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Review

Review on Valve Stiction. Part I: From Modeling to Smart Diagnosis

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Abstract: Valve stiction is indicated as one of the main problems affecting control loop performance and then product quality. Therefore, it is important to detect this phenomenon as early as possible, distinguish it from other causes, and suggest the correct action to the operator in order to fix it. It is also very desirable to give an estimate of stiction amount, in order to be able to follow its evolution in time to allow the scheduling of valve maintenance or different operations, if necessary. This paper, in two parts, is a review of the state of the art about the phenomenon of stiction from its basic characterization to smart diagnosis, including modeling, detection techniques, quantification, compensation and a description of commercial software packages. In particular, Part I of the study analyzes the most significant works appearing in the recent literature, pointing out analogies and differences among various techniques, showing more appealing features and possible points of weakness. The review also includes an illustration of the main features of performance monitoring systems proposed by major software houses. Finally, the paper gives indications on future research trends and potential advantages for loop diagnosis when additional measurements are available, as in newly designed plants with valve positioners and smart instrumentation. In Part II, performance of some well-established methods for stiction quantification are compared by applications to different industrial datasets.

Keywords: control loop performance monitoring; oscillation detection; stiction detection and quantification

1. Introduction

Valve malfunctions, hysteresis, backlash, dead-band, and especially stiction, have been known since early times to be important causes of performance deterioration in control loops [1]. They affect plant routine operation and force periodical shutdown to remove them; therefore, they influence the overall product quality and plant economy.

Oscillations in process variables, induced by stiction, can be confused with other causes as incorrect tuning, presence of external disturbances, multi loop interaction and other valve internal problems. In addition they cannot be eliminated by controller detuning or by the presence of valve positioners.

Therefore, the problem must be diagnosed as early as possible and appropriate actions to take should be suggested to the plant operator. This explains the large research effort on the subject, carried out by academic research in the last years, facing different aspects of the phenomenon. As fall out, the techniques originated by research work have been adopted in most commercial software packages, initially proposed mostly for retuning purposes.

Several review works also appeared, even though mostly devoted to specific issues: on stiction detection techniques [2–5]; on stiction models [6], and on stiction compensation methods [5,7]. Global reviews, not including smart diagnosis, have been recently proposed by [8,9].

Following this short recall about the impact of valve stiction, this paper aims to be a comprehensive survey of the most significant works concerning the phenomenon of valve stiction, starting from modeling and ending with potentiality made possible by smart instrumentation. The survey consists of pointing out analogies and differences among several recent techniques and showing their more appealing features and possible weak points. Results from the comparison of different approaches are synthesized in tables reporting significant indices of merit. Section 2 presents an illustration of basic aspects of the phenomenon and related oscillations in the control loop, while Section 3 presents more established models to reproduce its effects. Section 4 is devoted to the illustration of stiction detection techniques, to recognize its presence since the early stage, and Section 5 covers stiction quantification methods which allow one to estimate the amount of stiction and its evolution in time. Section 6 deals with compensation techniques, and Section 7 with possibilities created by the availability of additional measurements (smart instrumentation). Part I of the paper ends with Section 8, where features of different commercial and academic software packages are synthesized, followed by Section 9 where conclusions are drawn.

2. Phenomenon Description

The word stiction results from the contraction of static and friction and was coined to emphasize the difference between static and dynamic friction. Despite the large number of works about friction, only Choudhury *et al.* [10] have tried to define such phenomenon formally and have proposed a description of the mechanism, thus differentiating it from similar malfunctions, as backlash, hysteresis, dead-band. Stiction is defined as a “property of an element such that its smooth movement in response to a varying

input is preceded by a sudden abrupt jump called the ‘slip-jump’. Slip-jump is expressed as a percentage of the output span. Its origin in a mechanical system is static friction which exceeds the friction during smooth movement”. The phenomenon is measured as the difference between the final and initial position values required to overcome static friction. For instance, 5% of stiction means that when the valve gets stuck, it will restart to move only after the difference between the control signal (OP) and the valve stem position (MV) exceeds 5%. Note that 1% of stiction is considered enough to cause performance problems [11].

The very first challenge for process control purposes is to evaluate the significance of the oscillation. Techniques which detect significant loop oscillation can be broadly classified into the following categories [12]: (i) time-domain approaches, e.g., integral absolute error (IAE) and autocorrelation function (ACF) methods; (ii) frequency domain approaches, e.g., fast Fourier transform (FFT) method; and (iii) hybrid approaches including wavelet transform (WT) method. Once single/multiple significant oscillations have been identified, the hard following step is to assess the sources of these malfunctions. Therefore, stiction analysis is also strictly linked with the more general issue of oscillation diagnosis.

Hägglund [13] first proposed a simple oscillation detection technique based on the IAE of subsequent zero-crossings of the control error (e), between Set Point (SP) and Controlled Variable (PV). Then, Forsman and Stattin [14] improved this method by regularizing the upper and lower IAEs. In parallel, Miao and Seborg [15] developed a technique using a decay ratio index of the autocorrelation coefficients of the control error. Thornhill *et al.* [16] introduced a regularity index of the zero-crossings in the ACF to assess loop oscillation, but its accuracy is limited by the manual choice of band pass filters in the case of multiple oscillations. In the meanwhile, Matsuo *et al.* [17] presented an oscillation detection approach with wavelet transform. More recent techniques include discrete cosine transform (DCT) by Li *et al.* [18] and empirical mode decomposition (EMD) by Srinivasan R. *et al.* [19], and by Srinivasan B. and Rengaswamy [20], which also provide solutions for nonstationary data. Zakharov and Jämsä-Jounela [21] proposed a method by identifying peak positions of the dominant frequency component in oscillating signals. The technique is compared against five other methods reported in the literature and also introduced two indices to quantify the mean-non stationarity and the presence of noise.

Very recent techniques are able to detect multiple oscillations in control loops. Naghoosi and Huang [22] detect and cluster the peak values of the ACF of the variables. No frequency-selection filtering is required in order to separate different oscillations. In parallel, Guo *et al.* [23] propose a detection technique of nonstationary multiple oscillations based on an improved wavelet packet transform (WPT), which integrates Shannon Entropy with a non-Gaussianity test and a quasi-intrinsic mode function index. Recently, Srinivasan B. *et al.* [24] also developed an integrated approach to identify and detect single and multiple sources of loop oscillation.

When stiction appears, the behavior of a control loop deteriorates producing steady-state control errors or unwanted oscillations and limit cycles in MV and, therefore, in PV and OP (Figure 1). A control loop characterized by high valve stiction shows particularly poor performance. Increasing the amount of stiction, the amplitude and the period of oscillation of OP and PV signals increase significantly, and the oscillation behavior is also altered [25]. Ideally, the limit cycles caused by stiction are characterized by distinctive wave shapes from those caused by other sources of malfunction. The stem velocity of a sticky valve remains at zero for a certain period of time, producing a square-shaped MV signal, while other sources generate limit cycles behaving more as sinusoidal waves.

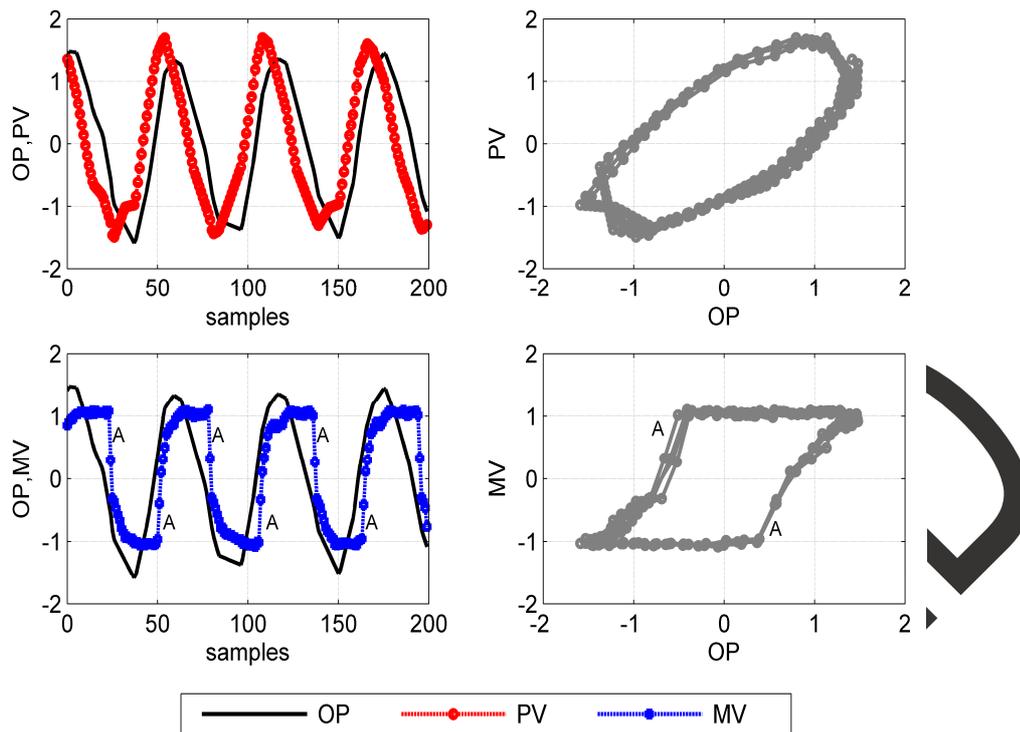


Figure 1. Limit cycles of a sticky valve: (left panels) oscillating time trends of PV, OP, and MV; (top right) PV(OP) diagram; (bottom right) MV(OP) diagram.

The distinctive signature of a control valve affected by stiction can be observed in the MV(OP) diagram: a parallelogram-shaped pattern is registered (Figure 1, bottom right). The valve is stuck even though the integral component of the controller increases the active force on the stem. Then, the valve jumps abruptly when the active force overcomes friction forces (marked as *A* in Figure 1), and it moves with a offset respect with the desired position. Note that this signature is typical both of a sticky pneumatic valve and a sticky electric valve. These two types of valve differ only for the actuator, while the valve body, subjected to the majority of friction forces, is the same.

Unfortunately, MV signal is hardly available in practice; therefore MV(OP) diagrams are rarely accessible. Flow control loops, with fast dynamics, allow one to approximate MV with PV and to assess stiction presence on PV(OP) diagram. Conversely, loops with slower dynamics (level control, temperature control) show PV(OP) diagrams having elliptic shapes also in the case of stiction (Figure 1, top right). But, similar paths on PV(OP) are obtained also for other types of oscillating loops: external stationary disturbance or aggressive controller tuning. Furthermore, the presence of field noise and the cases of simultaneous sources of oscillation can significantly alter waveforms, making the diagnosis a very difficult task simply by using OP and PV signals.

3. Stiction Modeling

Different approaches have been proposed to model stiction, although all of them represent a tradeoff between accuracy and simplicity. Stiction models can be classified into two major categories: first-principle and data-driven models [10]. The first-principle models use the balance of forces and Newton's second law of motion to describe the physics of phenomenon and fall into two classes: static

or dynamic friction models. The static models describe the friction force using time-invariant (static) functions of the valve stem velocity. Conversely, in the dynamic models there are time-varying parameters. Two well-known examples of first-principle stiction models are reported in pioneering works by Karnopp [26] and Canudas de Wit *et al.* [27].

A detailed first-principle stiction model requires the knowledge of several parameters that are difficult to estimate, such as the diaphragm area, the air pressure, the spring constant and the stem mass. In addition, computational times of such models may be too long for practical purposes. Since data-driven modeling approaches overcome these two disadvantages, several works in this direction have been reported in the literature. However, such empirical models also present some drawbacks. In fact, they cannot fully capture the dynamics of the valve, since—for example—not all the proposed models passed the specific tests applied following standards of International Society of Automation (ISA) [6]. Only empirical models will be discussed in the sequel, being the scope of this paper also to make use of stiction models in order to compare different quantification techniques based on them.

Stenman's, Choudhury's, Kano's, and He's models are nowadays widely adopted data-driven models. The first model, proposed by Stenman *et al.* [28], reproduces the jump of the valve stem after the stickband through a single parameter (d).

Afterwards, Choudhury *et al.* [10] showed that the predicted and observed behaviors of the Stenman's model do not match in the case of a sticky valve excited with a sinusoidal input. A different version of the model was suggested in order to improve the representation of the phenomenon. The new model contains two parameters: the amplitude of deadband plus stickband (S), and the amplitude of the slip-jump (J).

Since Choudhury's model was able to cope accurately only with deterministic signals, Kano *et al.* [29] developed a modified version that can handle broader situations. Trying to relate the parameters of the empirical model with physical variables, the two stiction parameters were redefined. In their model, S and J correspond to the sum and to the difference of static and dynamic friction, respectively. Note that these parameters are quantitatively equivalent to those of Choudhury's model, but, for a given input signal OP , the two models can produce different MV signals with the same values of parameters.

He *et al.* [30] developed a novel model that reduces the complexity of the two previous formulations. Despite the structural simplification, the model, with a more straightforward logic, naturally handles stochastic signals. This model also uses two parameters, static f_S and dynamic f_D friction, but it is closer to the first-principle-based description. To reduce the complexity, it uses a temporary variable that represents the accumulated static force.

These three two-parameters models describe the behavior of a sticky valve on the $MV(OP)$ diagram through a sequence of three components (Figure 2):

- (1) *deadband + stickband*. When the valve stem arrives to a rest position or changes the direction, the valve sticks (point A). While it does not overcome the frictional forces, the valve maintains the position (AC) resulting in deadband (AB) and stickband (BC).
- (2) *slip-jump*. After overcoming the static friction, the valve converts the potential energy stored in the actuator into kinetic energy, jumping in an abrupt way to a new position (from C to D).

- (3) *moving phase*. Once the stem jumps, it continues to move until it eventually sticks again because of a stop or inversion of the direction of the movement (between G and H). During the moving phase, the stem may have a reduced velocity. This condition may stick the valve again while it keeps its traveling direction; in this case, only stickband is present (between E and F).

The parameters of He's model have their equivalent in Kano's and Choudhury's models, according to simple equations: $S = f_s + f_d$; $J = f_s - f_d$ (Figure 2). However, due to different logics, He's stiction model can generate a very different MV sequence for a given OP signal and with equivalent stiction parameters.

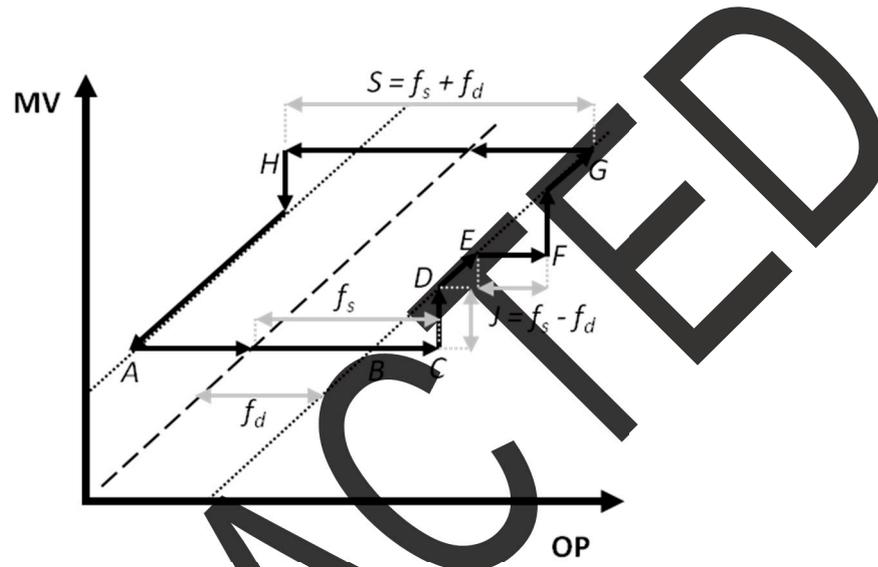


Figure 2. MV(OP) Diagram: Modeling a sticky valve with a standard two-parameters model.

Choudhury's and Kano's models were subsequently compared in ([11], Chap. 2): both proved to predict satisfactorily the stiction effects. It is worth underlining that these two models assume that the valve moves slowly and stops only when the control signal changes its direction or the same signal is applied for two consecutive sampling intervals. Conversely, He's model specifically assumes that the static friction is associated with all valve movement, that is, the valve is sufficiently fast—and not *sluggish* as in the other two models—to stop at the end of each sampling interval.

Following this line, He and Wang [31] have then proposed a semiphysical model to better reproduce the first-principle model predictions. Three parameters are now used: K , the overshoot observed in the physical model, which is proved to be substantially constant ($K = 1.99$), f_s , the static friction force, and f_d , the dynamic friction force.

Other data-based models have also been presented in the literature. Chen *et al.* [32] modified the first He's model by introducing a two-layer binary tree logic. Although two extra variables are added, the approach generalized static and dynamic friction, improving the inclusion of various types of stiction patterns. In parallel, Ivan and Lakshminarayanan [33] simplified the first He's model proposing a one-parameter model specifically oriented to stiction quantification and compensation. An improved version of Choudhury's model, termed as the XCH model, has been proposed by Xie *et al.* [34]. This model passed all the ISA standard tests providing a more accurate simulation of a real industrial valve affected by stiction. Karthiga and Kalaivani [35] proposed a novel nonlinear data-driven model considering three parameters: the deadband (d), the maximum pressure required to move the stem (u_{max}),

and the stick-slip magnitude (f). Very recently, Li *et al.* [36] revised the previous model of Chen *et al.* [32] to overcome its limitations in handling instantaneous input commands on reverse motion. The accuracy of the revised model is validated using the full set of ISA standard tests.

Note that all the previous data-driven stiction models imply uniform parameters for the whole valve span. Conversely, stiction could be inhomogeneous, having various amounts for different operating conditions—that is different OP values—and then producing complicated signatures on MV(OP) diagram. In order to overcome these limitations, Wang and Zhang [37] proposed two point-slope models to describe the ascending and descending paths of valve stem, so that asymmetric stiction can be captured. An even more flexible model has been recently introduced by Fang and Wang [38]. This new type of model (Preisach-type), can deal with complicated patterns of sticky control valves and encloses the classical data-driven stiction models as special cases, at the expense of a very complex and non-parametric modeling.

Recently, Daneshwar and Noh [39] developed a model for the whole process with sticky valves, which can be used in controller design to mitigate stiction-induced oscillations. A dynamic fuzzy model of Takagi–Sugeno-type is derived through an iterative well-developed fuzzy clustering algorithm; model parameters are then estimated through least-squares regression.

In Table 1, all stiction models reviewed in this survey are synthetically compared, showing their more appealing features and possible weak points.

Table 1. Synthesis of data-driven stiction models.

Model	Features				
	Stiction Parameters	Auxiliary Variables	Application on Industrial Data	Pros	Cons
Stenman <i>et al.</i> [28]	1 (d)		√	simple	inaccurate
Choudhury <i>et al.</i> [10]	2 (S, J)	I, x_{ss}	√	established	no stochastic signals
Kano <i>et al.</i> [29]	2 (S, J)	stp, d, u_s	√	accurate	-
He <i>et al.</i> [30]	2 (f_s, f_d)	u_r	√	accurate	-
He and Wang [31]	3 (f_s, f_d, K)	-	√	accurate	recently stated
Chen <i>et al.</i> [32]	2 (f_s, f_d)	$stop, cum_u$	√	accurate	-
Ivan and Lakshminarayanan [33]	1 (f)	u_r	√	accurate	-
Xie <i>et al.</i> [34]	2 (S, J)	I, x_{ss}	×	accurate	recently stated
Karthiga and Kalaivani [35]	3 (d, u_{max}, f)	-	×	accurate	recently stated
Li <i>et al.</i> [36]	2 (f_s, f_d)	$stop, cum_u$	×	accurate	recently stated
Wang and Zhang [37]	many	-	√	flexible	recently stated
Fang and Wang [38]	many	-	×	flexible	very complex
Daneshwar and Noh [39]	many	-	√	flexible	very complex

Symbols: “×”, no; “√”, yes.

Observing Table 1, it is clear that first stiction models (e.g., [10,28]) are more established in the literature, but, at the same time, they show some basic inaccuracies. Conversely, more recent models potentially allow better performance but should be further applied to industrial data for a complete validation.

4. Detection Techniques

Many techniques for stiction detection have been proposed in the literature. Following Jelali and Huang [11], they can be broadly classified into four categories: cross-correlation function-based [40], limit cycle patterns-based (e.g., [29,41,42]), nonlinearity detection based (e.g., [43,44]), and waveform shape-based (e.g., [30,45–47]).

Typically, specific indices are computed using recorded time trends of OP and PV; thresholds values are then established after simulations and applications on industrial data. Most of these detection methods, assuming the presence of a significant oscillation in the control loop, have the main objective of operating a distinction between external disturbance and valve stiction. Reliability is usually reduced in the case of contemporary presence of stiction and disturbances.

The first technique to diagnose oscillations can be considered the one developed by Horch [40]. The method is based on the cross-correlation between OP and PV signals and is applicable to non integrating processes controlled by proportional-integral (PI) controllers.

Later, Horch [48] developed a method specific for integrating processes using the probability density function (PDF—approximated with the normalized raw histogram) of the second derivative of the process output. Basically, theoretical PDFs characteristic of the stiction and non stiction cases are compared with the PDF of the measured PV. The best fit determines whether stiction is present. Similarly, PDF of the first derivative of the error signal is used for self-regulating processes.

Kano *et al.* [29] proposed two methods based on the relationship between the valve input OP and the valve output MV. The MV(OP) diagram shows a parallelogram-shaped limit cycle in case of a sticky valve (Figure 1), while it would be linear without stiction. However, since MV is frequently unmeasured, this signal is substituted by the controlled variable PV. This approximation can be considered reasonable for the case of fast dynamics (flow control loop FC), whereas it may yields large errors in the case of loops with slower dynamics (level control LC, temperature control TC), for which PV(OP) diagram shows cycles with elliptic shapes.

Yamashita [41] also proposed a detection method based on typical patterns on MV(OP). The valve movements are classified using the notation I (for increasing), D (for decreasing), and S (for steady), and specific sequences of these letters represent the stiction pattern. The idea consists of counting the number of periods of sticky movement and calculates three weighted indices. These indices, which vary between 0 and 1, detect stiction if their values are greater than the threshold value of 0.25, typical of a random signal.

Scali and Ghelardoni [42] investigated the performance of Yamashita's method using a large number of industrial flow control loops and concluded that the method correctly identifies the presence of stiction in 50% of the cases. The authors improved also the original method introducing additional MV(OP) reference patterns and computing corresponding detection indices.

Very recently, Daneshwar and Noh [49] presented a stiction detection technique for flow control loops based on a well-developed fuzzy clustering approach. Observing a dramatic change of the slope of the lines obtained from successive cluster centers in the presence of stiction, a performance index to distinguish different causes of oscillation is proposed.

Yamashita [50] also developed a technique for systems with slower dynamics, such as the LC loops, based on a simple index that evaluates the excess kurtosis. A loop suffering from stiction presents a two-peak distribution of the first derivative of PV, which means a negative large value of excess kurtosis.

Farenzena and Trierweiler [51] also tackled the problem for integrating loops. They used the PV patterns of a valve with backlash or stiction to detect the phenomena and distinguish between them. An index is computed on the first-order derivatives, but the diagnosis seems to be affected by the sampling time and the tuning of the controller.

The presence of nonlinearity in the signals can mean that stiction is the possible source of oscillation. Choudhury *et al.* [43] proposed a method based on higher-order statistical techniques, as cumulants, bispectrum, and bicoherence of the control error signal in order to infer two metrics: the non-Gaussianity index (NGI) and the nonlinearity index (NLI).

Other approaches applied the surrogate analysis to evaluate the nonlinearity of a signal. Thornhill [44] developed a method to compare the signal and its surrogate data predictability, using a specific index. The surrogate data provide a reference distribution against which the properties of the signal under test may be evaluated. Once the signal is more structured and more predictable than the surrogate data, the method evaluates the distribution properties of the original signal and of the respective surrogate data. Mohammad and Huang [52] presented a detection method designed for multiloop control systems using both surrogate analysis and qualitative shape-based approach. The method has the peculiarity to detect multiple sticky valves.

The first technique based on qualitative shape analysis for stiction detection was presented by Rengaswamy *et al.* [53]. Seven types of primitives and a complex neural network were used to detect and diagnose different kinds of oscillations.

The approach of Srinivasan *et al.* [45] consisted of pattern recognition using the dynamic time warping technique. An optimal alignment between measured data and a stiction template pattern for each oscillating cycle and a global pattern for the whole dataset is performed. The method was tested in different scenarios including non constant behavior, intermittent stiction, and external disturbances.

The Relay technique, developed by Rossi & Seali [46], is based on the fitting of significant half cycles of the oscillation by means of three different models: a sine wave, a triangular wave and the output response of a first order plus time delay under relay control. The last one is specifically suitable to approximate square waves shapes generated by stiction and modified by the process dynamics. Once fittings have been performed, a Stiction Identification Index (SI) is defined.

This technique presents analogies with the Curve Fitting method proposed by He *et al.* [30] in which, assuming that stiction is associated to a square wave in MV, a triangular wave is looked for as the distinctive feature of stiction after the first integrator element of the loop. This means in the OP signal (for self regulating processes) or in the PV signal (for integrating processes), the Relay method always analyses the PV signal and uses the relay shape as an additional primitive.

Singhal and Salsbury [47] proposed a method based on the calculation of the ratio between areas before and after the peak of an oscillating signal using the quantity R . The decision rule is then summarized as: if $R > 1$, the valve is sticking, but if $R \approx 1$, the controller is aggressive. The method is not applicable to integrating processes and does not distinguish stiction from other nonlinearities. In addition, noisy signal and sampling times must be carefully considered to avoid misleading results.

The detection method of Hägglund [54] is also based on a shape analysis of the waves. The final decision relies on the averaged value of a normalized index, which involves the fitting of the control error signal between two consecutive zero crossings. If the fitting corresponds best to a sine wave, no stiction is assessed; otherwise, if a square wave is best fitted, stiction is detected.

Zabiri and Ramasamy [55] developed a method that calculates an index based on nonlinear principal components analysis (NLPCA) using the distinctive shapes of the signals caused by stiction and other sources. Together with its coefficient of determination, the index quantifies the degree of nonlinearity and determines the presence of stiction.

Ahmed *et al.* [56] also presented a stiction detection technique based on waveform shape. Data compression is used to compare patterns of a sinusoidal or exponential signal with a triangular signal. The basic idea is that triangular signals can be better compressed, since they can be approximated by a combination of straight line segments. A relative compressibility index is specifically defined so that a positive value is an indicator of integrating process with stiction and a negative value means self-regulating process with stiction; a close-to-zero value indicates no stiction.

In parallel, Ahammad and Choudhury [57] proposed a method based on harmonics analysis. The control error signal is decomposed using Fourier series. Amplitude, frequency and phases of each term of Fourier series expansion are estimated using least-squares regression technique. Then, the harmonic relationship among the frequencies is examined: odd harmonics indicate the presence of stiction.

Zakharov *et al.* [58] proposed a stiction detection system that selects four detection algorithms based on characterizations of the data. Novel indices are proposed: the presence of oscillations, mean-nonstationarity, noise and nonlinearities are quantified. The selection is then performed according to the conditions on the index values in which each method can be applied successfully. Finally, the stiction detection decision is given by combining the detection decisions made by the selected methods.

Table 2 briefly compares all stiction detection techniques reviewed in this survey, reporting the type of algorithm and the field of application.

In conclusion, stiction detection can be considered an established research area, even though different diagnosis techniques may not give the same verdict once applied on industrial data. Therefore, knowing the strengths and the weaknesses of different methods, it is possible to obtain a more reliable final detection decision by combining and weighting verdicts of different techniques.

5. Stiction Quantification

The ability of providing an estimate of stiction amount is a crucial step before scheduling valve maintenance or performing on-line compensation. While stiction modeling and detection can be considered relatively mature topics, stiction quantification should be considered still an open issue [11] and, consequently, a fervent research area. Some techniques perform detection and quantification of stiction in a single stage, while other methods can be applied only once stiction is clearly detected.

The first contributions about stiction quantification have proposed simple metrics to infer the amount of stiction without requiring the use of specific models of valve stiction and process dynamics.

Firstly, Choudhury *et al.* [59] quantified stiction by fitting an ellipse on the PV(OP) diagram and computing the maximum width of this ellipse. The authors also proposed two other simple algorithms, *c-means* and *fuzzy c-means* clustering, to estimate the degree of stiction on PV(OP) plot.

Table 2. Synthesis of stiction detection methods.

Method	Features	
	Type	Loop Applicability
Horch [40]	<i>cross-correlation</i>	no LC
Horch [48]	<i>statistics</i>	all type
Kano <i>et al.</i> [29]	<i>MV(OP) patterns</i>	all (better FC)
Yamashita [41]	<i>MV(OP) patterns</i>	only FC
Scali and Ghelardoni [42]	<i>MV(OP) patterns</i>	only FC
Daneshwar and Noh [49]	<i>MV(OP) patterns</i>	only FC
Yamashita [50]	<i>statistics</i>	only LC
Farenzena and Trierweiler [51]	<i>waveform shape</i>	only LC
Choudhury <i>et al.</i> [43]	<i>NL detection</i>	all
Thornhill [44]	<i>NL detection</i>	all
Mohammad and Huang [52]	<i>NL detection</i>	all
Rengaswamy <i>et al.</i> [53]	<i>waveform shape</i>	all
Srinivasan <i>et al.</i> [45]	<i>waveform shape</i>	all
Rossi & Scali [46]	<i>waveform shape</i>	all
He <i>et al.</i> [30]	<i>waveform shape</i>	all
Singhal and Salsbury [47]	<i>waveform shape</i>	no LC
Hägglund [54]	<i>waveform shape</i>	all
Zabiri and Ramasamy [55]	<i>waveform shape</i>	all
Ahmed <i>et al.</i> [56]	<i>waveform shape</i>	all
Ahammad and Choudhury [57]	<i>harmonics based</i>	all
Zakharov <i>et al.</i> [58]	<i>algorithms combination</i>	all

Afterwards, following this line, Cuadros *et al.* [60] proposed an improved algorithm that fits an ellipse just using the most significant points of OP and PV signals. Despite this method being applicable only to flow control loops, the procedure seems to have more precision than the previous approaches.

Yamashita [61], extending his first diagnostic method [41], proposed a simple approach where the amount of stiction is evaluated by calculating the width of the sticky pattern from OP and PV signals.

To emphasize, all these techniques give a relative estimate of stiction, termed as *apparent* stiction, which represents only an indication of its severity. Indeed, this value is influenced by all other loop parameters, such as controller and process gain. As they may change in time, these techniques cannot be considered completely reliable for stiction quantification. Techniques which estimate the parameters of a data-driven stiction model and predict the (unmeasured) MV signal, from OP and PV, are much more effective.

Significant developments were achieved by means of system identification using a Hammerstein model, composed of a nonlinear block in series with a linear dynamic block. The nonlinear element represents the sticky valve, while the linear part models the process dynamics.

The first example of this approach is the method of Stenman *et al.* [28], which, based on Stenman's stiction model and on an ARX process model, detected stiction inspired by multi model mode estimation techniques.

Srinivasan *et al.* [62] fitted OP and PV datasets to a Hammerstein model defined also by the nonlinear Stenman's model [28] plus a linear ARMAX model. A grid search algorithm was used to determine the

single parameter of the stiction model, while the process parameters were computed through separable least-squares method.

Afterwards, several variants of Hammerstein approach have been proposed. Lee *et al.* [63] used the ordinary least-squares method to identify the entire model. He's model was chosen as stiction model and the process was assumed having fixed structure: first or second order plus time delay models. In addition, a bounded search region for the stiction parameters was defined and a constrained optimization problem was formulated.

Choudhury *et al.* [25] improved the approach of Srinivasan *et al.* [62] by using their own stiction model [10], since the single parameter stiction model [28] was proved to be not able to capture the real stiction behavior. A two-dimensional grid search method was used to estimate both the stiction and the process model parameters.

Jelali [64] developed a method using a global optimization by means of genetic and path search algorithms. This method proved to be robust, but high computational times are required. The technique of Farenzena and Trierweiler [65] is considered to be an improvement over Jelali's method. A one-stage identification is performed by means of a deterministic algorithm of global optimization that is no longer dependent on the initial guess.

Ivan and Lakshminarayanan [33] introduced an alternative identification approach which includes the use of a modified He's stiction model, a refined ARMAX model for the linear part, and the introduction of data preprocessing, such as data isolation and denoising.

Karra and Karim [66] considered a nonstationary disturbance term in the linear model through an E(xtended)-ARMAX structure. This new term allows the inclusion of other possible root causes besides stiction, such as external disturbances and aggressive tuning. A grid search algorithm is used to determine all the system parameters: Kano's stiction model plus the extended linear model.

Sivagamasundari and Sivakumar [67] presented a method for stiction quantification based on particle swarm optimization. PV and OP data are used to estimate the parameters of the Hammerstein system, consisting of He's stiction model and ARX linear model. Afterwards, these two authors proposed a hybrid procedure combining the fundamental elements of standard genetic algorithms with Nelder-Mead simplex algorithm [68]. These two methods have been also compared and validated on a laboratory control facility.

Then, Shang *et al.* [69] also applied particle swarm optimization to estimate the parameters of the stiction model in a Hammerstein configuration where the nonlinear and linear blocks are described by Chen's stiction model [32] and by an ARX model, respectively.

Brásio *et al.* [70] also proposed a one-stage optimization technique for the detection and quantification of valve stiction. A Hammerstein model composed by Chen's model and a first-order linear model is identified. In order to simplify the identification procedure, the discontinuity of the stiction model is smoothed by means of a continuous function.

Srinivasan B. *et al.* [71] presented a methodology where the Hammerstein model and the Hilbert-Huang Transform are combined for root cause analysis. The method developed by Srinivasan *et al.* [62] was used to detect and estimate stiction, while the nonparametric transform was used to distinguish oscillations occurring due to marginally stable control loop and external disturbances.

Recently, Srinivasan B. *et al.* [24] improved their previous technique developing an integrated framework for a comprehensive diagnosis of single and multiple causes of oscillation. The problem is

addressed integrating a multiple oscillation detection algorithm [72], a model based stiction estimation [62], and additional information obtained by analyzing the data-driven model obtained from Hammerstein method.

Bacci di Capaci and Scali [73], based on Kano's stiction model and the ARX linear model, proposed a filtering methodology which detects and estimates stiction discarding outliers and restricting application to appropriate cases. Recently, Bacci di Capaci *et al.* [74] have performed a comparison of different linear and nonlinear models for stiction quantification in the presence of external disturbances.

Wang and Zhang [37] adapted the Hammerstein identification algorithm to their new asymmetric stiction model. More recently, Fang and Wang [38] have developed a method based on their flexible Preisach model that can capture complicated patterns of a sticky valve. An iterative methodology estimates the parameter vectors in two iterative linear steps. Parallel to the advantages of this method, a drawback involves stiction quantification: being nonparametric, the Preisach model does not have an index to directly establish the stiction amount.

While there are several studies modeling processes as linear, nonlinear processes have not received the same attention, despite many potential benefits. The few approaches to tackle nonlinearity are based on the Wiener model, which is composed of a linear dynamic block connected to a nonlinear static part. Overall, the control loop is described by a Hammerstein-Wiener model, which accounts for the valve stiction and the nonlinear process dynamics; in some cases, they can also address external disturbances. Next three contributions belong to this class.

Wang and Wang [75], extending the study of Jelali, used the Chen's stiction model and a non linear process model, and applied a novel global search grid identification algorithm. In the method of Romano and Garcia [76], stiction is described with Kano's model, the linear process with an ARMAX model, while external disturbances are represented by transfer models of n th order. For unknown nonlinear process dynamics, piecewise polynomials of the third degree are used to model the nonlinear block, and the Nelder-Mead Simplex algorithm is used to search for the optimal pair of stiction parameters. Despite reasonable results, the procedure seems too complex to be suitable in industrial contexts; the large number of parameters to be estimated also may affect the method effectiveness.

Ulaganathan and Rengaswamy [77] also considered the nonlinearity of the process. The Stenman's stiction model is used as first block and is connected to a nonlinear dynamics process block. Finally, a linear external disturbance, described by a moving average model, is considered.

Other stiction estimation approaches have been developed in the literature, few of them are briefly reviewed in the sequel. Chitrakleha *et al.* [78] developed an approach for estimating MV through the application of the unknown input observer technique. After the estimation, they fit a trapezoid to MV(OP) plot, solving a constrained optimization problem to find the four corner points of the polygon. Although the method does not assume any specific stiction model, Choudhury's model is used to validate the technique.

Zabiri *et al.* [79] adopted an algorithm that incorporated a neural network to simultaneously identify the model parameters and quantify the stiction phenomenon. This approach, which uses the Choudhury's model for the stiction modeling, has the advantage of being applicable to all types of processes.

Nallasivam *et al.* [80] used the Volterra model-based technique to detect stiction in closed-loop nonlinear systems, the Stenman's model to represent the stiction phenomenon and a known nonlinear process model to identify both the disturbance model parameters and the stiction model parameter.

A grid search technique is applied to obtain the stiction model parameter and a moving average model for the disturbance is estimated.

Araujo *et al.* [81] developed a stiction detection and quantification technique based on harmonic balance method and describing function (DF) identification. The DF method, a common tool to predict the period and amplitude of limit cycles in control loops, showed good performance also in the presence of model uncertainty, for processes with unknown models, and in the case of multiple frequency oscillations.

Based on the previously developed semiphysical model [31], He and Wang [82] proposed a noninvasive valve stiction quantification method by using linear and nonlinear least-squares methods and through simplifying assumption on signal oscillations.

More recently, in order to make the diagnosis more reliable, some authors have suggested an evaluation of the uncertainty associated with the stiction parameters estimate. Qi and Huang [83] built a bootstrap approach based on the Hammerstein model identification to determine the confidence interval of the stiction estimation. Afterwards, Srinivasan B. *et al.* [84] proposed a method to measure the reliability via frequency domain analysis of closed-loop systems. This measure is calculated independently by the detection method and is applicable only for linear systems.

Table 3 summarizes the main features of the quantification techniques reviewed in this survey in terms of kind of approach, type of model (linear/nonlinear), and application on industrial data.

Table 3. Synthesis of stiction quantification methods.

Method	Type	Features		
		Blocks		Application on
		NL Model	LIN Model	Industrial Data
Choudhury <i>et al.</i> [59]	<i>PV(OP) fitting</i>	-	-	√
Cuadros <i>et al.</i> [60]	<i>PV(OP) fitting</i>	-	-	×
Yamashita [61]	<i>PV(OP) fitting</i>	-	-	√
Stenman <i>et al.</i> [28]	<i>Hammerstein Id.</i>	Stenman	ARX	×
Srinivasan <i>et al.</i> [62]	<i>Hammerstein Id.</i>	Stenman	ARMAX	√
Lee <i>et al.</i> [63]	<i>Hammerstein Id.</i>	He	ARX	√
Choudhury <i>et al.</i> [25]	<i>Hammerstein Id.</i>	Choudhury	ARX	√
Jelali [64]	<i>Hammerstein Id.</i>	Kano	ARMAX	√
Farenzena and Trierweiler [65]	<i>Hammerstein Id.</i>	Kano	ARMAX	√
Ivan and Lakshminarayanan [33]	<i>Hammerstein Id.</i>	He (modified)	ARMAX	√
Karra and Karim [66]	<i>Hammerstein Id.</i>	Kano	EARMAX	√
Sivagamasundari and Sivakumar [67,68]	<i>Hammerstein Id.</i>	He	ARX	√ (pilot)
Shang <i>et al.</i> [69]	<i>Hammerstein Id.</i>	Chen	ARX	√ (pilot)
Brásio <i>et al.</i> [70]	<i>Hammerstein Id.</i>	Chen	ARX	×
Srinivasan B. <i>et al.</i> [24,71]	<i>Hammerstein Id.</i>	Stenman	ARMAX	√
Bacci di Capaci and Scali [73]	<i>Hammerstein Id.</i>	Kano	ARX	√
Bacci di Capaci <i>et al.</i> [74]	<i>Hammerstein Id.</i>	Kano/He	5 types	√ (pilot)
Wang and Zhang [37]	<i>Hammerstein Id.</i>	Asymmetric	ARX	√

Table 3. Cont.

Method	Type	Features		Application on Industrial Data
		NL Model	LIN Model	
Fang and Wang [38]	<i>Hammerstein Id.</i>	Preisach	ARX	√
Wang and Wang [75]	<i>Hamm.—Wiener</i>	Chen	Wiener	×
Romano and Garcia [76]	<i>Hamm.—Wiener</i>	Kano	Wiener	√
Ulaganathan and Rengaswamy [77]	<i>Hamm.—Wiener</i>	Stenman	Wiener	√
Chitralekha <i>et al.</i> [78]	<i>unknown input observer</i>	(Choudhury)	-	√
Zabiri <i>et al.</i> [79]	<i>Neural Network</i>	Choudhury	-	×
Nallasivam <i>et al.</i> [80]	<i>Volterra model-based</i>	Stenman	Volterra	√
Araujo <i>et al.</i> [81]	<i>Describing Function</i>	DF	ARX	√
He and Wang [82]	<i>Semiphysical stiction model</i>	He (3 parameters)	-	√

Symbols: “×”, no; “√”, yes.

From Table 3, it can be observed that the Hammerstein system identification is the most common type of approach, and maybe also the most robust and effective. However, as for stiction detection, in order to get a more reliable final estimation, combining and weighting the verdicts of different types of techniques—even the simplest ones—can be suggested as the best solution.

6. Stiction Compensation

Repair and maintenance are the most effective solutions for a sticky valve. However, these actions may not be feasible between plant shutdowns; therefore, as matter of principle, stiction compensation can be a valid alternative to mitigate its negative impact on loop performance.

A first classification of stiction compensators, derived from mechanical and robotics engineering, divided them into model-based and non-model-based. Although the non-model-based compensators do not directly use a model, they require one for the prediction of operating point stability, limit cycle stability or performance analysis. This encouraged the development of feedforward and feedback strategies relying on stiction models to delete the stiction force. In general, these methods utilize very complex models, which restricts significantly the possibility of industrial applications.

For example, the well-established method of Kayihan and Doyle [85] uses a first-principle stiction model (the Classical model) to describe stiction and estimates the immeasurable states providing a robust control action. The algorithm assumes that all model parameters are known, but such detailed valve information often is not available.

In addition, other most recent approaches, specifically oriented to control loop monitoring and assessment, tend to be simpler. These methods may be classified into six categories: compensation through controller retuning (e.g., [86]), knocker method (e.g., [87]), constant reinforcement [33],

alternate knocker method [88], two- or three-move compensators (e.g., [89,90]), and optimization approaches [89].

Gerry and Ruel [86] firstly suggested simple and practical techniques for tackling stiction online. Basically, a set of retuning rules for the controller are proposed to reduce the effect of the stiction-induced oscillations at the expense of a slower response (detuning) or steady-state control errors (switching from PI to P action). Mohammad and Huang [91] then proposed a compensation framework based on the oscillation condition previously introduced [52]. The occurrence and the severity of stiction-induced oscillations can be predicted and then can be reduced or eliminated by following some guidelines of controllers retuning.

The knocker approach, also known as the dither approach, consists of adding a high frequency signal to the control signal (OP) with the objective of preventing process output (PV) fluctuations. All these methods, producing a faster motion of the valve, however, can cause mechanical problems even worse than the normal operating. Therefore, they are just short-term solutions.

Hägglund [87] developed the first knocker compensation method specifically targeting stiction in control valves. A predesigned signal is added to OP so that the oscillations produced by stiction are minimized. The knocker output consists of short pulses with constant amplitude, width, and duration that must be tuned. This method removes oscillations at the cost of a faster and wider motion of the valve stem, which involves a high increased rate of wear of the valve.

To overcome such disadvantages, Srinivasan and Rengaswamy [92,93] proposed some suggestions for the automated choice of compensation parameters. The approach, which integrates stiction detection and compensation, were shown to reduce PV variability with less aggressive valve movements compared to Hägglund's formulation.

Cuadros *et al.* [94] proposed a method also based on the knocker approach. A supervision layer analyzes the control error and interacts with the proportional-integral-derivative (PID) controller. The strategy showed a reduced integral absolute error and an even lower number of valve movements.

Ivan and Lakshminarayanan [33] suggested an alternative approach. The compensating signal is a constant reinforcement, added to the valve input only when OP is not constant, whose value is related to the estimated amount of the stiction parameter. Although the method seems very useful for reduction of PV variability, it does not decrease the valve aggressiveness.

The alternate knocker method of Srinivasan and Rengaswamy [88] proposed the addition of a special block to the nominal PID algorithm. However, this control signal adaptation is not known by the nominal controller, and, consequently, it negatively affects the performance of the controller. Moreover, since it is not taken into consideration at the time of controller commissioning, the tuning parameters—determined without stiction compensation—may even produce instability and/or additional wear of the valve and the actuator.

The main focus of the two-moves compensation method, first introduced by Srinivasan and Rengaswamy [89], is to maintain the valve at its steady-state position performing at least two stem moves in opposite directions. The compensating signals should have magnitudes large enough to overcome stiction and move the valve, but not sufficient to saturate it. This method has some limitations related with setpoint changes, preventing its implementation on an automated tracking, and due to the use of Stenman's stiction model which decreases its accuracy.

More recently, Farenzena and Trierweiler [95] proposed a novel methodology to compensate stiction effects, which, instead of adding a compensator block, modified the traditional PI controller block. A two-moves method allows one to specify closed-loop performances faster than open-loop and to reject load disturbances efficiently. Unlike the previous method of Srinivasan and Rengaswamy [89], the method is able to track the setpoint, with a small offset and reducing the valve travel significantly.

Cuadros *et al.* [90] suggested two improved versions of the two-move compensation method in order to bypass the drawback related to the setpoint tracking. None of the methods require knowledge of the plant model and both may handle setpoint changes by detecting increases in the control error. Despite these advantages, the first method is still susceptible to disturbances, while the second one is more robust, since it was especially developed to overcome this aspect. The methods drawbacks are related to the requirement of having similar control valve and process dynamics.

A novel method based on two movements was also developed by Wang [96]. A short-time rectangular wave is added to the setpoint in two distinct movements and the valve is moved to the desired position, avoiding high variability. Robustness against modeling errors and against measurement noise seems to be the main advantages of this method.

Karthiga and Kalaivani [35] proposed a similar method that involved not two but three movements. This approach, exhibiting a lower overshoot and settling time than the previous ones, imposes a smoother valve operation, which results in a longer valve life.

Srinivasan and Rengaswamy [89] proposed also an optimization-based approach, in an attempt to balance between less-aggressive valve movement, reduced PV variability, and less energy in the signal added to OP. A cost function is built and minimized using the compensator moves as optimization variables. Compared to the classical approaches, significant improvements are observed, but the need for analyzing the model mismatch effect, the incorrect stiction measurement, and the real-time issues before online implementation are pointed out. In addition, the method is computationally expensive and, since the cost function is not smooth, a global minimum might be not attained and an offset between PV and SP may arise.

Based on previous works, Sivagamasundari and Sivakumar [97] used a model-based approach—with He's model—to determine the stiction amount; instead of tuning parameters that determine the waveform of the compensated signal, they developed few rules to determine those parameters. This mixed approach achieved a non oscillatory PV without forcing faster and wider moves of the valve. In addition, no extensive information of process or controller is required and good tracking of the setpoint changes is guaranteed.

Among other approaches of compensation, Zabiri and Samyudia [98] proposed a model predictive control formulation, based on mixed-integer quadratic programming (MIQP). Closed-loop performance may be significantly improved if stiction is taken into account explicitly in the optimization problem. However, the approach requires the a priori knowledge of the stiction parameters. Besides, the MIQP formulation may not perform well in highly nonlinear or highly dimensional systems, because of the required computational burden and the resulting feedback latency.

Recently, Li *et al.* [99] analyzed stiction induced oscillation in cascade control loops by using frequency analysis. A set of practical techniques of oscillation compensation through outer and inner controller tuning, and through changes of control strategies were proposed. Theoretical results are then validated through experiments on a pilot scale flow-level cascade control.

In parallel, Mishra *et al.* [100] introduced a stiction combating intelligent controller (SCIC) based on fuzzy logic. No additional compensator is required, since the SCIC is a variable gain fuzzy PI controller making use of Takagi-Sugeno scheme. This novel approach seems to outperform a traditional PI controller, yielding less PV and stem movement variability.

Silva and Garcia [7] developed an experimental comparison study of different stiction compensation methods using some metrics to evaluate their performance, such as the integral absolute error, a factor that is related to the stem position variation, the valve actuator pressure variation, and the rising time. The methods tested in the flow control loop of a pilot plant were applied to setpoint tracking and regulatory experiments. Although several methods exhibited good compensation capacity, the choice of the best method depends on the tradeoff between all the issues.

Table 4 summarizes the features of the reviewed compensation methods, in terms of reduction of PV oscillation, reduction of valve movement, and no *a priori* process knowledge requirement—except for routinely available operating data, and set point tracking and disturbance rejection.

Table 4. Synthesis of stiction compensation methods.

Method	Type	Features			
		Reduction of PV Oscillation	Reduction of Valve Movement	no a-Priori Process Knowledge Requirement	Set Point Tracking and Disturbance Rejection
Gerry and Ruel [86]	retuning	√	√	√	×
Mohammad and Huang [91]	retuning	√	√	√	×
Hägglund [87]	Knocker	√	xxx	√	√
Srinivasan and Rengaswamy [92,93]	Knocker	√	xx	√	√
Cuadros <i>et al.</i> [94]	Knocker	√	×	√	√
Ivan and Lakshminarayanan [33]	Constant Reinforcement	√	xx	√	√
Srinivasan and Rengaswamy [88]	Alternate Knocker	√	×	√	×
Srinivasan and Rengaswamy [89]	2-Moves	√	√	×	xx
Farenzena and Trierweiler [95]	2-Moves	√	√	×	×
Cuadros <i>et al.</i> [90]	2-Moves (A)	√	√	×	×
	2-Moves (B)	√	√	×	√
Wang [96]	2-Moves	√	√	×	√
Karthiga and Kalaivani [35]	3-Moves	√	√	×	√
Srinivasan and Rengaswamy [89]	Optimization	√	√	√	√
Sivagamasundari and Sivakumar [97]	Mixed	√	√	√	√

Symbols: “×”, no/low; “xx”, bad; “xxx”, very bad; “√”, yes/good.

From Table 4, it is worth noting that all methods exhibit good capacity in reducing PV oscillation, but most of them also shows some drawbacks regarding other issues. For example, knocker approaches tend to produce a too fast motion of the valve, while two-moves techniques usually require a-priori process knowledge and may not achieve good set point tracking and disturbance rejection.

7. Smart Diagnosis

All techniques described in previous sections have been developed for traditional control plant design, with ordinary valves and communication systems with analog signals in 4–20 mA. Being the manipulated variable (valve stem position—MV) not known, stiction must be detected and quantified on the basis of available measurements of the controlled variable (PV) and controller output (OP).

In newly designed plants, the adoption of intelligent instrumentation, valve positioner and field bus communication systems increases the number of variables that can be acquired and analyzed by the monitoring system. This fact enlarges the potentialities of performing a more precise diagnosis of actuator problems which are not only limited to the presence of valve stiction (and related problems, as deadband, hysteresis, backlash), but can also include other causes (changes in spring elasticity, dynamic friction (jamming), membrane wear or rupture, leakage in the air supply system).

The positioner itself can also be the source of other specific faults that can upset loop performance. All these malfunctions require specific actions to be counteracted by operators and, once more, it is very important to be able to diagnose different sources.

Diagnosis of smart actuators has been recently addressed in literature, but a comprehensive connection with the traditional research on control loop assessment and valve diagnosis is still lacking; some of the few works about smart diagnosis are briefly reviewed in the sequel.

Koj [101] firstly distinguished 19 different faults in a smart industrial actuator composed by control valve, pneumatic servo-motor, and positioner. Then, Bartyś and Kościelny [102] applied four different fuzzy logic methods to diagnose and isolate some of these faults. A minimum, a multiplicative, an additive, and a mixed approach were developed and specifically applied to monitor the smart actuator studied in [101]. Also Ould Bouamama *et al.* [103] dealt with fault detection and isolation (FDI) of smart actuators. They combined bond graphs and external models to assess different faults. An external model is a generic method which can be used to verify the functional specifications of a smart equipment. This technique has been applied to monitor the same valve with positioner of [101].

Bartyś *et al.* [104] provided the description and presentation of the actuator benchmark used in fault diagnosis studies within the Development and Application of Methods for Actuator Diagnosis in Industrial Control System (DAMADICS) European Research Training Network. This system is openly available, is FDI method-independent, and based on an accurate study of the phenomena that can lead to likely faults in valve actuator systems. The industrial application is focused on the sugar factory Cukrownia Lublin SA, Poland. This actuator benchmark can be used either for testing, evaluation, or ranking of different FDI methods.

Mendonça *et al.* [105] also proposed a FDI method based on fuzzy logic approach. Nonlinear models for the process running in normal condition and for each fault were derived. When a fault occurs, fault detection and isolation is performed using the model residuals. This method, applied to the actuator benchmark [104], was able to detect and isolate 10 abrupt and incipient faults.

In parallel, Huang and Yu [106] presented a simple method specifically addressed to detection of stick-slip fault. This method requires only valve position set OP and actual valve position signal MV; specific indices are defined, and an on-line sliding window algorithm is developed. Huang *et al.* [107] also proposed a series of methods based on trend analysis to detect different faults. Stick-slip fault, constant bias fault, change of valve gain, serious hysteresis, and stuck condition can be inferred by using OP, MV and PV signals. Industrial data sets from a power plant were used to test the methods' efficiency. Recently, Subbaraj and Kannapiran [108] proposed an Adaptive Neuro-Fuzzy Inference System to detect and diagnose the occurrence of various faults in a smart pneumatic valve of a cooler water spray system in cement industry. The training and testing data required for model development were generated at normal and faulty conditions in a laboratory setup.

Other interesting results about smart actuators were presented by Scali *et al.* [109]. In the framework of a cooperation with ENEL (major Italian electricity producer company), a pilot plant scale apparatus is appropriately equipped to reproduce different types of malfunctions for a pneumatic valve. The availability of MV allows one to compute TD (Travel Deviation), defined as the difference between real and desired valve position ($TD = MV - OP$). On the basis of different patterns and range of values of TD, stiction can be clearly detected and also other causes of malfunctions affecting the valve can be distinguished. An example is reported in Figure 3.

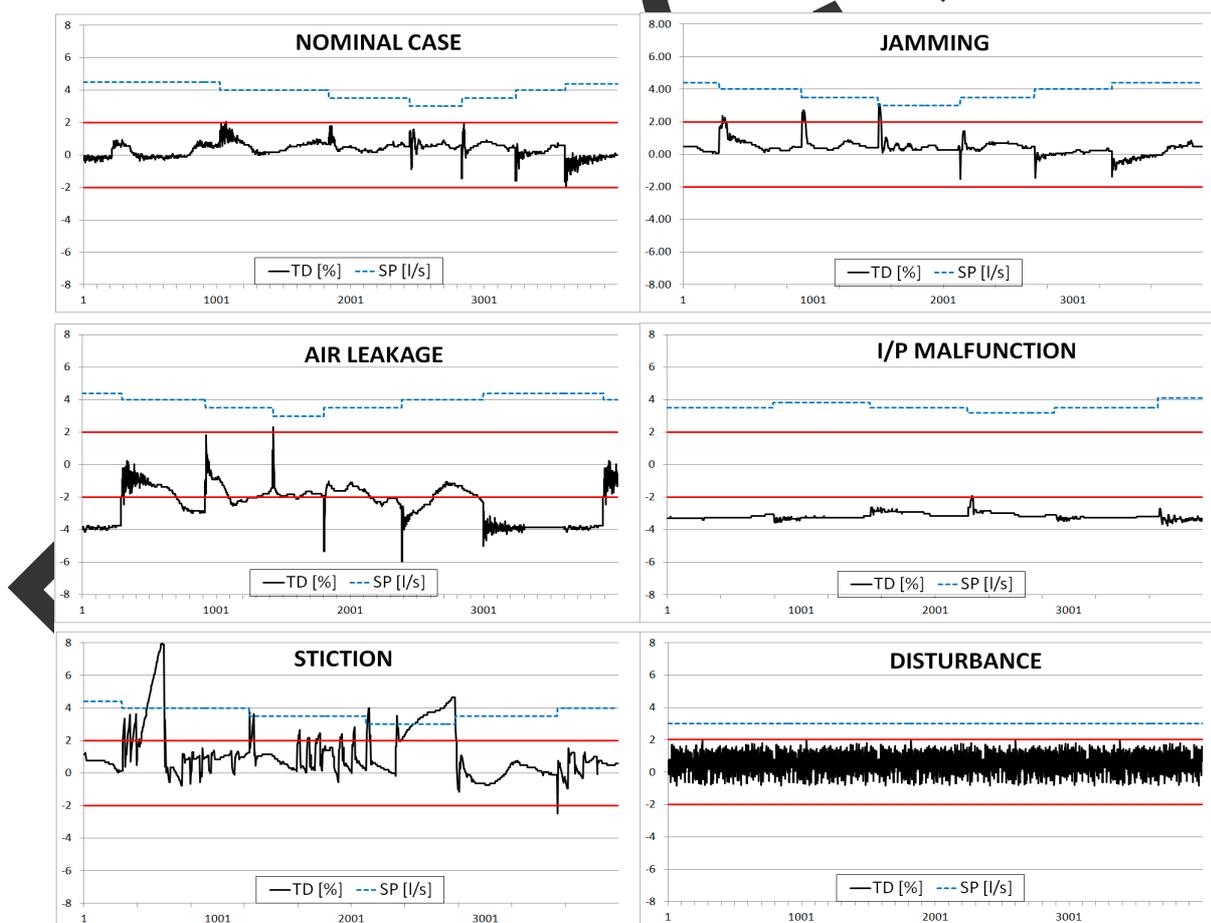


Figure 3. TD time trends for nominal case and different malfunctions: jamming, air leakage, I/P malfunction, stiction and disturbance.

As final result, by defining few Key Performance Indices (as simple metrics of TD), and fixing low and high thresholds for them, it is possible to assess valve status as Good, Alert, Bad, thus giving very specific indications to the operator about troubles affecting the valve and actions to perform. The same logics has been exported and validated on industrial processes (power plants), after a field calibration of some KPIs, by Bacci di Capaci *et al.* [110].

Referring to Figure 3, it is worth putting into evidence that typical waveforms and distinctive limit cycles on PV(OP) and MV(OP) diagrams generated by a traditional sticky valve (cfr. Figure 1) are no more observed in the case of a sticky valve augmented by smart instrumentation. The positioner, performing an additional control action as an internal cascade controller, can significantly alter frequencies and amplitudes of oscillation, even though, contrary to popular belief, it does not allow elimination of oscillations.

8. Software Packages

Many software packages, addressing the issue of control loop performance assessment (CLPA), have been proposed in recent years by major companies. Among the few surveys including software packages, papers by Shardt *et al.* [111] and Brásio *et al.* [9] should be mentioned. Historically developed for controller re-tuning, nowadays these tools not only detect loops needing attention and/or maintenance but also include different features for a more general diagnosis of loop status.

Detailed illustrations of these systems can be found on the appropriate company web sites. Unfortunately, in most cases the available documentation is oriented towards a commercial approach rather than a scientific one. It is possible to find an indication of the main features and tackled issues, lists of successful implementations, benefits in terms of Return On Investment and enthusiastic comments by users. It is very unusual to have a complete explanation that includes theoretical issues (the problem, basic techniques and performance indicators) and practical issues to focus on for the success of the implementation (system architecture, key parameter calibration, field validation).

For this reason, a detailed analysis of all software packages for CLPA not being possible, basic features of 15 different systems today present in the market are reported following the approach of our review in Table 5 that highlights various options of stiction analysis: modeling, detection, quantification, compensation, and smart diagnosis.

From Table 5, it can be seen that stiction detection is a feature common to almost all packages (11/15), thus confirming to be now a mature subject; in general, no information about the adopted technique is available: about this point, the PCU software makes use of multiple techniques to get a more reliable final verdict in terms of oscillation detection and stiction diagnosis. Very few packages perform quantification (4/15), to indicate that there is still research to be carried out. Only 2/15 deal with modeling and only one with compensation: in our experience, this fact confirms the scarce interest of industry about these two subjects. On the contrary, it is a bit surprising that only one package (the PCU software [110], developed by the authors of the present review) includes smart diagnosis, taking into consideration the proved advantages by its adoption: this is probably due to the relatively few plants fulfilled with advanced instrumentation, but this feature will certainly find a place in future packages.

Table 5. Synthesis of Performance Assessment Software.

Software	Organization	Features of Stiction Analysis				
		Modeling	Detection	Quantification	Compensation	Smart Detection
Control Performance Assessment [112]	Petroleum University of Technology, Iran	×	√	×	×	×
Plant Check—Up (PCU) [110,113,114]	University of Pisa, Italy	√	√	√	×	√
Process Assessment Technologies and Solutions [115]	University of Alberta, Canada	√	√	√	√	×
Aspen Watch Performance Monitor [116]	AspenTech	×	√	×	×	×
Automatic Control Loop Monitoring and Diagnostics [117]	PAPRICAN	×	×	×	×	×
Condition Data Point Monitoring [118]	Flowserve	×	√	×	×	×
Control Monitor [119]	Control Arts, Inc.	×	√	×	×	×
Control Performance Monitor (Process Doctor) [120]	Matrikon—Honeywell	×	√	√	×	×
Control Loop Optimisation [121]	PAS	×	×	×	×	×
EnTech Toolkit (DeltaV Inspect) [122]	Emerson Process Management	×	×	×	×	×
INTUNE [123]	ControlSoft	×	×	×	×	×
Loop Scout [124]	Honeywell	×	√	×	×	×
LPM, Loop Performance Manager [125]	ABB	×	√	×	×	×
Plantstreamer Portal [126]	Ciengis	×	√	√	×	×
Plant Triage [127]	Expertune	×	√	×	×	×

Symbols: “×”, no; “√”, yes.

9. Conclusions

A review of research work on valve stiction is indeed a heavy burden to carry out, owing to very large efforts devoted to this phenomenon in the last years. This is certainly an indication of its relevance as issue affecting loop performance and then the global efficiency of the plant.

In this first part of the study, we tried to give a general overview starting from basic aspects of the problem, analyzing different techniques, and ending with possibilities open by smart instrumentation.

We can now make some final considerations, based on personal experience as researchers and, more, on familiarity with end-user expectations: therefore, more attention is paid to the perspective of their impact in industrial applications.

Characterization of the phenomenon and its modeling has certainly reached an almost complete stage. While from the academic side many issues can still attract interest (for instance basic principle models), the adoption of data-driven model can be considered fully satisfactory for the evaluation of stiction effects.

Stiction detection techniques, based on available measurements in old-design plants (SP, PV, OP), can also be considered a mature research topic, even though a combined application of more than one technique is recommended to reduce possible errors in distinguishing stiction from similar causes of oscillations.

Stiction compensation techniques are certainly a valid help to mitigate the problem when a direct action is not possible; despite their potentiality, in our experience, very seldom are they implemented in the plant.

Smart instrumentation creates the opportunity for a very innovative scenario in the diagnosis of different problems which may affect the valve and their distinction from other troubles. While all other diagnosis approaches remain valid for classical plants, techniques which make use of additional measurements will be used more and more in the next few years.

About closed loop performance systems, understandably, techniques included in commercial packages are not illustrated with all details: it seems that they follow with some time delay the advances in research. At the moment, very few of them feature approaches that include benefits deriving from the availability of smart instrumentation.

Being able to quantify the amount of stiction is very important in order to follow its evolution in time and to predict the moment of valve maintenance; this is a field where all previous aspects play a role and where there is still research to do in order to improve reliability of estimations. To the comparison results of emerging quantification techniques on industrial data is devoted the second part of this review.

Conflicts of Interest

The authors declare no conflict of interest.

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