Title:

Stiction Quantification: a Robust Methodology for Valve Monitoring and Maintenance Scheduling

Authors:

Riccardo Bacci di Capaci *, Claudio Scali

Chemical Process Control Laboratory (CPCLab), Department of Civil and Industrial Engineering (DICI), University of Pisa, Via Diotisalvi 2, 56126, Pisa (Italy).

* Corresponding Author**:** e-mail: riccardo.rbdc@gmail.com

Notes

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Abstract

Valve stiction is one of the most common causes of poor performance in control loops. This paper presents a procedure which allows stiction quantification. The technique permits one to estimate the unknown real stem position and moreover, it does not need any process knowledge and it requires only the data normally registered in industrial plants. It is pointed out that the real problem consists in the lack of knowledge about the *true* value of stiction. A general methodology is proposed to discard data for which quantification is very likely to give wrong indications and to restrict its 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 application to industrial data: a significant number of valves are analyzed for repeated acquisitions before and after plant shutdown. The proposed procedure seems to be a valid methodology to monitor valve stiction and to schedule and check valve maintenance.

KEYWORDS: Process Control Applications, Performance Monitoring, Valve Diagnostics, Stiction Detection and Quantification, Maintenance Scheduling.

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1. Introduction

Performance monitoring plays an important role in process industries because poor performance considerably reduces their profitability and competitiveness. A control loop performance monitoring system detects poor performance loops, indicates different sources of malfunction and suggests appropriate ways of correction. Control valves are said to be the cause of oscillations and poor performance in control loops for a significant number of cases (about 30%, according to Jelali and Huang[1]). In particular, the most common problem is stiction (static-friction). An accurate characterization of this phenomenon was performed by Choudhury et al.[2] and since then research on this topics has found new emphasis. The research on valve stiction can be broadly categorized into the following four topics: modeling, detection or confirmation, quantification and compensation. In this section, the existing research on stiction modeling, detection and quantification is briefly reviewed to illustrate the motivations and scope of this paper.

Basically, two types of models are used to describe stiction: models derived from physical principles and models derived from process data. Physical models (Karnopp[3]) are certainly more accurate, but, owing to the large number of unknown parameters, they are not considered convenient for the purpose of stiction detection and quantification. Simplicity in the structure is the main reason why data-driven models are preferred (Choudhury et al.[2]; Kano et al.[4]; He et al.[5]). More details will be given in Section 2 when presenting the proposed methodology.

Many stiction detection techniques have been proposed in the literature. These techniques distinguish two common causes of oscillation: external disturbance and valve stiction. They can be broadly classified into four categories: cross-correlation function-based (Horch[6]), waveform shape-based (Kano et al.[4]; Srinivasan et al.[7]; Singhal and Salsbury[8]; Rossi and Scali[9]; Yamashita[10]; He et al.[5]), nonlinearity detection-based (Choudhury et al.[11]) and model-based algorithms (Karra and Karim[12]). A performance comparison of the most recent techniques on a large benchmark (93 loops) of industrial data is reported in Jelali and Huang[1]. In conclusion, these problems can be considered almost solved, even though different stiction models and diagnosis techniques cannot always give the same results once they are applied on industrial data. Therefore, it is important to know the strengths and the weaknesses of different models and methods.

On the contrary, stiction quantification should be considered an open issue (Jelali and Huang[1]). Knowing the value of stiction is very important in order to follow its evolution in time, to compare it with acceptable thresholds and to be able to schedule valve maintenance.

Both stiction detection and quantification techniques do not require invasive procedures for the plant. They only require algorithms based on data usually recorded for control and monitoring purposes, that is: Set-Point (SP), Controlled Variable (PV) and Controller Output (OP). The measure of the stem position (MV) is not generally available and it must be estimated from the other available measurements. Once MV is recorded, owing to the availability of smart equipment (valve positioners) and advanced communication systems (Field Bus), the task is quite easier. Not only can stiction be detected and quantified directly on MV(OP) diagram, but also other causes of malfunction can be indicated (for instance: air leakage, I/P converter troubles, etc.). Details can be found in Scali et al.[13], Bacci di Capaci et al.[14].

In one of the first significant papers on stiction quantification Choudhury et al.[15] proposed fitting the limit cycle on PV(OP) with a geometrical ellipse in least-square sense. A stiction index is evaluated as the ellipse width in OP direction. This technique gives a relative estimate of stiction, called *apparent*, which represents only an indication of stiction severity. Indeed, this value is

influenced by all other loop parameters (starting from controller and process gain). As they may change in time, this technique cannot be considered completely reliable for stiction quantification.
Techniques which estimate the parameters of a data-driven stiction model and predict the MV signal are much more effective. In stiction quantification, the objective function does not generally have a concave shape, but shows many flat regions where the gradient is zero or close to zero. A global search algorithm for the minimum is necessary; a gradient method would be too influenced by the initial guess and would stop in a local minimum. In many techniques, the control loop is modeled by a Hammerstein system: a non-linear block for valve stiction, followed by a linear block for the process. Some of these techniques are briefly reviewed in the sequel.
Firstly, Srinivasan et al.[16] used a one-parameter stiction model and the linear dynamics was identified by an ARMAX (AutoRegressive Moving Average with eXternal input) model. Choudhury et al.[17] performed a grid search of the two stiction parameters of Choudhury's model. The stiction parameters combination and the corresponding process parameters vector which minimize mean squared error on PV are evaluated. Jelali[18] used a stochastic optimization approach for the non-linear part. A two-stage quantification is performed: stiction parameters are obtained with genetic algorithms or pattern search methods, then the linear part is identified using ARX or ARMAX models and a time delay estimation algorithm. The method of Farenzena and Trierweiler[19] is said to be an improvement over Jelali's method. It performs a one-stage identification of stiction and process parameters by means of a deterministic algorithm of global optimization which is no longer dependent on the initial guess. Lee et al.[20] described valve stiction with the He et al.[5] model and identified a linear process model of first or second order plus time delay. A triangular search grid is a remarkable improvement because it constrains the search space of stiction parameters and fastens the method. Romano and Garcia[21] modeled the control loop with a Hammerstein - Wiener 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 the linear part and third grade spline functions for the non-linear part. This approach avoids a possible process non-linearity to be wrongly included in the stiction model. Karra and Karim[12] described the control loop with Kano's stiction model and a specific linear model (E(xtended)-ARMAX type), which also accounts for non-stationary disturbances entering the process.
Regarding quantification, the main difficulty to put into evidence, is that the *true* value of stiction is not known in industrial data (rather, it may be known in *ad hoc* experiments or in simulations). Therefore, the validation of a proposed technique on a single set of industrial data can be incomplete, apart from the mathematical elegance of the solution. This is confirmed by the fact that different quantification techniques can strongly disagree when applied on the same benchmark of industrial data (Chapt.13 in Jelali and Huang[1]).
Recently, methods to evaluate the reliability of stiction detection and quantification techniques have been presented. Qi and Huang[22] have proposed a *bootstrap* method to obtain the statistical distribution of stiction estimation. They defined a region for stiction parameters with 95 % confidence. Srinivasan et al.[23] have performed a frequency domain analysis of loop oscillation and determined a confidence function for the estimated stiction parameters.
Following these considerations, the objective of this paper is twofold:
- firstly, to overcome the problem that the *true* value of stiction is not known, the proposed methodology will be performed on many applications available for long periods of time (before and after plant shutdown) and for a significant number of valves.

- secondly, to show how the most common causes of loop perturbation may influence stiction estimation, a robust methodology is proposed, including a filtering procedure able to discard data for which stiction quantification is very likely to fail.
This paper is organized as follows: in Section 2, the proposed method for stiction quantification is illustrated; in Section 3, the results are presented in simulation; in Section 4, the technique is analyzed on a large number of industrial data and in Section 5, conclusions are drawn.

2. The proposed method

The proposed stiction quantification technique is based on a grid search, a method which is simple and mathematically sound, but may require quite a long computational time. The choice of a grid technique is on purpose, to show that even in this case, unreliable estimates may be caused by the presence of perturbations in the data. Long computational times do not represent a disadvantage for three reasons: the technique is oriented towards an offline application which requires data registered for hours (versus minutes of computational time), the wear phenomena in valves occur slowly (weeks or months) and valves maintenance usually occurs periodically every some years in occasion of plant shutdown.
The control loop is modeled by a Hammerstein system (Figure 1, left). Kano's stiction model describes the non-linear valve dynamics and an ARX (AutoRegressive model with eXternal input) model describes the linear valve and the process dynamics.

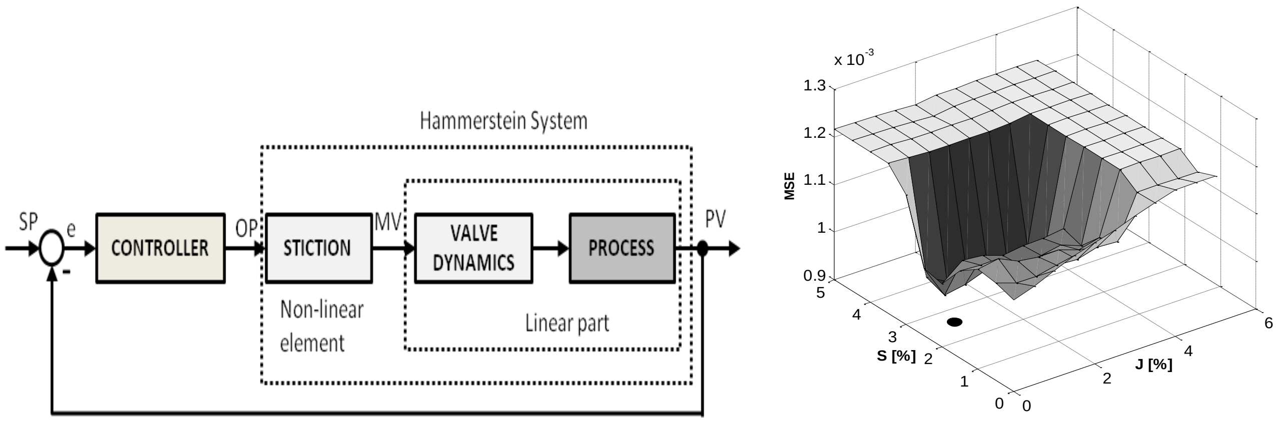

Figure 1: left) Hammerstein system: control loop with valve stiction; right) grid search.

More details about the model are added here to better understand the algorithm. The relation between the controller output (desired valve position) OP and the real valve position MV is described in three phases (Figure 2, left):
1. Sticking: MV is steady and the valve does not move, owing to the static friction force (deadband + stickband, *S*).
2. Jump: MV changes abruptly because the active force unblocks the valve, *J*.
3. Motion: MV changes gradually and only the dynamic friction force can possibly oppose the active force acting on the valve diaphragm (the valve stops again when the force generated by the control action decreases under the stiction force).
Valve stiction produces an offset between control variable PV and Set Point SP and this causes loop oscillation because the valve is stuck even though the integral action of the controller acts and

increases the pressure on valve diaphragm. The MV(OP) diagram shows a parallelogram-shaped limit cycle, while MV(OP) would be perfectly linear without valve stiction. Figure 2 (right) represents the PV(OP) plot for a case of Flow Control loop, for which the fast dynamics allows one to approximate MV(OP) with PV(OP), since MV is usually not measured. To be recalled that also in the case of stiction, loops with slow dynamics (PC, LC, TC) show PV(OP) diagrams having elliptic shapes. Similar paths on PV(OP) are obtained for other types of oscillating loops (external stationary disturbance or aggressive controller tuning) and this creates some problems in assigning causes.

It is worth saying that the value of J is critical to induce limit cycles (Choudhury et al.[17]). However, while S is easy recognizable, J is hardly detectable in industrial data, owing to its small value and the presence of field noise (Figure 2, right).

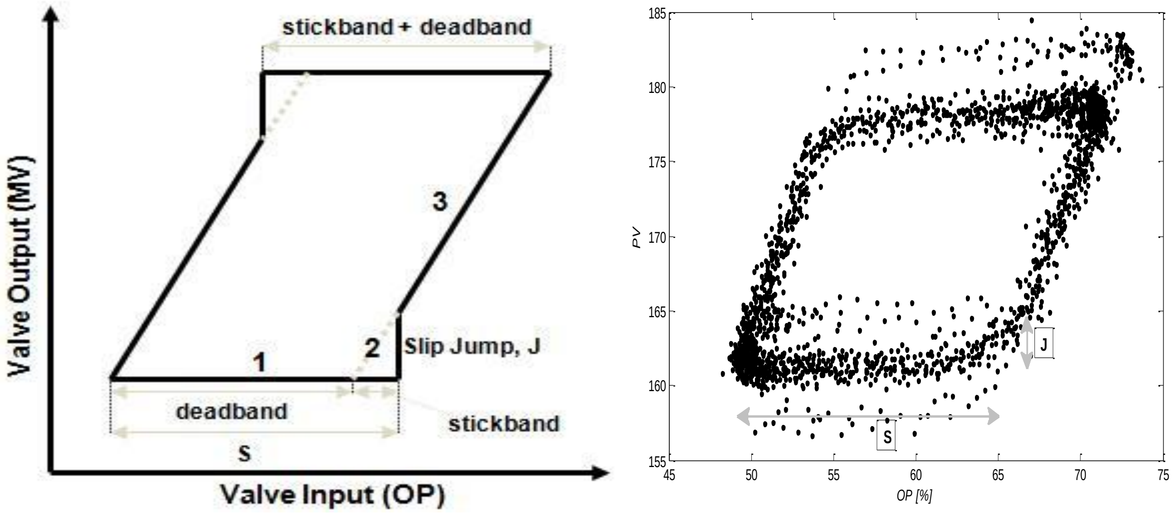

Figure 2: left) valve stiction modelling: MV(OP) diagram; right) typical industrial limit cycle.

The ARX model used has the following structure in discrete time form:

$$y_k = \sum_{j=1}^{n} -a_j \cdot y_{k-j} + \sum_{j=1}^{m} b_j \cdot u_{k-j-L} + e_k \qquad (1)$$

Where y_k denotes the measured value of controlled variable PV at time *k-th*; u_k is the value of manipulated variable MV at time *k-th*; a_j are the coefficients of the vector for PV; b_j are the coefficients of the vector for MV; e_k is the error committed in the prediction. The (n, m) pair is the order of the model and L are the time-delay units of the process.

The proposed method goes as follows: a grid of the two stiction parameters *S/J* is built (Figure 1, right) and, for each possible combination, the MV signal is generated from the measured OP signal using Kano's stiction model. Another grid of possible process time delay L is performed: L is taken as a multiple of the sampling time. For every triad *S/J/L*, the overall vector θ of the coefficients of the ARX model is identified in linear least-square sense based on MV and measured PV. The range of the grid, as well as the order of the ARX model, are discussed afterwards.

The following maximization problem is stated:

$$(\bar{S}, \bar{J}, \bar{\theta}, \bar{L}) = \max_{S,J,\theta}(\max_L(F_2))$$

$$F_2 = 1 - \frac{|\widehat{PV} - PV|_2}{|PV - PV_m|_2} \qquad (2)$$

F_2 is a fitting index related to the mean squared error between measured (PV) and predicted ($\widehat{PV}$) control variable; PV_m is the mean value of PV. F_2 is equal to 1 in the case of perfect estimation and tends to -∞ for large errors.

The stiction parameter grid has a triangular shape to restrict the search space. Overshoot stiction cases ($J>S$) are excluded because the waveforms generated for these combinations are rarely observed in practice. The largest value of S (and J) is the OP oscillation span. Therefore, at boundary conditions (when $S = J$ and $S = OP$ span), the valve jumps between two extreme positions generating an exactly squared wave for MV.

To avoid different estimations depending on the examined time window, data are divided into two sets and the method is applied separately. Two stiction models (S_1/J_1; S_2/J_2) and two linear ARX models (θ_1/L_1,; θ_2/L_2) are identified; consequently two fitting indices are calculated ($F_{2,1}$; $F_{2,2}$).

Then, a comparison of the two data windows is performed using the two specific indices defined below:

$$MD^{NL} = 1 - \frac{|MV_1^{OL} - MV_2^{OL}|_2}{|MV_{1,2}^{OL}|_2} \qquad MD^{LIN} = 1 - \frac{|PV_1^{sr} - PV_2^{sr}|_2}{|PV_{1,2}^{sr}|_2} \tag{3}$$

MD^{NL} is a deviation index between non-linear models. MV_1^{OL} and MV_2^{OL} are respectively the output signal of the first and the second estimated stiction model in response to a specific sinusoidal OP input signal. $MV_{1,2}^{OL}$ is the mean signal of these two. MD^{LIN} is a deviation index between linear models. The output signal of the first (PV_1^{sr}) and the second (PV_2^{sr}) linear model in response to a unitary step are compared; $PV_{1,2}^{sr}$ is the mean signal of these two.

MD^{NL} and MD^{LIN} are equal to 1 when the two responses are exactly the same, that is, when the two couples of stiction parameters and the two linear models perfectly correspond; MD^{NL} and MD^{LIN} tend to -∞ when differences become significant. The identified stiction and linear model parameters are related to the best data set, that is, the one with the highest F_2 index (between $F_{2,1}$ and $F_{2,2}$). In the calibration step, it was found that, to obtain reliable results from the algorithm, the three following conditions have to be satisfied:

$$MD^{NL} > 0.95 \qquad MD^{LIN} > 0.80 \qquad \min\{F_{2,1};\ F_{2,2}\} > 0.80 \tag{4}$$

Concerning the choice of model type, Srinivasan et al.[16] have shown that the accuracy of identification of the non-linear part is not affected by the complexity of the linear model structure. This statement justifies the use of a simple model to describe linear dynamics. The adoption of an ARX model gives an exact solution for the least-square problem and, differently from an ARMAX, implies only an iterative estimation of non-linear parameters. Concerning model order, intensive simulations have shown that an ARX(2,2) model is suitable to quantify stiction with good precision even for complex process dynamics, with acceptable computational times. The step size of stiction parameters (S,J) plays a key role: small values allow one to increase accuracy, avoiding the effect of local minima, at the expense of longer computational times. By assuming as acceptable an error on the estimation of S and J equal to 0.1 (which is 1/1000 of stroke of valve stem, 0-100 %), according to simulation results, a step size equal to 0.05 can be considered adequate. The technique also shows robustness to noise; the errors become significant only in case of Signal to Noise Ratio (SNR) equal or smaller to 2.

These considerations concern the mathematical statement and the solution of the problem. In the perspective of application on industrial data, there are some practical issues which might affect the accuracy of stiction quantification. They are mainly correlated to the presence of different sources of oscillation (with or without valve stiction): irregular oscillations, periodic external disturbances, variable set point loops and incorrect controller tuning 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 procedure is proposed as described in the sequel (compare Figure 3).

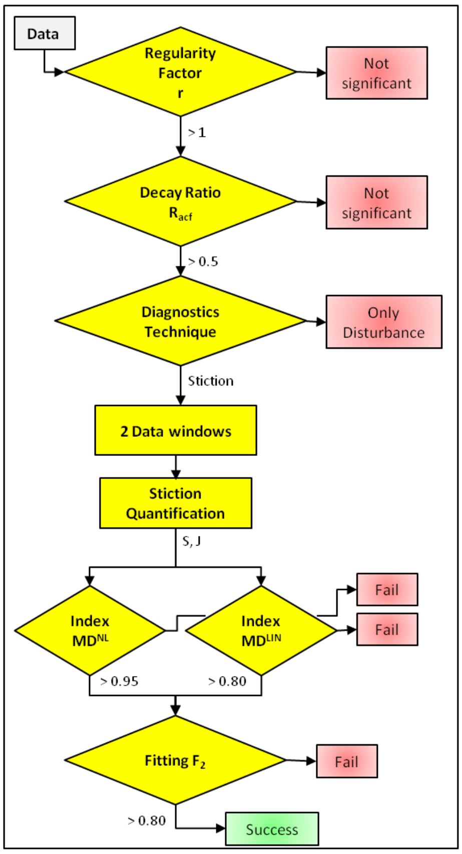

Figure 3: Flow diagram of the proposed technique: oscillation detection, stiction detection, data division and stiction quantification.

Firstly, two appropriate techniques to detect significant loop oscillations are applied. Loop oscillation is, in fact, the main reason for stiction detection. Regularity factor r (Thornhill et al.[24]) and decay ratio R_{acf} (Miao and Seborg[25]) of autocorrelation function (ACF) of control error ($e = PV - SP$) are calculated. If these two indices exceed threshold values, set respectively to 1 and 0.5, as suggested by the authors, the control loop is considered to oscillate significantly (that is: regularly and steadily) and the quantification continues; otherwise the analysis should be stopped, because it is assumed that non-substantial stiction is present.

Secondly, a stiction diagnostic technique is applied to avoid the application of the algorithm when a periodic disturbance is the unique source of oscillation. Among several available techniques (see the list reported in the introduction), the Relay-based technique developed in our laboratory few years ago was adopted (Rossi and Scali[9]). When stiction is not clearly detected, the procedure should be stopped, since the estimated values can be unreliable.

Subsequently, when stiction is detected, data are divided into two sets; stiction quantification is applied separately and results are compared in terms of the indices previously defined.
It is worth saying that the appropriate number of data samples and data sets depend on the whole data length. Usually, a number of data samples which includes at least 4-5 periods of oscillation is needed to have a significant data window; therefore the number of data windows can be just one, two or even more. In the last case, the proposed procedure compares the two best windows in terms of fitting indices F_2.
Next section illustrates the effectiveness of the proposed procedure on simulation results and section 4 on industrial data.

3. Simulation results

As an illustrative example, a control loop is simulated, where the process P is described by a First Order Plus Time Delay (FOPTD) transfer function and the controller C has PI tuned by the Continuous Cycling method of Ziegler-Nichols. Valve stiction is described with Kano's model. Sampling time is set to 1 second. This loop is a specific case study, but the results have general validity, as verified by intensive simulations; other types of process models were used and different values for stiction parameters were adopted.

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

The methodology is applied to different sources of oscillation, as described above. In detail, 10 different cases have been examined (see Table 1):

- In case 1 and 2, the stiction is the only source of oscillation; different amounts of stiction in the valve have been simulated.
- In case 3, the loop oscillates due to Set Point 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 (no stiction).
- In case 6, an aggressive tuning (Kc=3.66) acts together 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.
- In case 10, an irregular disturbance acts with low valve stiction.

Results are reported in Table 1. In columns from left to right: simulated stiction parameters ($S°$, $J°$), regularity and decay ratio factors (r, R_{acf}), diagnosis verdicts issued by the Relay technique, estimated stiction parameters (S, J), models deviation indices (MD^{NL}, MD^{LIN}) and F_2 index.
It can be seen that the oscillation is regular and steady for all cases (except for case 10), as indicated by values of r and R_{acf} 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 might fail (non-zero S and J estimation), but the Relay technique indicates disturbance (not stiction), so these data should not be examined by the stiction estimation algorithm. In cases of simultaneous stiction and disturbance (8 and 9), the Relay

technique correctly indicates 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 indices are above thresholds, but a wrong stiction estimation is obtained.
In case 10, stiction and disturbance act simultaneously, producing an irregular oscillation; therefore the procedure is stopped.

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
10	irregular disturbance + low stiction	0.5	0.5	0.47	0.35	-	-	-	-	-	-

The first conclusions after the simulations are:

- it is confirmed 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 even in case of oscillations caused by Set Point variations and incorrect tuning, with or without the presence of stiction.
- On the contrary, in the presence of external sinusoidal disturbances, the methodology may give wrong stiction estimations. The screening by means of Relay diagnosis technique and checks on the deviation indices of models in the data windows are not enough to eliminate the problem completely, but they can reduce the number of wrong evaluations, sometimes allowing one to reject the (wrong) estimated stiction parameters.
- In the presence of irregular or non-steady oscillation, the procedure is stopped because both stiction diagnosis technique and stem position estimation give unreliable results. Stiction detection and quantification are postponed to a later data registration with significant oscillation.

4. Application to industrial data

As stated in the introduction, the main problem with stiction detection and quantification is that, in industrial data, the *true* position of valve stem (MV) and the *true* value of stiction are not known. Therefore, stiction quantification of an industrial valve - based on a single set of data - can be insufficient, as one single result can be inaccurate and meaningless. On the contrary, the analysis of a large number of valves, under repeated acquisitions, before and after plant shutdown, can be suggested as a sound procedure to validate the proposed technique.
In fact, before valve maintenance, constant or increasing trends of stiction parameters are expected and after maintenance, negligible oscillations and low stiction values are recorded. Repeating the procedure for different acquisitions allows one to follow the evolution of stiction values in time and to disregard anomalous cases (which appear as outliers with respect to the main trend).

The effectiveness of the proposed stiction quantification technique has been checked by its application on a wide number (62) of refinery valves. The data consist in about 750 acquisitions before and after plant shutdown for periodic maintenance. The availability of industrial data is made possible by referring to the archives of a performance monitoring system (PCU, Scali and Farnesi[26]) implemented on refinery units for continuous loop assessment.

As examples of successful application of the technique, the results are presented in the sequel for four control loops which can be considered representatives of general situations.

4.1 Loop #1

This case refers to a pressure loop where the presence of stiction is also evident from visual inspections; 2 different registrations of data are available before valve maintenance (MTA) and one after MTA. The controller has a PI algorithm with parameters set to $Kc = 1$ and $Ti = 0.4$. The first two registrations show oscillations with wide amplitudes, regular ($r > 1$) and steady ($R_{acf} > 0.5$). Large values of stiction parameters are estimated. The procedure gives reliable results because uniform values of S parameter are quantified (see Table 2).

After valve maintenance, no significant oscillation is detected ($r < 1$ and $R_{acf} < 0.5$) and no stiction estimation is performed: the valve operates correctly. The removal of the stiction problem is also confirmed by the comparison of time registrations of SP, PV, OP and estimated values of PV and MV ($\widehat{\mathrm{PV}}$, $\widehat{\mathrm{MV}}$) for one set of data collected before and the one collected after valve maintenance, as shown in Figure 4.

Table 2. Loop #1: valve stiction estimation.

Time	Run #	r	R_{acf}	*Verdict*	S	J	MD^{NL}	MD^{LIN}	F_2
Before MTA	i	6.35	0.93	Stiction	27.8	4.3	0.98	0.83	0.98
Before MTA	ii	5.96	0.94	Stiction	25.9	0.9	0.99	0.97	0.97
After MTA	iii	0.43	0.11	-	-	-	-	-	-

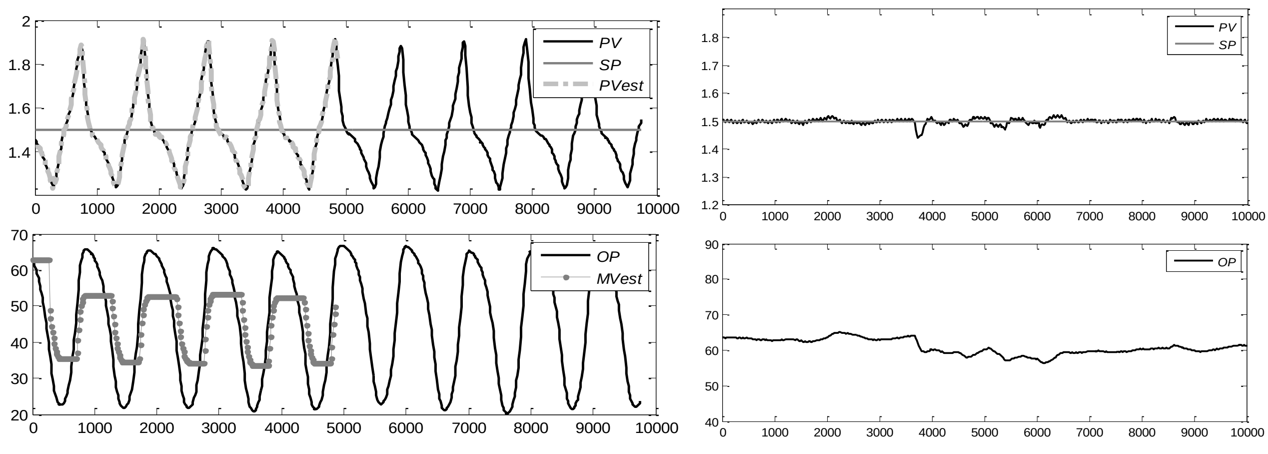

Figure 4: left) Run i (before MTA): wide oscillations due to valve stiction; right) Run iii (after MTA): no significant oscillation.

4.2 Loop #2

For this level loop, 4 different registrations of data are available before valve maintenance and 4 after (see Table 3). The controller has a PI algorithm with parameters always set to $Kc = 4$ and $Ti = 400$. The first 4 registrations show oscillations with wide amplitudes, regular ($r > 1$) and steady (R_{acf}

> 0.5) and the stiction diagnosis is always positive. Therefore, the proposed methodology can be always applied and it estimates large values of stiction. In particular, an increasing trend of *S* parameter is quantified. Note that the methodology is performed on an unique data window because only a few peaks are available due to the long period of oscillation compared to the whole data length available. Therefore, the two deviation indices between models are not calculated. It is worth noticing that these 4 data registrations are close in time (4 months), the Set Point is constant (always equal to 40 %) and the valve works around 15 % of its span. Therefore, the stiction estimations are particularly reliable: the phenomenon is rapidly increasing in time.
The data collected after valve maintenance are completely different. The methodology does not detect any significant oscillation and no stiction estimation is performed. The loop is no longer oscillating because the valve now operates correctly (due to effective valve maintenance).

Table 3. Loop #2: valve stiction estimation.

Time	Run #	SP_m	OP_m	r	R_{acf}	*Verdict*	S	J	F_2
Before MTA	i	40	13	2.97	0.78	Stiction	7.0	5.0	0.98
Before MTA	ii	40	11.5	1.55	0.56	Stiction	7.4	7.4	0.98
Before MTA	iii	40	11.8	2.94	0.89	Stiction	9.0	1.1	0.99
Before MTA	iv	40	17.1	1.44	0.80	Stiction	13.1	8.5	0.98
After MTA	v	50	19.3	0.42	0.25	-	-	-	-
After MTA	vi	50	19.1	0.83	0.31	-	-	-	-
After MTA	vii	55	18.5	0.37	0.36	-	-	-	-
After MTA	viii	50	15.8	0.70	0.47	-	-	-	-

The removal of stiction is also confirmed by the comparison of time registrations of SP, PV, OP, estimated PV and MV ($\widehat{PV}$, $\widehat{MV}$) and PV(OP) diagrams for a set of data collected before and a set collected after valve maintenance (see Figure 5).

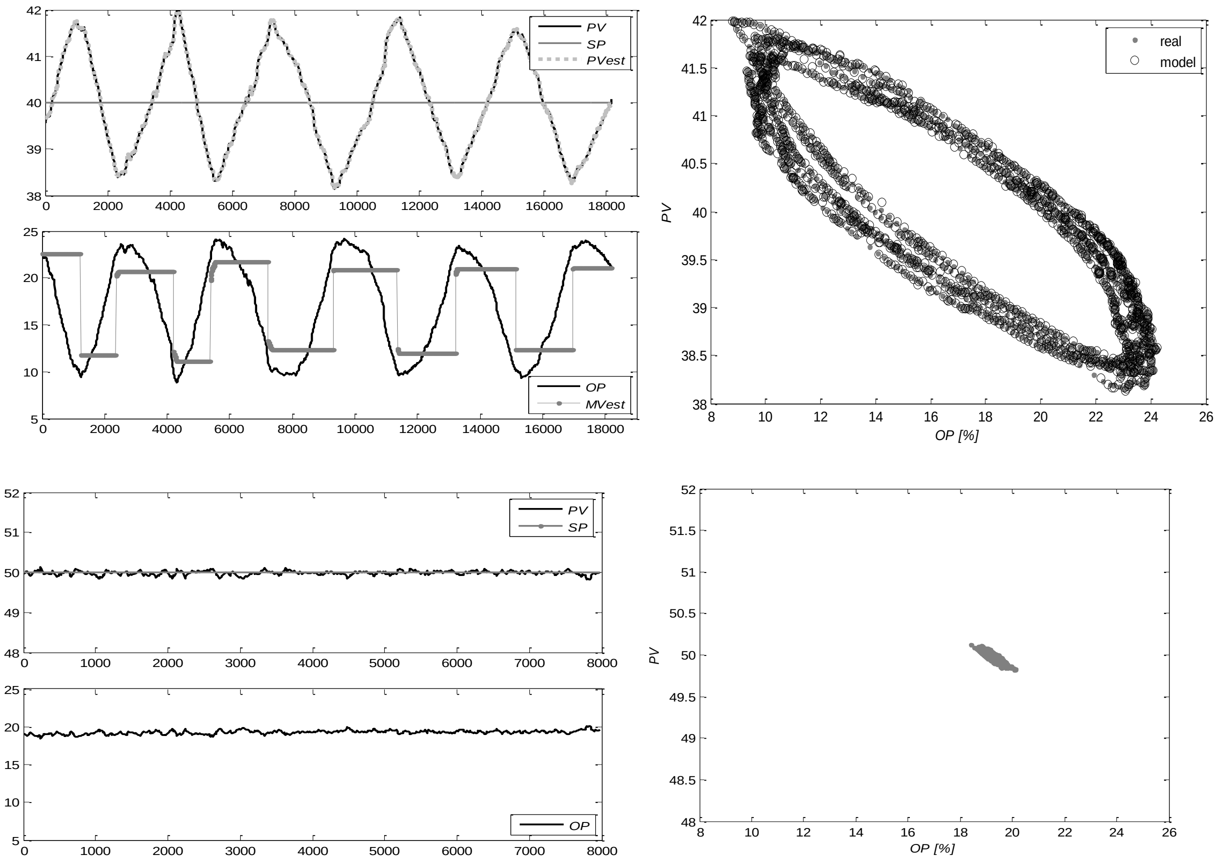

Figure 5: top) Run iv (before MTA:) wide oscillations due to valve stiction and large PV(OP) ellipse-shaped diagram; bottom) Run v (after MTA): no significant oscillation and no limit cycle.

4.3 Loop #3

For this pressure loop, 7 different registrations of data are available before valve maintenance and 4 after. The controller has a PI algorithm with parameters set to Kc = 1 and Ti = 24, apart from acquisition number (vii): Kc = 1.2 and Ti = 36. In this case, the loop operates under MPC control, therefore, the Set Point oscillates (low frequency). Before valve maintenance, significant oscillation is detected in 5 data sets: regular, $r > 1$, and steady, $R_{acf} > 0.5$, excluding run number (ii) and (vi). Significant values of stiction parameters are estimated in 4 cases; MD^{LIN} is under its threshold (0.80) only for acquisition number (v) and this result must be rejected (see Table 4). The procedure gives overall reliable results because uniform values of S parameter are quantified, with mean value equal to 4.9 and little deviation of 0.6. As illustrated in previous simulations, the causes of these three unreliable results might be seen in the presence of perturbations and stiction acting simultaneously.

After valve maintenance, the loop shows good performance and the error signal is close to zero. The procedure detects no significant oscillation.

Table 4: *Loop #3: valve stiction estimation.*

Time	Run #	r	R_{acf}	*Verdict*	S	J	MD^{NL}	MD^{LIN}	F_2
Before MTA	i	2.1	0.62	Stiction	5.5	2.6	0.98	0.88	0.93
Before MTA	ii	0.61	0.56	-	-	-	-	-	-
Before MTA	iii	4.56	0.71	Stiction	5.3	0.8	0.99	0.97	0.93
Before MTA	iv	3.0	0.50	Stiction	4.3	0.05	0.98	0.91	0.93
Before MTA	v	4.52	0.61	Stiction	(3.8)	(0.05)	0.99	0.62	0.93
Before MTA	vi	1.15	0.40	-	-	-	-	-	-
Before MTA	vii	1.75	0.55	Stiction	4.4	0.3	0.99	0.86	0.91
After MTA	viii	1.27	0.47	-	-	-	-	-	-
After MTA	ix	0.49	0.24	-	-	-	-	-	-
After MTA	x	0.47	0.45	-	-	-	-	-	-
After MTA	xi	0.62	0.67	-	-	-	-	-	-

The removal of the stiction problem is also confirmed by the comparison of time registrations for a set of data collected before and a set collected after valve maintenance, as shown in Figure 6.

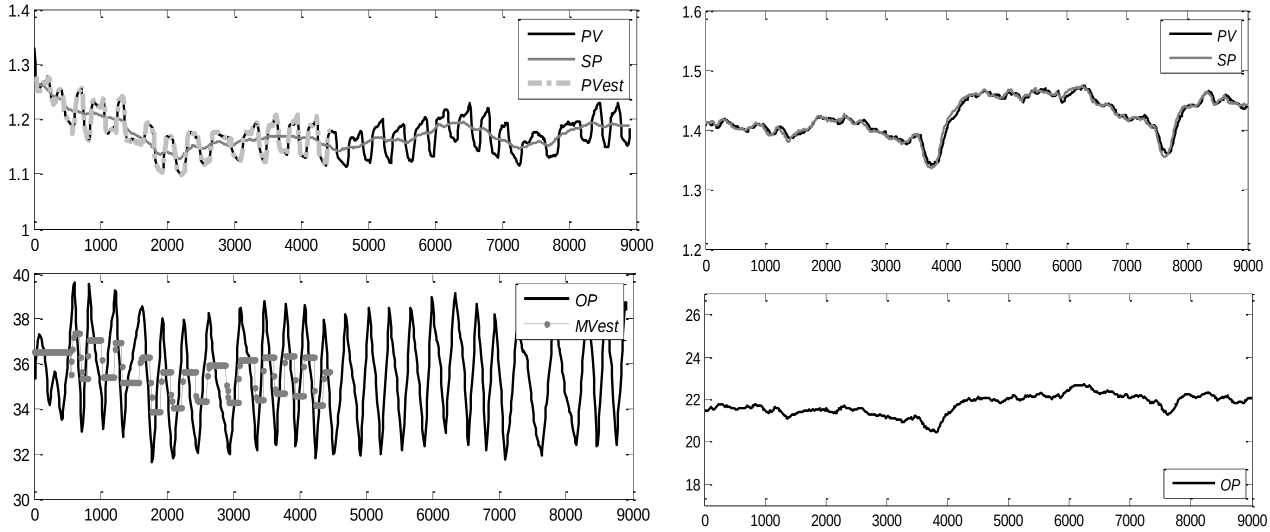

Figure 6: left) Run iv (before MTA): wide oscillations due to valve stiction; right) Run ix (after MTA): no significant oscillation.

4.4 Loop #4

For this pressure loop, 10 different registrations are available before valve maintenance and 3 after (see Table 5). The controller has a PI algorithm with parameters always set to Kc = 1 and Ti = 21. Before valve maintenance, regular and steady oscillation is detected in 8 data sets, except run number (iii) and (ix). For acquisitions number (v) and (viii), MD^{LIN} is under its threshold and these results must be rejected. Stiction parameters are accepted in the other 6 cases, but uniform values of parameter S are quantified only in 5 registrations. Number (vi) seems to be a case of unreliable results, because its value differs a lot from the general stiction trend (mean value of 15 with deviation of 1). The proposed filtering methodology allows one to discard only registration number (v) and (viii), but would accept results for number (vi). Also for this loop, the causes of unreliable results might be seen in the presence of perturbations and stiction acting simultaneously.

Unlike the previous three loops, this loop still shows significant oscillation in all three acquisitions after valve maintenance and uniform values (9-10%) of stiction are now quantified. A possible explanation could be unresolved stiction despite valve maintenance or a recurrence of stiction. It is worth noticing that, in this case, after plant shutdown, the loop starts to operate under MPC control and this explains why Set Point oscillates (low frequency).

Table 5: Loop #4: valve stiction estimation.

Time	Run #	*r*	R_{acf}	*Verdict*	*S*	*J*	MD^{NL}	MD^{LIN}	F_2
Before MTA	i	1.09	0.56	Stiction	15.3	7.1	0.99	0.88	0.85
Before MTA	ii	1.11	0.66	Stiction	16.5	11.0	0.93	0.84	0.87
Before MTA	iii	1.41	0.38	-	-	-	-	-	-
Before MTA	iv	1.02	0.56	Stiction	15.2	2.59	0.99	0.89	0.92
Before MTA	v	3.36	0.61	Stiction	(13.3)	(0.2)	0.96	0.01	0.87
Before MTA	vi	1.38	0.57	Stiction	[6.3]	[0.1]	0.99	0.90	0.84
Before MTA	vii	2.24	0.63	Stiction	14.0	7.0	0.99	0.82	0.95
Before MTA	viii	1.36	0.62	Stiction	(13.4)	(3.2)	0.94	-0.26	0.87
Before MTA	ix	0.47	0.25	-	-	-	-	-	-
Before MTA	x	0.95	0.68	Stiction	14.2	1.26	0.97	0.87	0.85
After MTA	xi	19.4	0.88	Stiction	10.6	2.2	0.99	0.86	0.96
After MTA	xii	0.79	0.57	Stiction	9.1	1.0	0.98	0.96	0.94
After MTA	xiii	4.28	0.61	Stiction	9.3	4.5	0.99	0.94	0.95

The presence of stiction, both before and after valve maintenance, is confirmed by the comparison of time registrations, as shown in Figure 7.

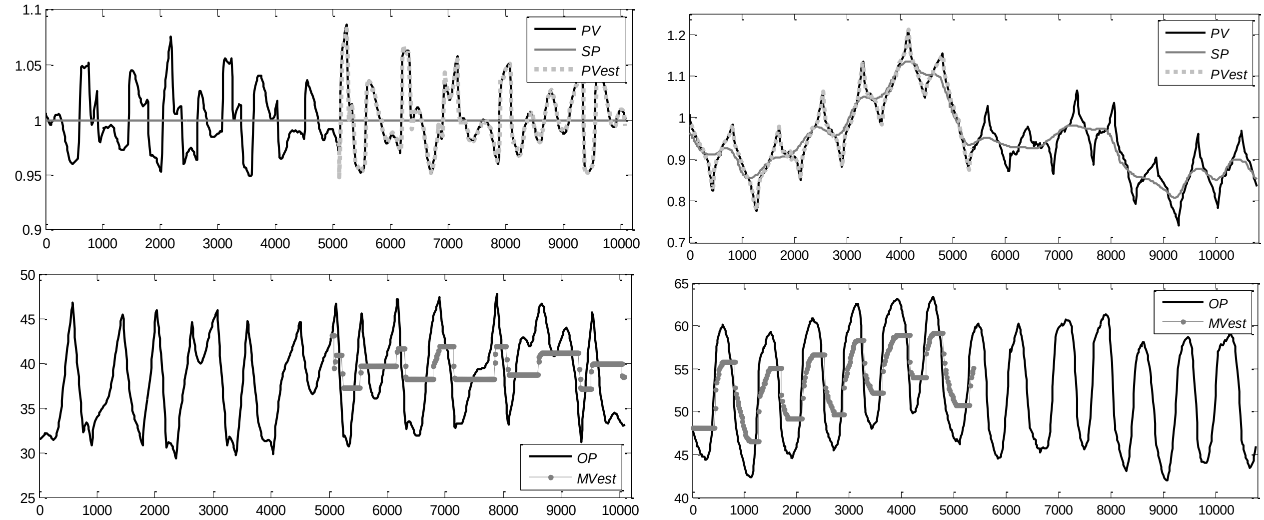

Figure 7: left) Run x (before MTA): wide oscillations due to valve stiction; right) Run xi (after MTA), still significant oscillation - again valve stiction.

Results for the four different loops illustrated above are synthesized in Figure 8, where values of the stiction parameter *S* are reported for different time acquisitions. Before valve maintenance (MTA), loops #1, #3 and #4 have almost constant values of stiction, while loop #2 shows an increasing trend. Trends are drawn only on the basis of values considered reliable; disregarded cases and motivations are repeated here: runs ii and vi for loop #3 and runs iii and ix for loop #4 (irregular oscillations); run v for loop #3, runs v and viii for loop #4 (different results in the two windows of data); run vi for loop #4 (outlier with respect to the main trend).

After maintenance, no significant oscillation is detected for loop #1, #2 and #3 and negligible values of stiction are estimated; on the contrary, significant values of stiction are still quantified for loop #4.

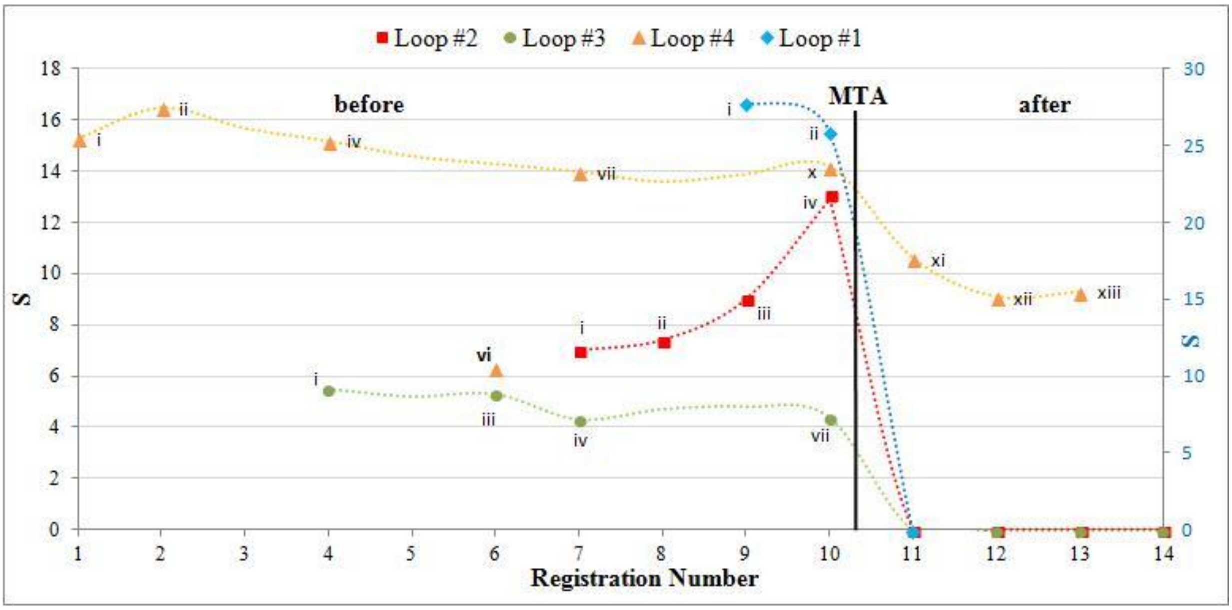

Figure 8: Trends of stiction parameter S before and after valve maintenance.

As global considerations, the proposed procedure has allowed us to issue results which are considered reliable for 43 out of 62 industrial loops examined. The other 19 loops are cases of unreliable results probably due to the presence of perturbations and stiction acting simultaneously. This result can be considered encouraging, taking into account that different perturbations may be present in an industrial environment.

5. Conclusions

Stiction quantification is certainly important for valve monitoring and maintenance scheduling. In the perspective of application on industrial data, the first problem consists in the lack of knowledge about the *true* valve stem position (MV) and the *true* stiction values. In addition, the presence of irregular perturbations and of different sources of oscillation acting simultaneously might affect the accuracy of any estimation technique.

The proposed methodology, based on a grid search and a filtering procedure, permits one to discard data for which stiction quantification is very likely to fail. It allows reliable quantification when stiction is the only cause of oscillation and even in the case of stiction together with incorrect tuning and setpoint variation. However, the technique may fail in the case of simultaneous presence of disturbances and stiction. Repeating the procedure for different acquisitions for the same valve allows one to follow the evolution of stiction values in time and to disregard anomalous cases (outliers). Therefore, even though it is not sufficient to eliminate the problem completely, the methodology is able to reduce the number of wrong evaluations. Successful applications on 43 out of 62 industrial loops demonstrate the effectiveness of the proposed method which seems to be valid for valve stiction monitoring and for valve maintenance scheduling and checking.

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