An autonomous valve stiction detection system based on data characterization

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Abstract: This paper proposes a valve stiction detection system which selects valve stiction detection algorithms based on characterizations of the data. For this purpose, novel data feature indexes are proposed, which quantify the presence of oscillations, mean-nonstationarity, noise and nonlinearities in a given data sequence. 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. The paper ends demonstrating the effectiveness of the proposed valve stiction detection system with benchmark industrial data.

Keywords: Valves, Stiction, Oscillations, Control Loops, Fault Detection and Diagnosis, Industrial Applications

1. INTRODUCTION

As is well-known, oscillations in control loops result in high variability of product quality, increased energy consumption, and accelerated equipment aging, which significantly reduce plant profitability. Valve static friction, or valve stiction, as is called in the literature, see Choudhury (2008), is recognized as one of the main causes of oscillations and poor performance in the control loop. The selection of the right stiction detection method in connection with the properties of the available data often requires a huge investment of time and efforts. Moreover, because of the large number (i.e., hundreds or even thousands) of control loops that must be processed, the development of an autonomous valve stiction detection system, based on routine operation data, is essential to improve process efficiency. Specifically, characterizing the properties of the available data sequences can lead to an automatic selection of the applicable methods among a wide array of them. Furthermore, the various degree of suitability of the methods selected, with respect to the properties of the data processed, can be exploited in order to obtain the final stiction detection decision as a weighted combination of the decisions provided by the single methods, thus enhancing the reliability of the whole detection procedure.

The contribution of this work consists in providing an autonomous system for valve stiction detection based on the aforementioned ideas. In particular, deep investigations have been carried out in order to accomplish the following objectives: i) define appropriate indexes aimed at characterizing the main features of the available data; ii) determine the relations between the features of the available data and the properties of the stiction detection methods; iii) devise an algorithm for the automatic selection of the stiction detection methods applicable to the given sets of data; iv) devise an algorithm for achieving the final detection decision on the basis of the decisions provided by the single detection methods applied, by exploiting information on their reliability in connection with the features of the given data sequences.

The autonomous stiction detection system presented in this work is based on the introduction of five indexes for quantifying the relevant properties of the given data sequences and the implementation of four stiction detection methods. The indexes are an oscillation index, a data-sampling index, a mean-nonstationarity index, a noise index, and a nonlinearity index. The methods are a curve-fitting method which integrates the triangular-fitting method (He et al., 2007) and the rectangular- fitting method (Hägglund, 2011), the cross-correlation method (Horch, 1999), the histogram method (Horch, 2006a and 2006b), and the area-ratio method (Singhal and Salsbury, 2005). All these methods are encompassed in the so-called data-driven approach to valve stiction detection, and, the former two, more specifically, are known as shaped-based methods. Data-driven methods are herein preferred to the so-called model-based approaches (e.g. Qi and Huang, 2011; Nallasivam et al., 2010; Jelali, 2008; Srinivasan et al., 2005) not only because, as mentioned above, they do not require a detailed model of the process, but also because their implementation is less demanding from the computational point of view.

The paper is organized as follows. An outline of the autonomous stiction detection system is presented in Section 2. Data characterization through the definition of appropriate indexes is discussed in Section 3. The impact of the data characteristics on applicability of the considered detection methods is analyzed in Section 4. The algorithm for selecting the applicable detection methods, given the data to be processed, and the algorithm for computing the final detection decision from the single decisions provided by each of the methods applied are shown in Section 5. Validation of the proposed autonomous stiction detection system with benchmark industrial data is discussed in Section 6. Some concluding remarks are set forth in Section 7.

2. OUTLINE OF THE AUTONOMOUS STICTION DETECTION SYSTEM

The system processes the available data sequences and computes the values of a set of indexes characterizing the data, in order to establish whether each of the four valve stiction detection methods considered is applicable or not. On this basis, a decision algorithm operates the selection of the applicable methods. Then, the selected methods are run in parallel and each of them provides its own detection decision. The definitive detection decision is finally provided by an algorithm that weights the single decisions with information on the reliability of each of the selected methods with respect to the given data sequences. A schematic diagram of the autonomous stiction detection system proposed in this work is shown in Fig. 1.

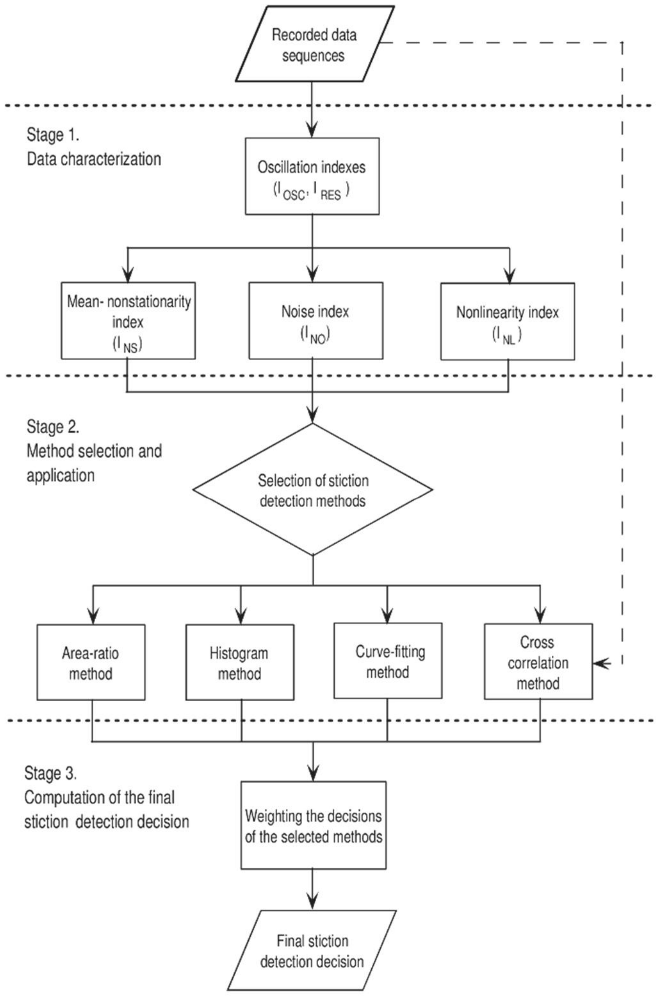

Fig. 1. Flowchart of the autonomous stiction detection system

3. DATA CHARACERIZATION AND DEFINITION OF THE INDEXES USED IN THE SYSTEM

This section concerns the determination of the features suitable for characterizing process data prior the selection of the applicable stiction detection methods. A preliminary study of the performance of the selected valve stiction detection methods on a benchmark set of seventy six industrial control loops (Jelali and Huang, 2010) was carried out to reveal the typical causes of deteriorated detection results. The outcome of the study is reported below.

3.1 Oscillation index

In some control loops, the oscillation shape can change significantly from one period to another. On the other hand, the selected stiction detection methods assume the presence of the steadfast oscillation pattern, so that, if the oscillation shape is not stable enough, the results obtained can be misleading. Therefore, stability of the oscillation pattern in the signals is the first feature selected to characterize the data.

The oscillation index introduced herein identifies the periods of the oscillation by considering various half-periods and defining the oscillation peaks. Namely, given a signal x and a possible integer half-period length d, the proposed method determines the periods of the oscillations by defining the locations of the peaks. At the next stage, similarity of two subsequent periods is evaluated using the correlation coefficient $C(i)$. The presence of oscillation is recognized if most (80%) of the coefficients are close to 1 according to formula:

$$I_{osc}(d) = \max\{\theta : \theta \le C(i) \text{ for } 80\% \text{ of } i\}.$$

Finally, all possible lengths of the oscillation period are considered and the oscillation index is defined as the maximum value of the quantile:

$$I_{osc} = \max_d I_{osc}(d).$$

3.2 Mean-nonstationarity index

Most of the selected stiction detection methods use zero-crossings of the signal to determine the half-periods of the oscillation. However, the mean value of the signal may deviate from zero (mean-nonstationarity), which can lead to incorrect identification of the half-periods and, therefore, to the wrong stiction detection results. In the case the data exhibit such variations, either the low-frequency disturbances are filtered out, or the half-periods are identified with alternative algorithms, or other stiction detection methods, with the property of being insensitive to the fluctuation of the mean value, are employed. Thus, mean-nonstationarity is the second data feature considered in this work. However, since the mean value, as is usually defined, is very sensitive to signal outliers, a more robust ‘middle level’ of the signal is proposed and used herein to quantify the mean variations. The so-called ‘middle level’ of the signal in an oscillation period is defined as the point at which the respective areas of the upper and lower half-periods are equal. The mean nonstationarity index is finally computed as the ratio of the estimations of the standard deviation of the middle levels and the mean magnitude in the oscillation periods:

$$I_{NS} = \sqrt{\sum_{i=1,\dots,n} (L_i - \bar{L})^2 / n} \Big/ \left(\sum_{i=1,\dots,n} (x(m_i^+) - x(m_i^-)) / n\right),$$

where m_i^+ and m_i^- are the locations of the maximums and the minimums of the signal over each period and L_i is the middle level.

3.3 Noise index

High-frequency noise complicates the determination of the oscillation patterns and disturbs the results of all stiction detection methods. However, some methods are more robust to the presence of noise than others. Thus, the presence of high-frequency noise is the third data feature to take into account. The proposed index relies on the fact that half-periods of the oscillation patterns located between two peaks (the maximums and the minimums) are typically monotonous. In signals with high-frequency noise, the half-periods become not monotonous, and therefore, evaluation of the non-monotonousness strength is employed to estimate the level of noise. Hence the noise index is defined as an increase of the total variation of the signal caused by high frequency noise:

$$I_{NO} = \left(\frac{\sum_{i=m_1^+}^{m_n^+ -1} |x(i+1)-x(i)|}{\sum_{i=1}^{n-1}(|x(m_i^-)-x(m_i^+)|+|x(m_{i+1}^+)-x(m_i^-)|)} - 1 \right) / \sqrt{d} \, .$$

3.4 Nonlinearity index

Many methods assume the presence of a specific oscillation patterns in the signals for sticky and non-sticky cases. However, the pattern can vary because of the valve functional nonlinearity. In particular, nonlinear valve operating curves may lead to a noticeable asymmetry in the oscillation shape and, therefore, may corrupt the detection results. Hence, the nonlinearity of the valve operating curve is assumed as the fourth feature of process data to be checked. The proposed index to evaluate the nonlinearity of the valve characteristic opening is defined as follows:

$$I_{NL} = \sum_{i=1}^{n} log \left| \frac{x(m_i^+)-L_i}{L_i - x(m_i^-)} \right| / n \, .$$

4. DATA FEATURES AND DETECTION METHODS: REQUISITE SET-UP

A quantitative analysis of how the data features examined in Section 3 affect successful application of the stiction detection methods is presented in this section. To this aim, the stiction detection methods are tested on a set of benchmark industrial data borrowed from Jelali and Huang (2010). Nineteen industrial loops concerning flow, temperature, level, and pressure control have been considered. In particular, these control loops have oscillating signals. The testing procedure consists of the following steps. First, the indexes are calculated for each data sequence. Next, the stiction detection methods are run. Finally, the detection decision provided by each of the methods applied is compared with the actual — either faulty or non-faulty — condition known from the literature and the outcome is analyzed in connection with the values taken by the feature indexes. The test results are synthetically reported in Table 1. The last four columns show the values of the stiction detection index provided by each of the methods applied for the specific data sequence. The symbol NA means that the method does not apply. Values of the stiction detection index greater than 0.59 indicate the detection of stiction. Values of the stiction detection index lower than 0.45 indicate that the loop is not affected by stiction. Values of the stiction detection index ranging between 0.45 and 0.59 means that no decisions can be made.

4.1 Presence of oscillations

The fact that all the considered stiction detection methods only apply to oscillating signals is a clear sign of the influence of this feature. In particular, the proposed oscillation index reveals not only the presence of oscillations, but also the consistency of oscillation parameters such as, shape, frequency, and amplitude: the higher is the index, the more consistent are the parameters.

Thus, applicability of the curve-fitting method, the cross-correlation method, and the area-ratio method can be related to an oscillation index at least equal to 0.7. Lower values of the index point out non-steadfast oscillations, which can affect the correct operation of all these methods. The histogram method is especially sensitive to inconsistencies in the oscillation parameters. Inaccurate data histograms are produced and matching to a specific shape is interdicted when the oscillation index is lower than 0.85.

4.2 Nonstationary mean-value

The mean-nonstationarity index indicates variations in the mean value of the oscillating signal. A low value of the index identifies a stationary signal, which can be analyzed by all the methods. Conversely, a high value of the index can affect the methods which employ zero-crossings to determine the oscillation periods. Nevertheless, an alternative procedure is used in this work for calculating the oscillation period. Thus, mean-nonstationarity has little effect on the curve-fitting and the area-ratio methods. On the contrary, methods like cross-correlation and histogram can successfully be applied only to clearly mean-stationary signals. Thus, the requirement for both these two latter methods is a value of the mean-nonstationarity index lower than 0.25, while, for the former two methods, the boundary value is set at 0.5.

4.3 High-frequency noise

In general, high-frequency noise seriously affects successful application of any stiction detection method. However, the investigation carried out in this work has brought to the following considerations, which allow some thresholds for the value of the noise index to be defined in connection with each of the considered methods. As to the area ratio method, Singhal and Salsbury (2005) point out that noise can affect the performance of their method and propose to use a low pass filter, otherwise it is impossible for the method to accurately locate the peak of the signal in each half-period. As a consequence, unreliable or false detection decisions are caused by the frequent occurrence of inconsistent area ratios between the half-periods. Similar reasoning also holds for the curve-fitting method as seen in Fig. 2. Therefore, a maximal acceptable value for the noise index can be set to 0.15 for

Table 1: Data features and diagnosis indexes of the tested control loops

Loop No		Oscillation	Non-stationarity	Noise	Data resolution	Non-linearity	Condition	Loop type	Curve-shape methods	Cross-correlation	Histogram	Are ratio
1	pv	0,92	0,04	0,13	80	-0,13	1	0	0,7	1	1	1
	op	0,96	0,24	0,01	83							
4	pv	0,96	0,39	0,02	8	-0,13	0	1	0,45	NA	1	NA
	op	0,97	0,55	0	8							
5	pv	0,85	0,09	0,15	5	-0,48	1	0	0,56	0,5	1	1
	op	0,95	0,26	0,01	5							
10	pv	0,97	0,01	0,13	69	0,00	1	0	0,87	1	1	1
	op	0,99	0	0	70							
11	pv	0,95	0,01	0,26	62	0,03	1	0	0,37	0,5	1	0.5
	op	0,98	0,01	0,11	64							
12	pv	0,72	0,02	0,28	233	-0,14	1	0	0,83	1	1	0
	op	0,91	0,03	0,01	228							
13	pv	0,98	0,18	0	11	0,00	0	0	0,31	0	0	0
	op	0,97	0,76	0	11							
14	pv	0,81	0,26	0,21	10	0,18	0	0	0,68	1	1	1
	op	0,97	0,31	0,01	10							
19	pv	0,7	0,11	0,21	67	0,16	1	0	0,49	1	1	0
	op	0,8	0,3	0,02	68							
20	pv	0,93	1,07	0,01	4	-0,65	1	0	0,5	0,5	1	0.5
	op	0,89	10,81	0,01	4							
22	pv	0,74	0,01	0,14	73	0,03	1	0	0,32	1	0,5	1
	op	0,8	0,03	0,02	65							
23	pv	0,83	0,01	0,48	64	0,31	1	0	0,92	1	1	0
	op	0,98	0,02	0	64							
25	pv	0,91	0,06	0,02	8	0,25	0	1	0,45	NA	1	NA
	op	0,94	0,18	0,01	8							
26	pv	0,9	0,1	0,37	66	0,00	1	1	0,58	NA	1	NA
	op	0,9	0,13	0,3	66							
28	pv	0,99	0,02	0,03	65	-0,03	1	1	0,55	NA	1	NA
	op	0,98	0,03	0	64							
32	pv	0,99	0,03	0,05	45	-0,03	1	0	0,77	0,5	1	0.5
	op	0,99	0,06	0,04	45							
35	pv	0,93	0,31	0,03	9	-0,20	1	0	0,6	0,5	1	0.5
	op	0,86	5,03	0,02	10							
36	pv	0,77	0,21	0,19	70	-0,01	0	1	0,59	NA	1	NA
	op	0,76	0,31	0,18	70							
38	pv	0,84	0,02	0,07	92	0,00	0	0	0,81	0,5	1	0.5
	op	0,99	0	0,03	92							

both methods. As to the cross-correlation method, one of main advantages is its intrinsic robustness with respect to high-frequency noise, mainly due to the processing of two different sequences of data. Also for the histogram method, the filtering action implicit in the method alleviates the issues related to high-frequency noise. However, since the presence of high-frequency noise can be combined with the presence of other unfavorable conditions, like, e.g., unclear oscillation patterns or low data resolution, a conservative threshold for the noise index can be set at 0.3 for the latter two methods.

4.4 Nonlinear valve characteristics

The presence of stiction in valves with a nonlinear characteristic generates oscillating signals whose shapes are different from those assumed in stiction detection methods devised to detect stiction in valves with linear characteristics. Thus, the nonlinearity index is used to define some tolerance of the stiction detection methods to variations in the shape of the oscillating signal. Thus, for the curve-fitting method, the absolute value of the nonlinearity index is required to be lower than 0.15. Similar arguments hold for the area-ratio method, which has approximately the same tolerance to oscillation shape variations, so that the requirement is still an absolute value of the nonlinearity index lower than 0.15. The cross-correlation method gives ambiguous detection results when applied to data characterized by a highly nonlinear behavior. The cause of the unreliable detection result is a phase shift between the *op (controller output)* signal and the *pv (process variable)* signal, which, in turn, derives from the erratic oscillation shape of both signals. Similarly, nonlinearity affects the expected stiction shape of the data histogram. Therefore, for both methods, the maximal admissible absolute value for the nonlinearity index is 0.3.

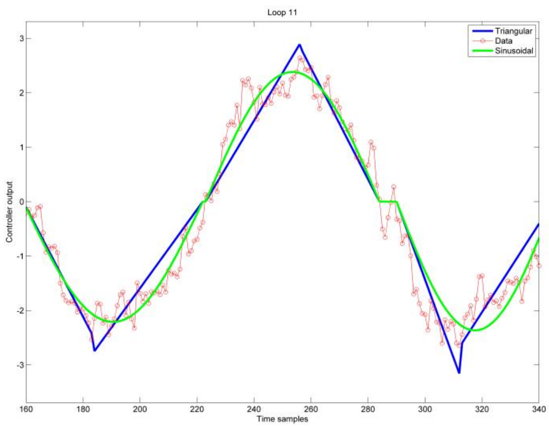

Fig. 2. Triangular and sinusoidal fitting in the control loop 11

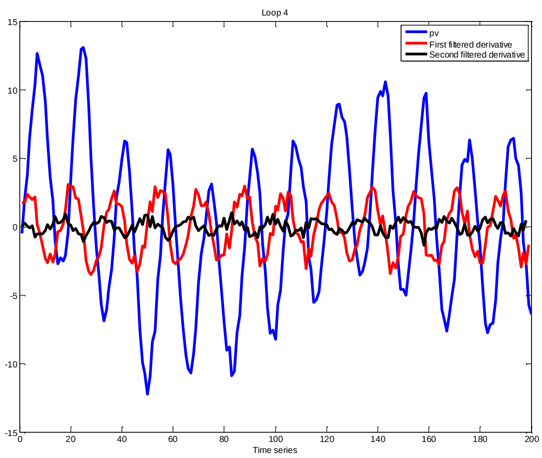

Fig. 3. Control loop 4, controller output (blue), first filtered derivative (red) and second filtered derivative (black)

4.5 Data resolution

As it is intuitive, low data resolution may compromise effective applicability of any stiction detection method. In fact, a small number of available samples makes the evaluation of any shape fitting an impossible task. The performance of the histogram method can be affected by a small amount of oscillation periods in the data, if this is coupled with systematic deviations from the oscillation pattern. This circumstance is indicated by relatively low values of the oscillation index, which causes the method to construct an inaccurate data histogram and classify it wrongly. Moreover, low data resolution limits the cut-off frequency of the filter. In fact, the cut-off frequency has to be such that the oscillating behavior of the signal and its derivatives till the second order must be preserved. Consequently, in loops with low data resolution the high-frequency noise cannot be removed completely and the histogram may be strongly corrupted by the noise, as seen in Fig. 3. Similarly, for the cross correlation method, when the data resolution is low, the recorded points are not consistent from one period to another, which can lead to indefinite or misleading results. The area-ratio method also produces unreliable results in control loops with low data resolution. In these cases, the poor data resolution hinders accurate identification of the half-periods and the level of the starting and finishing point of each half period becomes highly variable. This produces unreliable area calculation, which leads to indefinite or wrong stiction detection. Thus, for the selected stiction detection methods, the data resolution should be of at least 20 samples per half-period.

4.6 A summary of the requisites

The results are summarized in Table 2. The first column reports all the stiction detection methods which have been considered. The first row shows all the data feature indexes which have been defined to characterize the data to be processed. All indexes are followed by a sign, either ≥ or ≤, which indicates the inequality with respect to the values presented in the corresponding column. It is worth noticing that as far as the nonlinearity index is concerned, the bound is given on the absolute value since the index can also assume negative values. The average number of samples per half period is also considered and expressed through its inverse: i.e., the so-called resolution index, or I_{RES}. In conclusion, it is worth mentioning that these index thresholds can be used as a guideline, although they are not intended to be definitive under all circumstances.

Table 2. Summary of requisites on data feature indexes for applicability of detection methods

	$I_{OSC}\geq$	$I_{NS}\leq$	$I_{NO}\leq$	$\lvert I_{NL}\rvert\leq$	$I_{RES}\leq$
curve fitting	0.7	0.5	0.15	0.15	0.05
cross- correlat.	0.7	0.25	0.3	0.3	0.05
histogram	0.85	0.25	0.3	0.3	0.05
area-ratio	0.7	0.5	0.15	0.15	0.05

5. DECISION ALGORITHMS

Two algorithms are presented in this section. The first algorithm is devised for selecting the applicable detection methods for a given set of values of the data feature indexes (Section 5.1). The second algorithm is aimed at computing the final detection decision on the basis of the decisions respectively made by the selected methods (Section 5.2). The algorithms are presented with reference to a generic set of data feature indexes and a generic set of detection methods, in order to stress their flexibility: i.e., the possibility of applying the same decision algorithms to different sets of data feature indexes and different sets of detection methods, or, even, more generally, to different detection problems. The following notation is used. $\mathbb{R}$ stands for the set of real numbers. $\mathbb{B}$ stands for the set of Boolean elements: i.e., $\mathbb{B} = \{0, 1\}$. Matrices are denoted by upper-case letters, vectors and scalars by lower-case letters. The symbol $\bar{a}$, where a is a Boolean variable, denotes the complement of a (or, not a).

5.1 Algorithm for selecting the detection methods based on the data features

Let $\mathcal{I} = \{1, 2, \ldots, n\}$ be the finite index set associated with the set of the considered stiction detection methods, so that, for any $i \in \mathcal{I}$, M_i denotes the i-th stiction detection method considered. Let $\mathcal{J} = \{1, 2, \ldots, m\}$ be the finite index set associated with the features considered for the data sequences, so that, for any $j \in \mathcal{J}$, p_j denotes the j-th data feature considered. Let $\tilde{P} \in \mathbb{R}^{n\,x\,m}$ be an $n \times m$ matrix of real values defined in such a way that, for any $i \in \mathcal{I}$ and for any $j \in \mathcal{J}$, $\tilde{P}_{i,j}$ is the minimum value of the j-th feature index for the i-th method to be applicable. In particular, $\tilde{P}_{i,j} = 0$ means that the j-th feature is irrelevant for applicability of the i-th method. Let $p \in \mathbb{R}^m$denote the vector of the feature indexes computed for a given data sequence. Let $S \in \mathbb{B}^{n\,x\,m}$ denote an $n \times m$ matrix whose entries are boolean values computed as follows:

$$S_{i,j} = \begin{cases} 0, & if\ p_j \geq \tilde{P}_{ij} \\ 1, & otherwise, \end{cases} \qquad i \in \mathcal{I},\ j \in \mathcal{J}.$$

Let $a \in \mathbb{B}^n$ denote a n-dimensional vector of Boolean variables computed as follows:

$$a_i = \begin{cases} 1, & if\ \bigvee_{j=1}^{m} S_{i,j} = 0 \\ 0, & otherwise \end{cases}.$$

Then, the set of the methods that can be applied for the given data sequence is defined as follows:

$$\widetilde{M} = \{M_i : a_i = 1, i \in \mathcal{I}\}.$$

5.2 Algorithm for computing the final detection decision

Let $\tilde{\mathcal{I}} = \{1, 2, \ldots, \tilde{n}\}$, with $\tilde{n} \leq n$, denote the index set associated with the set of the applicable algorithms for a given data sequence, so that the set $\widetilde{M}$, can also be written as

$$\widetilde{M} = \{\widetilde{M}_i, i \in \tilde{\mathcal{I}}\}.$$

Let R_i, with $i \in \tilde{\mathcal{I}}$, denote the reliability of the applicable method $\widetilde{M}_i$, with $i \in \tilde{\mathcal{I}}$. Let R_i be defined as the product of so-called reliability of the applicable method $\widetilde{M}_i$, with $i \in \tilde{\mathcal{I}}$, with respect to each of the considered data features p_j, with $j \in \mathcal{J}$: i.e.,

$$R_i = \prod_{j \in \mathcal{J}} R_{i,j},\ i \in \tilde{\mathcal{I}}.$$

Moreover, let us assume that, for each of the considered features, the reliability $R_{i,j}$ be a function of the feature index p_j defined by the following rule

$$R_{i,j} = \begin{cases} 1, & if\ p_j \leq \alpha_{i,j}, \\ 1 - \dfrac{p_j - \alpha_{i,j}}{\beta_{i,j} - \alpha_{i,j}} & if\ \alpha_{i,j} < p_j < \beta_{i,j}, \\ 0, & if\ \beta_{i,j} \leq p_j \end{cases}$$

where $\alpha_{i,j}$, $\beta_{i,j}$ are nonnegative real numbers with $\alpha_{i,j}$ equal to or greater than the minimum value of the admissible range for the j-th feature index p_j and $\beta_{i,j}$ less than or equal to the maximum value of the admissible range for j-th feature index p_j. Hence, $0 \leq R_{i,j} \leq 1$ for all $j \in \mathcal{J}$ and $i \in \tilde{\mathcal{I}}$.

Consequently, $0 \leq R_i \leq 1$ for all $i \in \tilde{\mathcal{I}}$. For any $i \in \tilde{\mathcal{I}}$, let $F_i \in \mathbb{B}$ denote the decision obtained by running the method $\widetilde{M}_i$ for the given data sequence, according to the following rule:

$$F_i = \begin{cases} 1, & if\ fault\ is\ detected, \\ 0, & otherwise. \end{cases}$$

Let $W_F, W_{\bar{F}} \in \mathbb{R}$ be defined as follows

$$W_F = \sum_{i=1}^{\tilde{n}} R_i F_i,\ W_{\bar{F}} = \sum_{i=1}^{\tilde{n}} R_i \bar{F}_i.$$

If

$$\frac{|W_F - W_{\bar{F}}|}{W_F + W_{\bar{F}}} \geq \Delta,$$

where Δ is assigned on the basis of the reliability required for the decision to be made, then the final decision F is determined according to the following rule:

$$F = \begin{cases} 1, & if\ W_F - W_{\bar{F}} > 0, \\ 0, & otherwise, \end{cases}$$

where $F = 1$ means that the fault is detected, while $F = 0$ means that the fault is not detected.

6. VALIDATION OF THE AUTONOMOOUS STICTION DETECTION SYSTEM

In this section, the autonomous stiction detection system devised in this work is tested on a set of eight control loops still taken from Jelali and Huang (2010), but not used for the preliminary analysis presented in Section 4. It is worth mentioning that reducing all the applicability conditions pointed out in Section 4 to the syntax assumed in Section 5 is a question of mere technicalities and, therefore, will be skipped herein. The results of the validation process are shown in Table 3. In this table, the symbol NA in the column denoted as stiction decision indicates that the method is not applicable, the symbol 1 means the stiction is detected, the symbol 0 means that no stiction is detected.

Table 3. Data characterization and stiction detection results for the validation data

Process industry	Process variable		Oscillation	Non-stationarity	Noise	Data resolution	Valve characteristic curve Nonlinearity	Documented diagnosis	Loop type	Applicable methods	Stiction index
Commercial buildings	Temperature	pv	0,94	0,09	0,01	0,16	0,01	1	1	None	NA
		op	0,95	0,28	0,01	0,16					
Commercial buildings	Temperature	pv	0,70	0,05	0,18	0,03	0,83	1	1	None	NA
		op	0,83	0,10	0,01	0,03					
Pulp and paper	Flow	pv	0,73	0,02	0,02	0,047	0,18	1	0	Histogram, Area ratio	1
		op	0,91	0,13	0,01	0,047				Cross correlation	
Pulp and paper	Level	pv	0,89	0,14	0,26	0,029	0,34	1	1	Histogram	1
		op	0,86	0,19	0,21	0,029					
Pulp and paper	Concentration	pv	0,99	0,03	0,02	0,047	0,14	1	1	Curve-fitting	1
		op	0,99	0,06	0,01	0,047				Histogram	
Pulp and paper	Temperature	pv	0,98	0,04	0,01	0,014	0,02	0	0	Area ratio, Cross correlation, Curve-fitting	0
		op	0,98	0,04	0,01	0,014				Rectangular fitting, Histogram	
Power	Level	pv	0,99	0,02	0,00	0,034	0,19	1	1	Histogram	1
		op	0,99	0,04	0,01	0,034					
Power	Level	pv	0,96	0,07	0,05	0,04	0,43	1	1	Histogram	1
		op	0,95	0,14	0,01	0,04					

The system provides the correct results for the tested control loops that fulfill the applicability conditions for at least one method. Conversely, the system is able to correctly classify the control loops in which no method can be implemented. This is the case of the two first validation control loops. In the first control loop, the data resolution is too low for any of the methods to correctly analyze the data. While, in the second control loop, the high nonlinearity index indicates that none of the methods is applicable. In the control loops satisfying the applicability conditions for at least one method, the proposed system is able to select the methods which provide the correct diagnosis. However, the parameters concerning the reliability of each detection method in connection with the values of the feature indexes must be carefully tuned to avoid possible misdiagnoses.

7. CONCLUSIONS

The article presents an autonomous system for detection of valve stiction in control loops of industrial processes. Indexes have been introduced in order to quantify the features of processed data that most affect the correct application of some among the most common, data-driven, stiction detection methods. A preliminary analysis has been carried out in order to identify minimal requisites for the detection methods to be successfully applicable. A first decision algorithm has been devised for the automatic selection of the applicable stiction detection methods. A second decision algorithm has been designed in order to compute the final detection decision as a weighted combination of the detection decisions provided by the single algorithm, based on the reliability of each algorithm with respect to the processed data sequence. The system has been validated by testing on a set of benchmark industrial data.

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