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Detection of Stiction in Level Control Loops ⋆

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Abstract: Stiction is a persistent control valve problem in the process industry responsible for oscillations and, consequently, losses of productivity. Its early detection and separation from other oscillation causes is an important issue in the industrial context. One of simple and effective approaches to detect stiction has been proposed by Yamashita that employed a pattern recognition principle. While its performance is good in flow control loops, it fails to properly diagnose other types of processes.
The present work details a new approach that enables the application of the Yamashita pattern recognition principle to level and other integrating process control loops. A simulation study demonstrates its capabilities in clean and noisy environments and analyzes the impact of the noise on the diagnostic performance.

Keywords: pattern recognition, level control loop, stiction detection, Yamashita Method

1. INTRODUCTION

Stiction is an enduring problem of control loops in process industry. When it occurs, the real position of the valve stem can differ substantially from the controller output (see Fig. 1) deteriorating the performance of the control loop. The stiction phenomenon is responsible for losses of

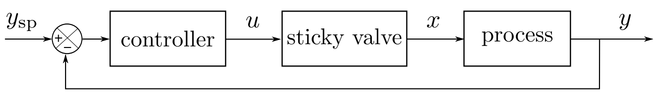

Fig. 1. Industrial control loop with stiction, where y_{sp} is the variable setpoint, u is the controller output, x is the real valve position, and y is the controlled variable.

productivity and considerable research efforts have been devoted to its mitigation (Brásio et al., 2014a). These include stiction modelling (Choudhury et al., 2005; Chen et al., 2008), detection and quantification (Zabiri and Ramasamy, 2009; Brásio et al., 2014b), and compensation (Xiang Ivan and Lakshminarayanan, 2009; Alemohammad and Huang, 2012).

Stiction is one of the common root-causes for oscillations of the controlled variable (approximately 20%-30% of the oscillating process loops). Therefore, its early detection and separation from other oscillation causes is an important issue in an industrial context (Nallasivam et al., 2010). Stiction diagnosis approaches may be based on the signal shape (Yamashita, 2006a; Kalaivani et al., 2014)), on system identification using the Hammerstein model (Babji et al., 2012; Brásio et al., 2014b) and the Hammerstein-Wiener model (Wang and Wang, 2009; Romano and Garcia, 2010). Other approaches have also been considered (Farenzena and Trierweiller, 2012; Arumugam, 2014). Shape based methods are the simplest approaches.

Yamashita (2006a) proposed a shape based method that identifies typical patterns in the graphical representation of the controller output signal versus the real valve position signal.

By applying the method to a considerable number of industrial flow control loops, Manum and Scali (2006) concluded that Yamashita's method diagnoses the presence of stiction in half of the occurrences. However, this method presents the disadvantage of requiring valve stem position data. Even though this data is often unavailable, it is nevertheless possible to apply the method in flow control loops with the assumption of linearity and fast dynamics. Indeed, in such case the controlled variable is proportional to the real valve position. Later, that disadvantage was addressed (Yamashita, 2006b) by developing a new index for systems with slower dynamics, namely level control loops, based on the detection of a two-peak distribution in the signal. However, this approach tends to produce false positive stiction detection, which undermines the method credibility.

The present work develops a new approach to detect valve stiction in level control loops that is based on the preprocessing of the variable profiles prior to the application of the pattern recognition of Yamashita (2006b).

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2. YAMASHITA'S METHOD

Yamashita's method is designed for control loops with pneumatic actuators. The algorithm is based on the qualitative description of the changes suffered by the signals to and from the valve and showed excellent performance in the detection (Yamashita, 2006a).

Yamashita's method describes the typical patterns in the graphical representation of the real valve position versus the controller output (x-u phase plot) associated with the stem movement. Fig. 2 shows those idealized typical patterns of a sticky valve.

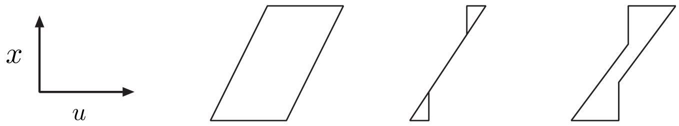


Fig. 2. Typical patterns of a sticky valve.

The qualitative changes of a signal may be represented using a sequence composed by the symbolic values **I**, **S**, **D** meaning increasing, steady and decreasing, respectively, and represented in Fig. 3 (top). The identification of the

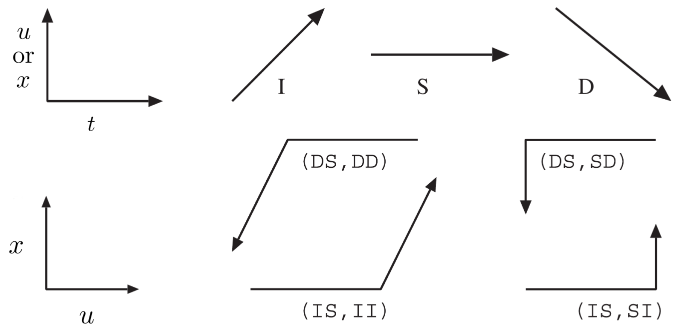


Fig. 3. Symbols used to represent a signal (top) and typical qualitative shapes found in sticky valves (bottom).

symbols is based on the time derivatives of the signals for each sampling point. For instance, at a given sampling point where the signal u increases while the signal y is steady, the symbolic representation is **IS**. For detecting stiction, Yamashita's method uses two main indexes: ρ_1 and ρ_3. The index ρ_1 counts the periods of sticky movements by finding **IS** and **DS** shapes in the phase plot. The index ρ_3 takes into account the fact that some fragments of the stiction patterns may be represented by several sequences of two shapes (**IS II**, **DS DD**, ... as shown in Fig. 3 (bottom)). Those indexes are calculated by

$$\rho_1 = \frac{\tau_{\text{IS}} + \tau_{\text{DS}}}{\tau_{\text{total}} - \tau_{\text{SS}}}\,, \tag{1}$$

$$\begin{aligned}\rho_3 =& \rho_1 - \frac{\tau_{\text{IS DD}} + \tau_{\text{IS DI}} + \tau_{\text{IS SD}} + \tau_{\text{IS ID}} + \tau_{\text{IS DS}}}{\tau_{\text{total}} - \tau_{\text{SS}}} \\ &+ \frac{\tau_{\text{DS DI}} + \tau_{\text{DS SI}} + \tau_{\text{DS ID}} + \tau_{\text{DS II}} + \tau_{\text{DS IS}}}{\tau_{\text{total}} - \tau_{\text{SS}}}\,,\end{aligned} \tag{2}$$

where τ_{total} is the width of the time window and τ_p is the time periods for pattern p (with p = IS, IS DD, ...). Varying between 0 and 1, these indexes get higher if the valve has severe stiction. The authors inferred that the loop is likely to have valve stiction if the index values are greater than 0.25.

Later, Yamashita (2006b) developed a new index for systems with slower dynamics based on the detection of a two-peak distribution in the signal . It is based on the idea that the distribution of the difference between consecutive level measurements contains two separate peaks. To monitor valve stiction, the author uses the excess kurtosis statistical index to verify the distribution peaks. The excess kurtosis is defined as

$$\gamma = \frac{1}{n}\sum_{i=1}^{n} \frac{(\Delta y_i - \mu_{\Delta y})^4}{\sigma_{\Delta y}^4} - 3\,, \tag{3}$$

where Δy is the differential of y, $\mu_{\Delta y}$ and $\sigma_{\Delta y}$ are the mean and the standard deviation of Δy, and n is the number of observations of Δy. A loop with stiction will present a two peaked distribution which means a negative large value of excess kurtosis.

3. PROPOSED APPROACH

The amount of the liquid stored in a vessel may be found by measuring the level of the liquid, y. The dynamics of a container filled with liquid is defined through the mass balance for constant density, ρ, and constant cross-sectional area, A, of the container as

$$\rho\ A\ \frac{\mathrm{d}y}{\mathrm{d}t} = F_{\text{in}} - F_{\text{out}}\,, \tag{4}$$

where F_{in} and F_{out} are the input and output mass flow rates, respectively. Considering linear installed flow characteristic $F = a\ x$, the balance shows that the valve position is directly proportional to the time variation of the vessel level, that is,

$$\frac{\mathrm{d}y}{\mathrm{d}t} \propto x\,. \tag{5}$$

As mentioned above, Yamashita's method performs well in flow rate control loops because it assumes that the controlled variable y is almost proportional to the real valve position x. However, such assumption is not valid for level loops and Yamashita's method fails because the dynamic patters are different from those expected in flow control loops.

The rationale behind the present approach consists in applying a transformation function to the data to obtain a direct relation to the real valve position and only then apply the well-known Yamashita's method. Different transformation is required for self-regulating and integrating processes. In the later, which is the subject of this work, the transformation function $f(y)$ is defined by (5) using the finite difference approximation

$$f(y) = \frac{y(t+1) - y(t)}{\Delta t}\,, \tag{6}$$

where Δt is the sampling time.

Fig. 4 shows the real valve position x (first row) and the controlled variable y (second row) from a simulated level control loop containing a healthy valve (left column) and a sticky valve (right column). The application of the transformation function $f(y)$ to the level data is also drawn in the same figure (third row) showing how similar the transformed signal becomes to the real valve position for both cases.

Although this extension is only applicable to level control loops data, it merely uses operational data easily available

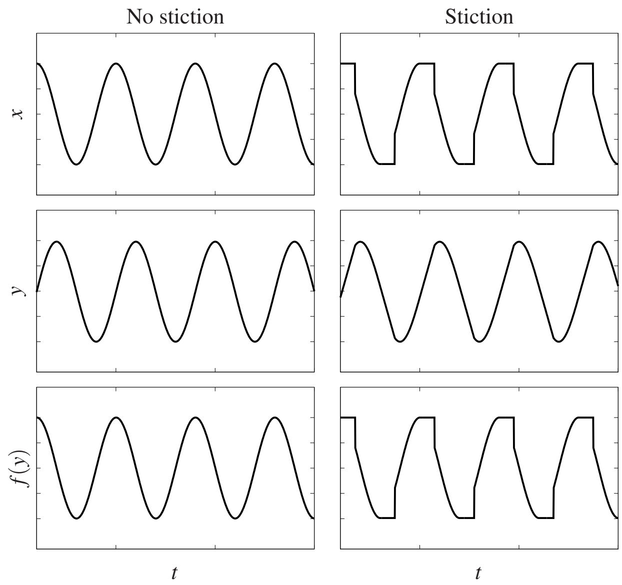


Fig. 4. Real valve position x, controlled variable y and transformation function $f(y)$ applied to the level for no stiction and stiction cases.

in plants (the controller output u and the controlled variable y) and requires no parameter tuning.

4. APPLICATION TO A SIMULATED SYSTEM

This section presents an evaluation of the proposed approach using simulated data sets generated by an Hammerstein Model which is frequently used to model the stiction phenomenon. The Hammerstein Model consists of a non-linear element in series with a linear dynamic part. In the present context, the non-linear element represents the sticky valve while the linear part models the process dynamics. The present work uses the Choudhury Model to model stiction and the state-space model

$$\dot{y}(t) = a\ y(t) + b\ x(t)\,, \tag{7}$$

where a and b are state-space model constants, to model the process dynamics.

In order to collect the experimental data, a plant simulation was carried out using the defined Hammerstein Model and the control algorithm

$$u(t) = u(t-1) + k_{\mathrm{C}}\ e(t) + \frac{1}{\tau_{\mathrm{I}}}\int_0^t e(t)\ dt + \tau_{\mathrm{D}}\ \dot{e}(t)\,, \tag{8}$$

where $e(t)$ is the error signal, k_{C} the proportional gain, τ_{I} the integral time (or reset time), and τ_{D} the derivative time. Model parameters of Choudhury et al. (2005) were used to generate data of a level control loop: $a = 0$ min, $b = 1$ m/%, $k_{\mathrm{C}} = 0.4$ %/m, $\tau_{\mathrm{I}} = 0.2$ min^{-1}, and $\tau_{\mathrm{D}} = 0$ min. The Choudhury Model parameters (S, J) were defined as: $(0, 0)$% for no stiction, $(3, 0)$% for pure deadband, $(3, 1.5)$% for stiction with undershoot, and $(3, 3)$% for stiction with no-offset.

Fig. 5 shows the collected data in a situation of regulatory control.

It is composed by two parts: part (a) exhibits u and x signals while part (b) displays u and y signals. Each of these parts (a) and (b) is constituted by two columns showing the signals time trends at the left-hand and the corresponding phase plots at the right-hand. It is noteworthy that only u and y data are usually available from plants.

The first row shows a healthy valve (no stiction) where the real valve position x follows the input u. The second row exemplifies the pure deadband case. The third and forth rows represent cases of stiction with undershoot and with offset, respectively. When there is stiction in a control loop, its behavior deteriorates giving rise to unwanted limit cycles in the real valve position x and, consequently, in the controlled variable y. The third, forth and fifth rows of Fig. 5a and 5b clearly exhibit these cycles. The second row evidences that an integrator produces limit cycles even in the presence of pure deadband.

The approach developed in the present work was applied to the generated closed-loop data. The transformation function $f(y)$ was calculated using (6) for the level data y. Then, Yamashita's method was applied to the variable u and to the transformed signal $f(y)$. Table 1 presents the numerical results for all the data sets, under the reference "New Approach".

The expected evaluation for detection of stiction is pointed out in the second column.

With comparison purposes, two other techniques were applied to the same data sets. Yamashita's original method was applied using variable u and the controlled variable y. The study was complemented with the results of the version of Yamashita's method for slower dynamics (Yamashita, 2006b). The later was applied using just the controlled variable y. The results of these two techniques are also shown in Table 1.

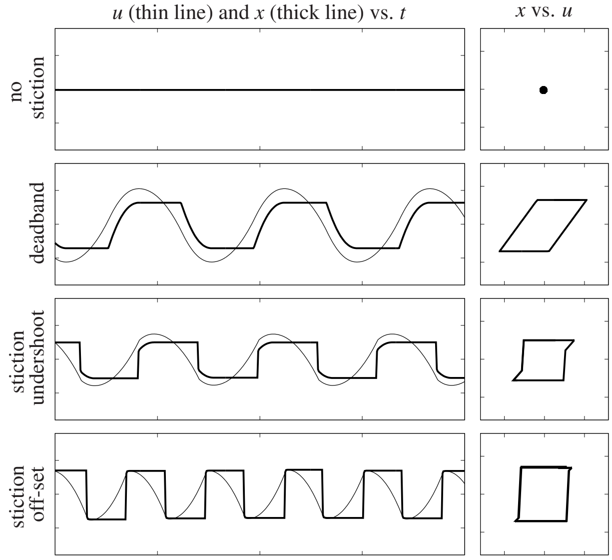
The performance evaluation of the methods on the simulated noise free closed-loop data (shown in Fig. 5) reveals that Yamashita's method produces two wrong detections in the cases of deadband and stiction with undershoot whereas Yamashita's index for slower dynamics detects correctly the stiction phenomenon for the four studied cases. The results of the new approach proposed in this work are also correct and consistent for all the cases.

It is worth emphasising that such results were obtained for noise-free simulated data, which is uncommon in real industrial practice.

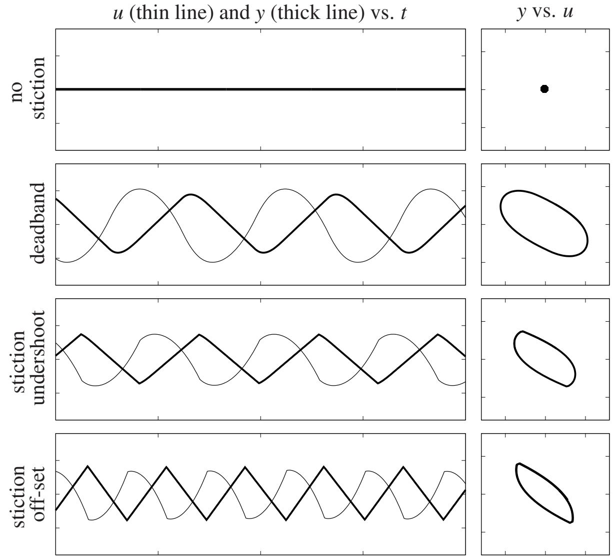
5. INFLUENCE OF NOISE IN THE DETECTION

The presence of noise in industrial data greatly impacts the plant performance analysis as it may obfuscate relevant information and, consequently, affect the algorithms. In this section, the influence of noise on the performance of the proposed stiction detection approach as well as on the performance of the other two techniques is studied. At first, the performance of the three methods was scrutinized by analysing how they handled sets of simulated data adulterated by noise. Moreover, different intensities of noise were studied. Finally, the three methods were compared when dealing with industrial data.

The dataset undergoes filter and downsampling as follows. The generated dataset is subdivided in 10 datapoint windows and a straight line is fitted within each of the intervals using the least-square criterion. The obtained



(a) u and x signals.



(b) u and y signals.

Fig. 5. Closed-loop response of a level control loop obtained by simulation using the Choudhury Model.

Table 1. Stiction detection results for free-noise closed-loop data of the level control.

	True	Yamashita's Method			Yamashita's index for slower dynamics		New Approach		
Case	Eval.	ρ_1	ρ_3	Eval.	γ	Eval.	ρ_1	ρ_3	Eval.
No stiction	×	0.22	0.22	×	48.87	×	0.05	0.05	×
Pure deadband	✓	0.20	0.20	×	-1.80	✓	0.48	0.48	✓
Stiction undershoot	✓	0.02	0.02	×	-1.97	✓	0.96	0.93	✓
Stiction no-offset	✓	0.27	0.25	✓	-1.99	✓	0.95	0.90	✓

function is used to calculate the value at the beginning of the interval.

5.1 Using Simulated Data

Noisy closed-loop data was generated with the parameters mentioned above and with several degrees of noise n added to the controlled variable. The PID controller (8) parameters are $k_C = 0.2$ % m^{-1}, $\tau_I = 0.2$ min^{-1}, and $\tau_D = 0$ min. The results of the detection methods are presented in Table 2 where the characterization of the added noise is also explicitly defined.

The presence and intensity of noise degrades the performance of Yamashita's original method and, especially, of Yamashita's index for slower dynamics. In the presence of noise, both methods give false positives and the second method additionally gives false negatives when the noise is more intense. In opposition, the proposed method produced the expected diagnosis results for all the cases highlighting its capacity to detect stiction even in noisy environments.

The trends of the indexes ρ_1 and ρ_3 (Table 2) are represented in Figures 6a and 6b for the cases of no stiction, pure deadband, and stiction with undershoot, and no-offset.

Additionally, the indexes obtained for the closed-loop data sets without noise are also illustrated.

It is possible to observe that the values of the indexes obtained from the no-stiction data are clearly in the no stiction zone ($0 \leq \rho_i \leq 0.25$). The pure deadband renders intermediate values ($\rho_i \sim 0.5$). The case of stiction with undershoot obtains higher values for ρ_i than the other two stiction cases, probably justified by the larger jump component in these two cases ($J \geq S$). In the presence of noise mitigated with the use of filtering, the indexes maintain correct trends in all the cases, even though an evident influence of the noise may be observed. For instance, for the no-stiction case, ρ_1 is very close to 0.25 and almost results in a false positive. In comparison, ρ_3 copes better with the presence of noise and achieves a bigger distance from the limit value. In the pure deadband case, ρ_i values experienced a slight decrease. The most significant change was observed in the stiction cases where the index values were radically reduced to values near the ones obtained by the pure deadband case. Such behavior may be attributed to the fact that the jump component of stiction is hidden by the noise as it has fast dynamics and amplitude compared to the stick component and the process dynamics.

Although the present approach is affected by the presence of noise, it showed adequate performance after a simple data filtering.

5.2 Using Industrial Data

The new approach was also applied to three industrial data sets collected by Jelali and Huang (Jelali and Huang,

Table 2. Influence of noise in stiction detection by the three compared methods.

	$n_1 \sim \mathcal{N}(0, 0.1^2)$			$n_2 \sim \mathcal{N}(0, 0.2^2)$			$n_3 \sim \mathcal{N}(0, 0.3^2)$			$n_4 \sim \mathcal{N}(0, 0.4^2)$			$n_5 \sim \mathcal{N}(0, 0.5^2)$		
Case	Indexes		Eval.	Indexes		Eval.	Indexes		Eval.	Indexes		Eval.	Indexes		Eval.
Yamashita's Method	ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3	
No stiction	0.41	0.22	✓	0.41	0.22	✓	0.41	0.22	✓	0.41	0.22	✓	0.41	0.22	✓
Pure deadband	0.41	0.29	✓	0.39	0.25	✓	0.43	0.27	✓	0.43	0.26	✓	0.42	0.26	✓
Stiction undershoot	0.40	0.25	✓	0.41	0.24	✓	0.42	0.25	✓	0.40	0.24	✓	0.42	0.26	✓
Stiction no-offset	0.37	0.21	✓	0.41	0.25	✓	0.40	0.23	✓	0.42	0.26	✓	0.39	0.23	✓
Y. Slower Dynamics		γ			γ			γ			γ			γ	
No stiction		-0.07	✓		-0.07	✓		-0.07	✓		-0.07	✓		-0.07	✓
Pure deadband		-0.91	✓		-0.01	✓		-0.04	✓		-0.08	✓		0.08	×
Stiction undershoot		-0.70	✓		-0.09	✓		-0.12	✓		-0.05	✓		0.15	×
Stiction no-offset		-1.13	✓		-0.04	✓		-0.12	✓		-0.12	✓		-0.04	✓
New Approach	ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3		ρ_1	ρ_3	
No stiction	0.23	0.16	×	0.23	0.16	×	0.23	0.16	×	0.23	0.16	×	0.23	0.16	×
Pure deadband	0.39	0.39	✓	0.42	0.35	✓	0.47	0.43	✓	0.41	0.38	✓	0.39	0.36	✓
Stiction undershoot	0.42	0.38	✓	0.46	0.42	✓	0.44	0.39	✓	0.38	0.31	✓	0.43	0.39	✓
Stiction no-offset	0.58	0.56	✓	0.46	0.41	✓	0.37	0.32	✓	0.37	0.34	✓	0.37	0.31	✓

2013). The first data set is identified by CHEM4 in Jelali's database and is characterized by containing a controller with tuning problems. The second data set, identified by CHEM27, corresponds to a control loop containing valve stiction. Finally, the third data set is identified by CHEM73 and corresponds to a control loop performing well (the root cause of the oscillation is an external disturbance).

Table 3 presents the results obtained by the three methods.

The first case (CHEM4) is correctly undetected by Yamashita's original method, but Yamashita's index for slower dynamics produces a false positive. As for the case CHEM26, both methods fail in detecting the existence of stiction. In what concerns the case CHEM73, the first method fails while the second indicates a correct negative result. These results show that these two methods don't consistently detect the presence/absence of stiction. However, the new approach was able to diagnose all the cases under consideration.

6. CONCLUSION

A new method based on the pattern recognition approach of Yamashita was proposed in the present work in order to detect stiction in level control loops. Using simulated data, the new method performance was compared to two Yamashita methods and showed superior performance. The influence of the noise on stiction detection of the pattern based algorithms was carried out using both noisy simulated data and industrial data. Although the stiction phenomenon gets obfuscated by the noise, correct stiction diagnosis is possible with data filtering. The proposed method may be further extended to auto regulatory processes using adequate data transformation, such as the fitting of linear dynamic models.

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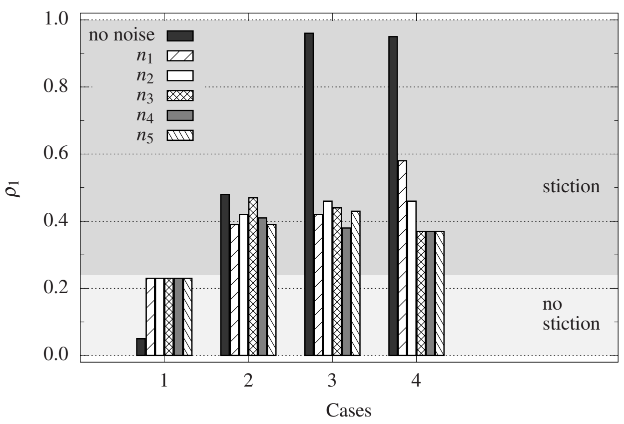
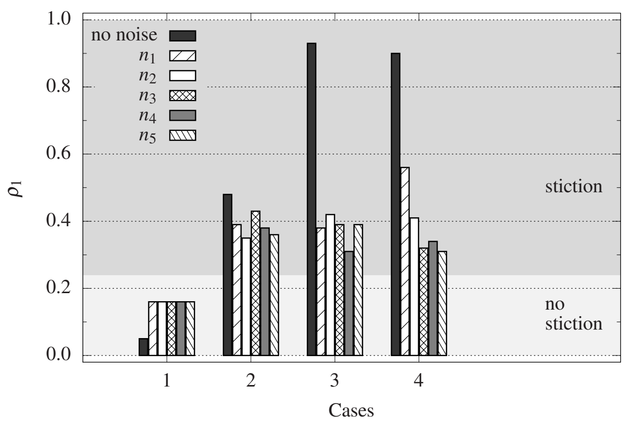


(a) Index ρ_1.



(b) Index ρ_3.

Fig. 6. Influence of noise in ρ_1 and ρ_3 using the proposed approach for the cases: (1) no stiction, (2) pure deadband, (3) stiction with undershoot, and (4) stiction with no-offset.

Table 3. Stiction detection results for level control industrial data.

Data set	True Eval.	Yamashita's Method ρ_1	Yamashita's Method ρ_3	Yamashita's Method Eval.	Yamashita's index for slower dynamics γ	Yamashita's index for slower dynamics Eval.	New Approach ρ_1	New Approach ρ_3	New Approach Eval.
CHEM4	×	0.15	0.09	×	-1.22	✓	0.11	0.00	×
CHEM26	✓	0.03	0.01	×	0.90	×	0.48	0.21	✓
CHEM73	×	0.29	0.15	✓	32.10	×	0.24	0.11	×

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