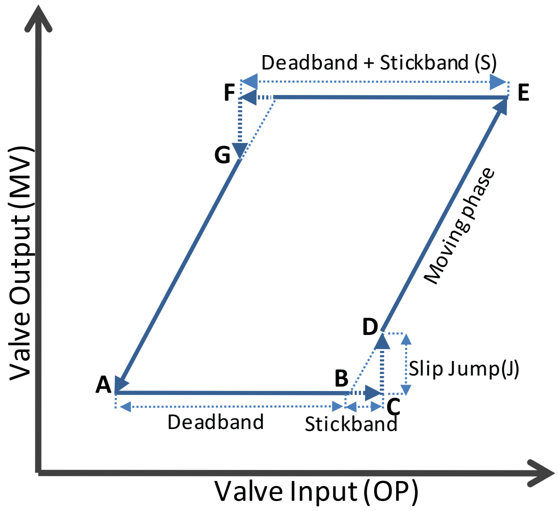

Fig. 1. Relation between controller output (OP) and valve position (MV) for a sticky valve.

When the valve changes the direction (A), the valve becomes sticky. The controller should overcome the deadband (AB) plus stickband (BC), and then the valve jumps to a new position (D). The stiction model consists of these two parameters: *S* (deadband+stickband) and *J* (jump).

Next, the valve starts moving, until its direction changes again or the valve comes to rest, between D and E.

The deadband and stickband represent the behaviour of the valve when it is not moving, although the input of the valve keeps changing. Slip jump represents the abrupt release of potential energy stored in the actuator chambers due to high static friction in the form of kinetic energy as the valve starts to move. The magnitude of the slip jump is crucial to determine the limit cycle amplitude and frequency.

The stiction model used in this work is proposed by Kano (2004), which is an extension of Choudhury's method, where stiction is modeled using two parameters. Their main advantage is that it can deal with both stochastic and deterministic signals. Kano's model flowchart representation is shown in Fig. 2.

The first two branches check the valve bounds. In the Kano's model, two valve states are distinguished: moving (*stp=0*) or resting (*stp=1*). When the valve changes its direction, its actual position state (us) is kept, until the static force is overcome. The friction force direction is denoted by $\pm d$.

2.2 Stiction: computation

In the literature, two methods to compute stiction parameters, using only normal operating data are proposed.

In the method proposed by Jelali (2008), a two step procedure is described. In the first step the stiction parameters are quantified using pattern search methods or genetic algorithms (GA). Next, the low-order linear plant model is identified, using a least-squares estimator. Both simulation and industrial valves are analyzed, and the errors between predicted and actual values for stiction parameters are less than 10%.

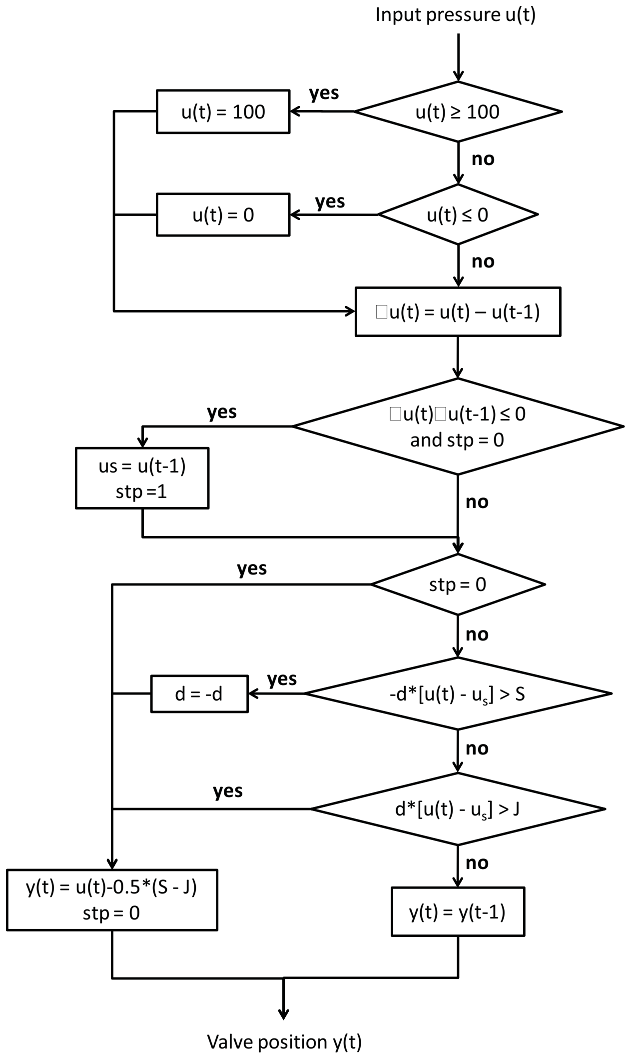

Fig. 2. Flowchart for Kano model.

a second method proposed by Choudhury *et al.* (2008) describes a method based on a grid search. Initially, a grid using several different values of *J* and *S* is built and then based on the process output, the plant model is identified. Based on the mean square error (MSE) between predicted process output and actual output in each grid point, the stiction parameters are estimated.

3 STICTION QUANTIFICATION

This section describes a new method to compute both stiction parameters and plant model, using only normal operating data. Data from process variable (PV) and controller output (OP) are required. Here, only first order with time delay models (FOPTD) will be used. However, the methodology is adequate for second orders, integrating process, among others.

Our approach uses the following assumptions, which are quite similar to the other methods available in the literature:

- The plant model is (locally) linear;
- The loop nonlinearity is caused by the valve;
- The stiction model can be considered a Hammerstein model;

The proposed method computes both plant stiction parameters in a single step, using a global optimization algorithm. This is the first difference between this work and the work proposed by Jelali (2008), where a two step procedure is proposed.

3.1 Optimization problem

The optimization problem to be solved is a non-linear programming type, where the objective function is the mean square error (MSE) of the difference of model output (PV_P) and plant output (PV).

$$MSE = \sum_{i=1}^{n} \frac{\left(PV_i - PV_{P_i}\right)^2}{n}$$

Where n is the length of PV.

In this class of problems, the function inside the search space is non-smooth and has some flat areas, where the gradient is zero, or close to this values. Fig 3 illustrates this behavior, using a FOPTD model and a sticky valve. The MSE was computed, varying J and S. In the process output, white noise is added, with signal-noise ratio equal to 1.

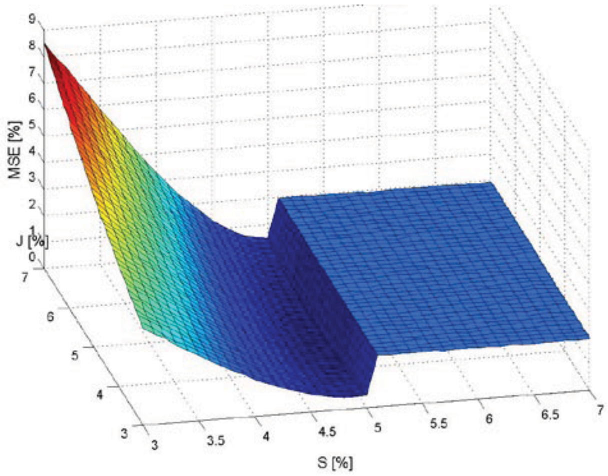

Fig 3: Objective function shape for variable S and J

Fig. 3 clearly shows that this class of function pattern requires global search algorithms; otherwise probably it will stick, depending on the initial guess. One possibility is to use stochastic algorithms, as proposed by Jelali (2008). A second possibility is to use global optimization deterministic algorithms, where the convergence is guaranteed, as proposed in this work.

The optimization problem for a FOPTD model to be solved is:

$$\min_{J,S,K,\tau} (MSE)$$

Where K and τ are the static gain and process time constant, respectively. The time delay is assumed to be known. Several methodologies available in the literature can be used to estimate this loop parameter (Elnaggar *et al.*, 1991, Ahmed *et al.*, 2006, Liang *et al.*, 2003).

The proposed technique can be easily extended to higher order or integrating processes. In this case, the plant model is replaced by an integrating transfer function $\left(\frac{K}{As}\right)$. In this case, the K and A are estimated by the optimization algorithm.

To allow the industrial application of the proposed method, the computational time should be reasonable. Thus, an efficient global optimization algorithm should be selected. Several optimization methods have been evaluated, and the best obtained by the authors is DIRECT (Finkel and Kelley, 2006). All algorithms are deterministic and deal with bounded decision variables.

4 CASE STUDIES

This section illustrates the applicability of the proposed methodology. Over a thousand simulation systems and a dozen of industrial sticky valves were analyzed and the proposed methodology has shown reliable results, what corroborates its industrial usefulness. Some of these systems will be shown here.

All computations were performed in an Intel Pentium D, 2GHz with 1 GB Ram.

4.1 Simulation case-studies

The objective of this section is to show the applicability of the proposed method in a set of simulation studies. All simulations use a PI controller and a first order plus time delay transfer function. Tab. 1 shows the models used in this work.

Tab. 1: Process and controller models used in the simulation case studies

Parameter	Model
Plant	$G(s) = \dfrac{1}{\tau s + 1} e^{-3s}$
Controller (PI)	$C(s) = 2\dfrac{\tau s + 1}{\tau s}$

Here, only twelve cases are shown, where a closed loop system is investigated with variable stiction parameters (*S* and *J*) and different plant time constant. The remaining parameters are maintained constant. Kano's model was used in all cases. The stiction parameters are specified as percentage of input and process variable span (%). Tab. 2 provides the summary of the results obtained by the application of the proposed methodology, where the true plant and valve stiction parameters (τ, *S*, and *J*) were compared with their values obtained by the proposed methodology. (τ_p, S_p, and J_p). The computation time (CPU_t) is also shown. All default settings in the DIRECT algorithm were used, except the maximum number of evaluations of objective functions, which was increased by 1000.

Tab. 2 corroborates the applicability of the proposed method, where the model parameters have deviation less than 3% of the actual values. These values are comparable with Jelali's simulation cases, where the errors are less than 10%. If the maximum number of evaluations of objective function is increased by 3000, then the deviation reduces by less than 1%, however the CPU time increases to 12 min each.

Tab. 2: Results for process simulations

Case	*J* (%)	J_p (%)	Error (%)	*S* (%)	S_p (%)	Error (%)	τ (min)	τ_p (min)	Error (%)	CPU_t (min)
1	2,3	2,3	0,1%	3,0	3,0	0,1%	30,0	30,0	0,0%	4.3
2	2,3	2,3	0,1%	3,0	3,0	0,1%	10,0	10,0	0,0%	4.3
3	3,0	3,0	0,1%	3,0	3,0	0,1%	30,0	30,0	0,0%	4.3
4	3,0	3,0	0,0%	3,0	3,0	0,1%	10,0	10,0	0,0%	4.3
5	3,8	3,8	0,1%	3,0	3,0	0,1%	30,0	30,0	0,0%	4.2
6	3,8	3,7	-1,2%	3,0	3,0	0,0%	10,0	9,9	-1,0%	4.2
7	0,8	0,8	0,6%	1,0	1,0	1,1%	30,0	30,0	0,1%	4.4
8	0,8	0,8	2,9%	1,0	1,0	3,1%	10,0	10,1	1,3%	4.4
9	1,0	1,0	0,0%	1,0	1,0	0,1%	30,0	30,0	0,0%	4.0
10	1,0	1,0	-1,7%	1,0	1,0	-1,2%	10,0	10,0	-0,1%	4.1
11	1,3	1,3	1,3%	1,0	1,0	0,4%	30,0	30,1	0,2%	4.0
12	1,3	1,2	-1,6%	1,0	1,0	-0,9%	10,0	10,0	0,0%	4.3

The second factor also analyzed in this work, was the impact of white noise. Using the same case study of Tab. 1 with $\tau = 20, J = 5$, and $S = 5$, and different level of added white noise to the process variable several optimizations have been performed and the results are summarized in Tab. 3 where SNR is the relationship between Signal-Noise Ratio and the predicted stiction parameters, expressed in percentage of actual value.

Tab 3. White noise impact over the predicted stiction parameters – % change in each parameter

SNR	% *S*	% *J*
100	0.09%	-0.23%
50	0.29%	0.87%
5	0.50%	1.23%
0.5	5.9%	25%

As shown in Tab 3, the methodology is not very sensitive to white noise impact. Only when the noise is significant (i.e. SNR = 0.5) the results have been corrupted.

4.2 Industrial case-studies

This section shows some of the industrial application where the proposed methodology was applied. One flow control (case 1) and one pressure control (case 2) with sticky valves, from a Brazilian refinery, are analyzed.

Fig. 4 illustrates the PV and OP for industrial case study 1, where the presence of stiction can be easily seen. The application of the procedure proposed in this work leads to the estimates of $J = 2.6$, $S = 4.0$, and $\tau = 80$ sec. The comparison between the measured and predicted curves is shown in Fig. 5. This comparison shows that the estimated curve is in good agreement with the measured process variable.

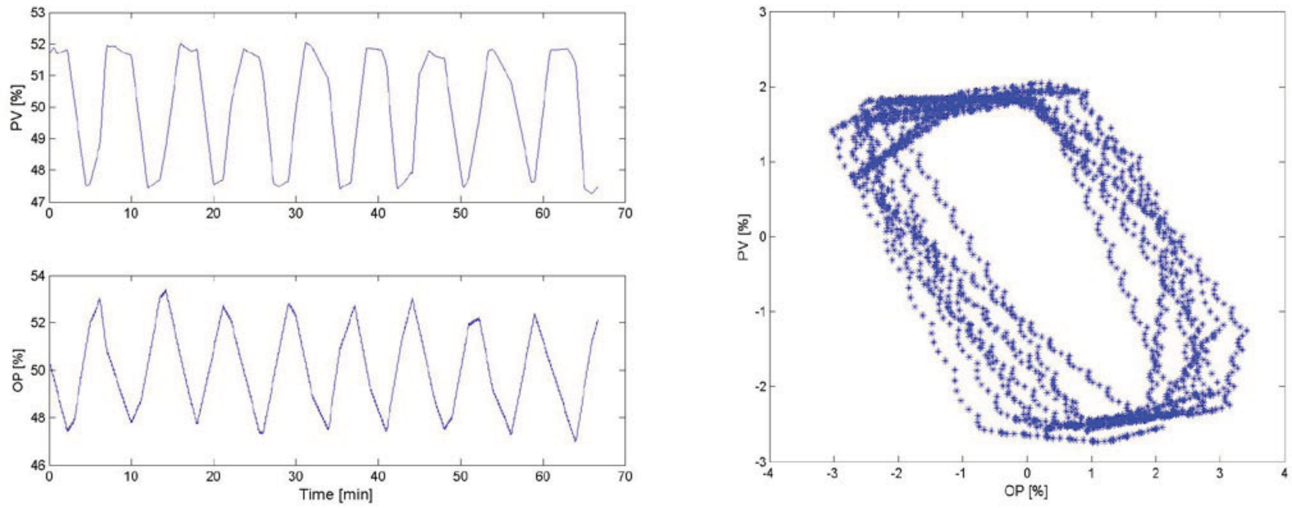

Fig. 4: Data trend for industrial case study 1 – flow control.

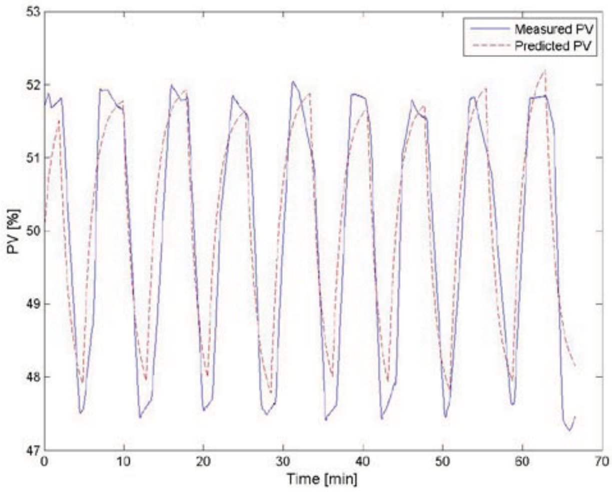

Fig 5: Comparison between measured and predicted PV for industrial case study 1 – flow control.

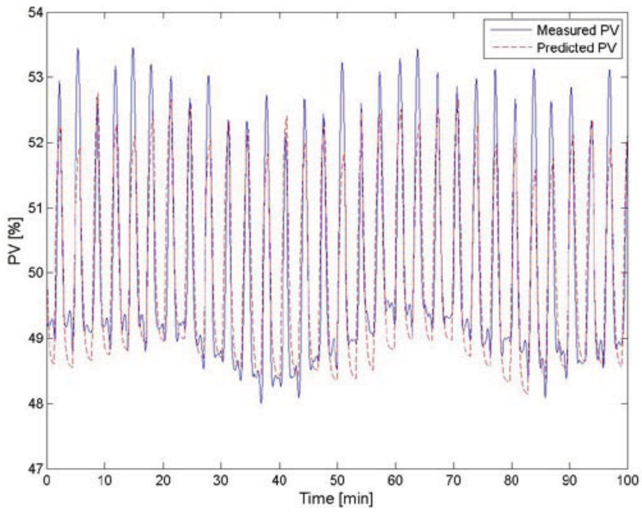

Fig 7 Comparison between measured and predicted PV for industrial case study 2 – pressure control.

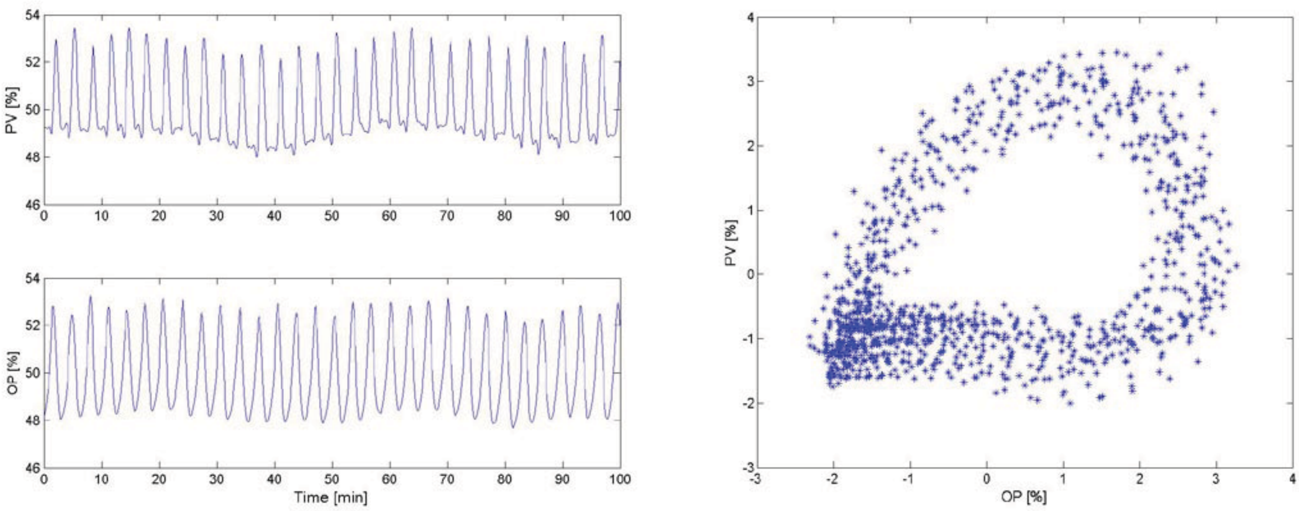

Fig. 6: Data trend for industrial case study 2 – pressure control.

The PV and OP signals for the second industrial sticky valve are shown in Fig. 6. Again, the stiction can be detected by visual inspection of PV versus OP plot, where a parallelogram shape is seen. The proposed estimation algorithm leads to the parameters estimates: $J = 1.6$, $S = 2.9$, and τ=18 sec. The comparison between the measured and predicted curves is shown in Fig. 7.

5 CONCLUSIONS

This work proposes a new method for quantifying valve stiction based on global optimization, using a one-step procedure, where both stiction parameters and plant model are simultaneously quantified, using only process variable (PV) and controller output (OP). The objective function minimized the mean square error between the measured and predicted process output and the optimization algorithm used for this class of problem is called DIRECT (Finkel and Kelley, 2006).

The validity of the method is successfully demonstrated by comparing simulation results, where valves with known stiction parameters were evaluated. Industrial valves were also evaluated, providing very good results. Comparing the actual procedure with the available in the literature, the CPU time is considerably smaller – in this case lower than 5 min against 20 to 30 min – and the quality of the results is comparable – an error lower than 3% against 10%. The industrial applicability of the proposed method has been corroborated by two industrial applications, where reliable results have been obtained.

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