Identification techniques for stiction quantification in the presence of nonstationary disturbances

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Abstract: The paper presents a detailed comparison of different identification techniques applied to valve stiction quantification, possibly in the presence of nonstationary unknown disturbances. The control loop with sticky valve is modeled as a Hammerstein system, in which the nonlinearity is identified using enumeration of the parameters' space. Five different techniques for identification of the linear model are compared in terms of achievable performance. In particular, the capability to cope with the presence of nonstationary disturbances is analyzed. The techniques allow one to estimate the unknown actual valve position (MV), without requiring any process knowledge, being based only on data which are usually recorded in industrial plants: controller output (OP) and controlled variable (PV). Simulations show that external perturbations can be tolerated, thus ensuring a reliable evaluation of stiction in practical situations where external disturbances are usually present. Models which incorporate a time varying additive nonstationary disturbance grant a better process identification and a more accurate stiction estimation in the case of disturbance acting simultaneously with valve stiction. However, simpler models are the best choice when stiction happens to be the only source of loop oscillation. Results are confirmed by application to real data: pilot plant data are used to corroborate the effectiveness of the techniques.

Keywords: Control loop performance monitoring, stiction quantification, Hammerstein model identification, disturbance estimation

1. INTRODUCTION

Control loop performance assessment is recognized as an important aspect to improve profitability of industrial plants. First of all, an effective monitoring system should be able to detect loops with poor performance, then to distinguish different causes of malfunction in order to suggest the most appropriate actions to carry out. Main sources of malfunction are: external disturbances, controller tuning and valve problems. Valve stiction (static friction) is recognized as the more important cause of performance degradation (Jelali and Huang, 2010). After pioneering works by Karnopp (1985) and Canudas de Wit et al. (1995), new impulse to stiction characterization for performance assessment was given by Choudhury et al. (2005). Broadly speaking, research activity on stiction includes modeling, detection, quantification and compensation.

Models derived from physical principles, i.e. (Karnopp, 1985), are more accurate, but they require the knowledge of many parameters, something not possible in practice and therefore their use is not convenient. For this reason models derived from process data are generally preferred (Choudhury et al., 2005; Kano et al., 2004; He et al., 2007; Chen et al., 2008). A review of a significant number of stiction detection techniques recently presented in the literature, is reported in (Jelali and Huang, 2010); among them: cross-correlation function-based (Horch, 1999), waveform shape-based (Kano et al., 2004; Srinivasan et al., 2005a; Singhal and Salsbury, 2005; Rossi and Scali, 2005; Yamashita, 2006; He et al., 2007; Scali and Ghelardoni, 2008), nonlinearity detection-based (Choudhury et al., 2004), and model-based algorithms (Karra and Karim, 2009b). In (Jelali and Huang, 2010) a comparison of performance is also presented by applications on a large benchmark (93 loops) of industrial data.

Following their conclusions, research on stiction modeling and detection has to be considered a mature topic, also if it may happen that different results are obtained once applied on industrial set of data, owing to complexity and superposition of different phenomena. Stiction quantification instead, has to be regarded as an area where research contributions are still needed. The main difficulty arises from the fact that the valve stem position (MV) is not recorded in old designed control systems and then must be reconstructed from available measurements (controlled variable, PV, and controller output, OP) by using a data driven stiction model.

Many approaches use a Hammerstein system to model the control loop: a linear block for the process and a nonlinear block for the sticky valve (Srinivasan et al., 2005b; Choudhury et al., 2008; Jelali, 2008; Farenzena and Trierweiler, 2012; Bacci di Capaci and Scali, 2014). Karra and Karim (2009b) use a specific linear model, which includes also nonstationary perturbations affecting the process. Romano and Garcia (2011) adopt a Hammerstein-Wiener structure to model the control loop. More recently, Araujo et al. (2012) propose a technique based on harmonic balance method and describing function identification. He and Wang (2014) illustrate a simplified technique based on a new semi-physical valve stiction model.

In a recent paper by the authors (Bacci di Capaci and Scali, 2014) it is clearly put into evidence that the main difficulty about validation of stiction quantification techniques consists in the fact that the true value of stiction is not known in industrial data (only in simulation or in rare experiments it can be considered known). Therefore, while simulation is the first necessary step to check mathematical consistency of a proposed technique, its validation on a single set of industrial data can be pointless. As a confirmation, results obtained by different quantification techniques can be very different once applied on the same set of industrial data (as it happened in benchmark presented by Jelali and Huang (2010), Chp. 13). A second aspect focused in the paper by (Bacci di Capaci and Scali, 2014) is that stiction estimation may fail when nonstationary disturbances are present. To overcome this problem, it is suggested to repeat stiction estimation for different data acquisitions for the same valve, in order to follow the time evolution of the phenomenon and to disregard anomalous cases (outliers). The comparison of reasonable values of stiction with predefined acceptable thresholds allows one to schedule valve maintenance in a reliable way (on-line stiction compensation is also an alternative, though not very popular in industry).

Following the above considerations, this paper represents a continuation of the work reported in (Bacci di Capaci and Scali, 2014), and addresses the following new objectives: i) to compare some different identification techniques when applied on the same dataset; ii) to show how external nonstationary disturbances can influence stiction estimation and system identification. Both aspects were not considered in the methodology presented in (Bacci di Capaci and Scali, 2014) where a single (ARX) model structure and identification techniques was considered and nonstationary disturbances were assumed absent. The rest of this paper is organized as follows. In Section 2, different identification methods for stiction quantification are illustrated, and in Section 3, the results are compared in simulation. In Section 4 the techniques are applied to pilot plant data; conclusions are drawn in Section 5.

2. MODELING AND IDENTIFICATION TECHNIQUES

In the considered identification methods, the control loop is modeled by a Hammerstein system (Figure 1). Kano's (or He's) stiction model describes the nonlinear valve dynamics. Five different models describe the linear process dynamics:

- ARX: Auto Regressive model with eXternal input;
- ARMAX: Auto Regressive Moving Average with eXternal input;
- SS: State Space model;
- EARX: Extended Auto Regressive model with eXternal input;
- EARMAX: Extended Auto Regressive Moving Average with eXternal input (Karra and Karim, 2009a).

The proposed stiction quantification techniques are based on a grid search, a method which is simple and mathematically sound. Computational time may be long, but it does not represent a disadvantage for three reasons: the procedure is oriented toward an off-line application which requires data registered for hours, the wear phenomena in valves occur slowly (weeks or months), and valve maintenance usually occurs periodically on the occasion of a plant shutdown.

2.1 Nonlinear stiction models

In (Kano et al., 2004), the relation between the controller output (the desired valve position) OP and the actual position MV is described in three phases (Figure 2, left):

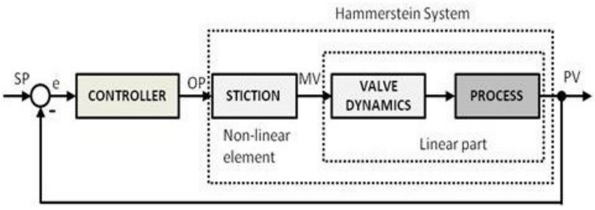

Fig. 1. Hammerstein model representing control sticky valve followed by linear process.

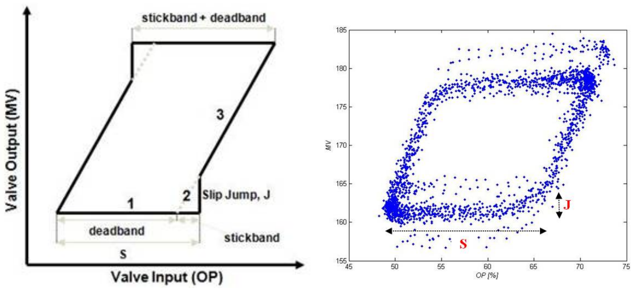

Fig. 2. Left) valve stiction modeling; right) typical industrial limit cycle.

1. *Sticking*: MV is steady and the valve does not move, owing to the static friction force (dead-band + stick-band, *S*).
2. *Jump*: MV changes abruptly because the active force unblocks the valve, *J*.
3. *Motion*: MV changes gradually, and only the dynamic friction force can possibly oppose the active force (the valve stops again when the force generated by the control action decreases under the stiction force).

In (He et al., 2007), the relation between OP and MV is slightly different and simpler. The model uses static f_S and dynamic f_D friction parameters and is closer to the first-principle-based formulation. To reduce the complexity, it uses a temporary variable that represents the accumulated static force.

Valve stiction produces an offset between controlled variable (PV) and set point (SP), and this causes loop oscillation because the valve is stuck even though the integral action of the controller increases pressure on the valve diaphragm. The MV(OP) diagram shows a parallelogram-shaped limit cycle, while MV(OP) would be perfectly linear without valve stiction. Figure 2 (right) represents the PV(OP) plot for a case of flow control loop, for which the fast dynamics allows one to approximate MV(OP) with PV(OP), since MV is usually not measured. It should be recalled that also in the case of stiction, loops with slower dynamics (level control, temperature control) show PV(OP) diagrams having elliptic shapes. Similar PV(OP) diagrams are obtained for other types of oscillating loops (in the presence of external stationary disturbance or aggressive controller tuning), and therefore assigning causes is not straightforward. It is also worth saying that the value of J is critical to induce limit cycles (Choudhury et al., 2008; Jelali, 2008). However, while S is easy recognizable, J is hardly detectable in industrial data, owing to its small value and the presence of field noise (Figure 2, right).

2.2 Linear process models

The linear part of the Hammerstein system has one of the following structures, in discrete time form.

- ARX:
$$A(q)y_k = B(q)u_{k-t_d} + e_k \tag{1}$$
where $A(q)$ and $B(q)$ are polynomials in time shift operator q (i.e. such that $q\,u_k = u_{k+1}$), and given as:
$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_n q^{-n} \\ B(q) &= b_1 q^{-1} + b_2 q^{-2} + \ldots + b_m q^{-m} \end{aligned} \tag{2}$$
where e_k is white noise, t_d is the time delay of the process, (n,m) are the orders on the auto-regressive and exogenous terms, respectively.
- ARMAX:
$$A(q)y_k = B(q)u_{k-t_d} + C(q)e_k \tag{3}$$
where $A(q)$ and $B(q)$ are defined in (2), whereas:
$$C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} + \ldots + c_p q^{-p} \tag{4}$$
in which p is the order of the moving average term.
- SS:
$$\begin{aligned} x_{k+1} &= \mathbf{A}x_k + \mathbf{B}u_k + \mathbf{K}e_k \\ y_k &= \mathbf{C}x_k + e_k \end{aligned} \tag{5}$$
where $\mathbf{A} \in \mathbb{R}^{n\times n}$, $\mathbf{B} \in \mathbb{R}^{n\times 1}$, $\mathbf{C} \in \mathbb{R}^{1\times n}$, $\mathbf{K} \in \mathbb{R}^{n\times 1}$, and n is the model order.
- EARX:
$$A(q)y_k = B(q)u_{k-t_d} + e_k + \eta_k \tag{6}$$
where η_k is a time varying bias representing the additive nonstationary external disturbance, to be estimated along with the polynomials $A(q)$ and $B(q)$.
- EARMAX:
$$A(q)y_k = B(q)u_{k-t_d} + C(q)e_k + \eta_k \tag{7}$$

2.3 Hammerstein system identification

The identification procedures are as follows. (i) A grid of the two stiction parameters (S,J) is built: for each possible combination of (S,J), the MV signal is generated from the (measured) OP signal using a stiction model (Kano's or He's). (ii) The coefficients of the linear models are identified using different techniques on the basis of (generated) MV and (measured) PV sequences. The overall model fit is quantified by F_{PV}:
$$F_{PV} = 100 \cdot \left(1 - \frac{\|PV_{est} - PV\|^2}{\|PV - PV_m\|^2}\right) \tag{8}$$
where PV, PV_m and PV_{est} are vectors containing values of the measured output, measured output average and estimated output sequences, respectively. The symbol $\|\cdot\|$ denotes the Euclidean norm. Thus, for each considered linear model, the optimal combination of (S,J) is computed as the one that maximizes the fitting index F_{PV}.

ARX model coefficients are identified by least-squares regression. SS model coefficients are estimated using a subspace identification method, the PARSIM-K technique (Pannocchia and Calosi, 2010). ARMAX, EARX and EARMAX models are identified using the recursive least-squares (RLS) identification algorithm proposed (for EARMAX model) by Karra and Karim (2009a). For EARX an EARMAX, a decoupled parameter covariance update procedure with variable forgetting factors is developed to identify the process parameters and the bias term (Karra and Karim, 2009a). To the best of the authors' knowledge, this is the first time that a SS model and an EARX model are used for Hammerstein system identification applied to valve stiction estimation.

3. SIMULATION EXAMPLES

The objective of this section is to investigate the effect of stiction amount and of external disturbance presence on the efficiency of the methods to yield accurate estimation. To this aim, as a first step, simulation results are provided to describe the capabilities of the compared algorithms for Hammerstein system identification. The systems are simulated in closed-loop operation, which is known to be a difficult task as compared to open-loop identification, because of the correlation between process noise and input sequences. OP and PV sequences are used without any filtering in the identification methodologies, which fall under the class of direct identification techniques.

An ARMAX process subject to an external disturbance is simulated as a test bed, and is given by the following discrete time model (Karra and Karim, 2009b):
$$\begin{aligned} y_k = 0.7358y_{k-1} - 0.1353y_{k-2} + 0.2642u_{k-1} \\ +0.1353u_{k-2} + e_k + 0.7e_{k-1} - 1.3e_{k-2} + \eta_k \end{aligned} \tag{9}$$
where:
$$\eta_k = a\big(sin(0.02\,k) + 0.5sin(0.05\,k)\big) \tag{10}$$
with $a \geq 0$. Stiction parameters are varied to cover a wide range of phenomena ($S \in [2, 12]$, $J \in [1, 4]$) using Kano's model. The stationary disturbance $\{e_k\}$ is a normally distributed white noise signal with standard deviation $\sigma_e = 0.1$. The process is in closed-loop with a proportional-integral (PI) controller having proportional gain $K_C = 0.4$, and integral gain $K_I = 0.3$ (values which allow stable response with acceptable performance).

The system is excited by introducing a random-walk signal, as controller set-point, which varies as follows:
$$SP_k = \begin{cases} SP_{k-1} + 2(R_{2k} - 0.5) & \text{if} \quad R_{1k} > 1 - \delta_{sw} \\ SP_{k-1} & \text{otherwise} \end{cases} \tag{11}$$
where δ_{sw} is the average switch probability and R_{1k}, R_{2k} are two random numbers drawn, at time k, from a uniform distribution in $[0,1]$. This type of set-point is thought to reproduce an industrial scenario of a control loop with variable reference commanded by a higher level Model Predictive Controller.

One hundred Monte-Carlo simulations are carried out, using different realizations of white noise $\{e_k\}$, for each set of stiction parameters and disturbance amplitude. The linear process model orders and the time delay are fixed a-priori in performing identification steps, namely $t_d = 0$, $(n,m) = (2,2)$ for ARX and EARX, $(n,m,p) = (2,2,2)$ for ARMAX and EARMAX, $n = 2$ for SS. No structural error is present in the nonlinear part: Kano's model is also used to generate MV sequences.

Note that data of PV and OP are divided into two sets. The first two-thirds of data are used as identification data set; the last third of data is used as validation set in order to test the models previously identified. As in (8), a fitting index for the estimation data set, $F_{PV}^{(id)}$, and for the validation data set, $F_{PV}^{(val)}$, can be defined. The linear model fit is quantified by the scalar E_G given as:
$$E_G = 100 \cdot \left(1 - \frac{\|G_{est}(z) - G(z)\|_\infty}{\|G(z)\|_\infty}\right) \tag{12}$$
where $G(z)$ and $G_{est}(z)$ are the true process and the identified model discrete-time transfer functions, respectively, and $\|g(z)\|_\infty = \max_{\omega\in[0,2\pi]} |g(e^{i\omega})|$. The nonlinear model fit is quantified by F_{MV}:

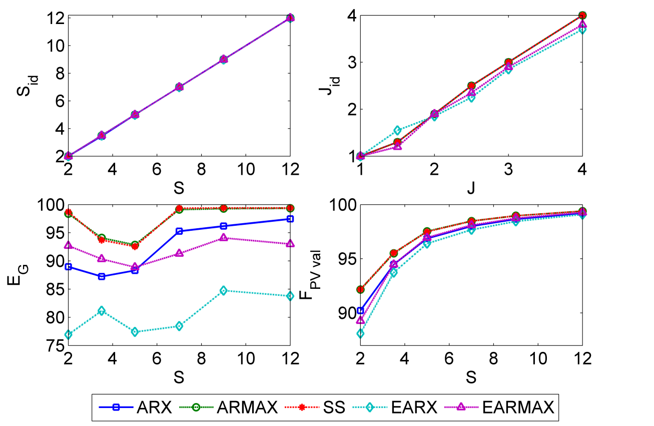

Fig. 3. Identification results for $a = 0$: top panels, left: S_{id} vs S, right: J_{id} vs J; bottom, left E_G vs. S, right $F_{PV}^{(val)}$ vs. S.

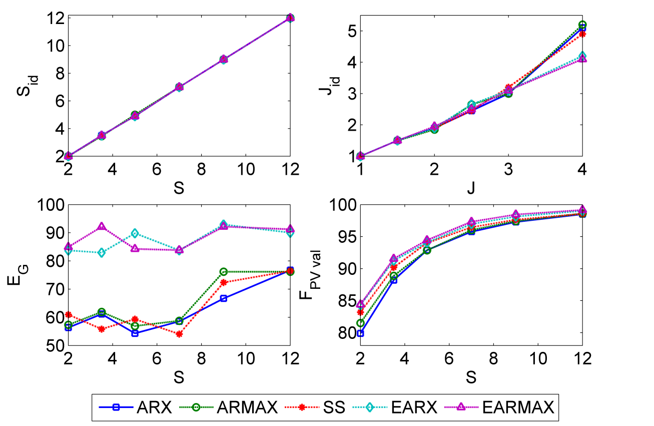

Fig. 4. Identification results for $a = 0.25$: top panels, left: S_{id} vs S, right: J_{id} vs J; bottom, left E_G vs. S, right $F_{PV}^{(val)}$ vs. S.

$$F_{MV} = 100 \cdot \left(1 - \frac{\|MV_{est} - MV\|^2}{\|MV - MV_m\|^2}\right) \quad (13)$$

where MV, MV_m and MV_{est} are vectors containing values of the actual valve position, average actual valve position and the estimated valve position.

Figure 3 shows a summary of the results for the case of $a = 0$ in (10), that is when valve stiction is the only source of oscillation. Top panels show the various simulated stiction cases (S, J) and the corresponding estimated parameters (S_{id}, J_{id}). Bottom panels show the values of the fitting indices E_G and $F_{PV}^{(val)}$ using the different proposed techniques. Figure 4 shows a summary of the results for the case of $a = 0.25$ in (10), that is when an external disturbance acts simultaneously with stiction. It can be clearly seen that, in the case of pure stiction oscillation, ARX, ARMAX and SS models ensure a more accurate stiction estimation and, mostly, perform a better linear model identification: E_G values are higher, especially for ARMAX and SS. On the other hand, in the presence of external disturbance, the stiction parameters and the linear model identified using EARMAX and EARX are of higher accuracy as compared to the other identification techniques: E_G and $F_{PV}^{(val)}$ values are higher.

Computational times are different for each technique. The ARX model, with a simple algorithm of LLS identification, requires really shorter times compared to ARMAX, EARX, EARMAX and SS models. There is approximately one order of magnitude: some seconds vs. some minutes. Similar outcomes have been obtained using different process dynamics, other disturbance amplitudes and frequencies, different types of SP signal (also constant), and with He's stiction model in place of Kano's model. Details are not reported in the sake of space. Note that, in general, to be able to obtain good model parameter estimates, the data has to be rich enough. Normal operating data may not be persistently exciting, especially if the set point is constant for long periods of time.

4. PILOT PLANT DATA: RESULTS AND DISCUSSION

In this section, the performances of the considered methods on pilot plant data are illustrated. A diagram of the pilot plant used in the experiments is shown in Figure 5. Water circulates between drums *D1* and *D2*, and a pneumatic actuator is coupled to a spherical valve (*V2*) which controls the flow rate. Further details on the experimental apparatus can be found in (Bacci di Capaci et al., 2013). The control valve, its stem and the packing are shown in Figure 5 (right). Friction is "introduced" into the valve by tightening the packing nut. The valve is equipped with a positioner, but the inner control loop of the positioner is opened: in this way the actual valve stem position (MV) is measured but the positioner does not perform any control action. The PV is the flow rate through the valve and the OP is the output signal from a PI controller.

Figure 6 shows the MV(OP) diagram of the valve obtained imposing triangular waves on OP, oscillating from 0 to 100% of the valve span. The valve shows an asymmetric behavior: S (dead-band + stick-band) is bigger in the closing direction and smaller in the opening direction, while the slip jump J is always really small. The stiction parameters obtained from off-line tests on the valve are approximately known: $S \in [22, 29]$ and $J \in [0.2, 1]$. Two different sets of data are collected with a sampling time of 1 s. In the first experiment, valve stiction is the only source of oscillation. In the second one, an external disturbance is introduced in the control loop and acts simultaneously with the stiction (same amount); the opening of the valve *V3* (installed downstream the sticky valve *V2*) is changed by imposing, as command (OP), a near sinusoidal profile in order to "generate" the external disturbance.

Kano's model and He's model are firstly used to fit the two measured MV signals. The best combinations of parameters for the two stiction models are respectively: S = 22.1; J = 0.2, with a fitting of 76.28%, and S = 22.0; J = 0.1, with a fitting of 76.27%. Both nonlinear models appear adequate. The five linear models with the two stiction models are then applied to detect and quantify the amount of stiction without the knowledge of the MV signal. Table 1 and Table 2 show, respectively, the results of the comparison for the first and the second experimental set.

Table 1 confirms good estimation performances obtained with the three models (ARX, ARMAX and SS) which do not implement the bias signal η. They grant a better identification of the nonlinearity: F_{MV} values are higher, i.e. that MV is better estimated. EARMAX and EARX models perform a higher PV fitting but produce a lower MV estimation: having one more degree of freedom, they tend to generate a bias term even when the external disturbance is not present in order to improve the PV fitting.

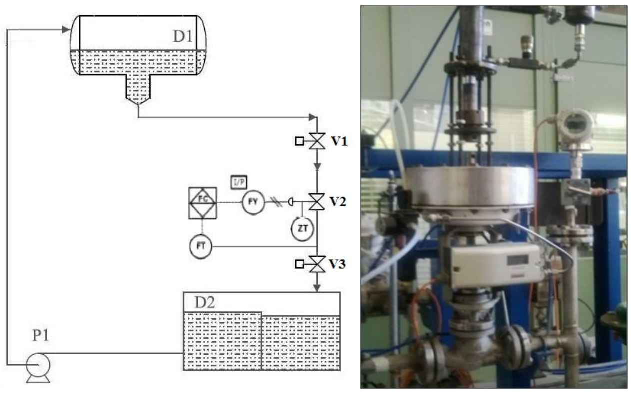

Fig. 5. Left) the pilot plant diagram; right) the sticky valve.

Table 1. First experiment: only valve stiction.

LIN technique	NL model	S	J	F_{PV}	$F_{PV}^{(id)}$	$F_{PV}^{(val)}$	F_{MV}
ARX	Kano	25.2	4.3	84.89	85.53	83.57	62.61
	He	23.6	1.5	85.08	85.59	83.99	63.44
ARMAX	Kano	24.5	3.5	85.19	85.62	84.27	71.85
	He	22.7	2.0	85.13	85.77	83.79	71.82
SS	Kano	24.5	3.5	85.22	85.67	84.26	71.85
	He	22.7	2.0	85.09	85.77	83.68	71.82
EARX	Kano	26.6	0.7	85.92	87.07	83.65	28.93
	He	25.0	1.6	86.02	87.25	83.63	41.39
EARMAX	Kano	26.8	3.3	85.57	87.37	82.22	25.33
	He	25.0	1.6	86.11	87.34	83.70	41.39

For the second experiment the results are basically opposite (cfr. Table 2): EARMAX and EARX models grant both a better PV fitting and a higher MV estimation. On the opposite, ARX, ARMAX and SS perform a worse identification of the linear dynamics and a completely wrong estimation of the nonlinearity. The presence of the external disturbance can alter stiction estimation when a nonextended model is used to identify the linear dynamics.

Figure 7 shows the registered time trends of SP, PV, OP, MV, and the estimated values of PV and MV (PV_{est}, MV_{est}) of the first experiment when He's model for the sticky valve and the SS model for the linear dynamics are used. Both the PV fitting indices are sufficiently high (cfr. Table 1): $F_{PV}^{(id)} = 85.77\%$ for the identification dataset and $F_{PV}^{(val)} = 83.68\%$ for the validation dataset. Also the estimation of the valve stem position is rather accurate: $F_{MV} = 71.82\%$. A nonextended model is appropriate when only valve stiction is present in the control loop.

Figure 8 shows the corresponding registered time trends and estimated signals of the second experiment when Kano's model and the EARMAX model are used. In the bottom panel the stem position of valve *V3* is reported; this signal is proportional to the disturbance entering the process. The extended model gives an accurate overall PV fitting (cfr. Table 2) $F_{PV} = 78.79\%$ and a reasonable MV fitting $F_{MV} = 36.71\%$ (especially compared to values obtained with ARX, ARMAX and SS models). The estimated stiction values obtained with EARX and EARMAX are close to the real parameters unlike those obtained with nonextended models (ARX, ARMAX and SS). The presence of the external disturbance does not affect significantly stiction estimation when an extended model is used.

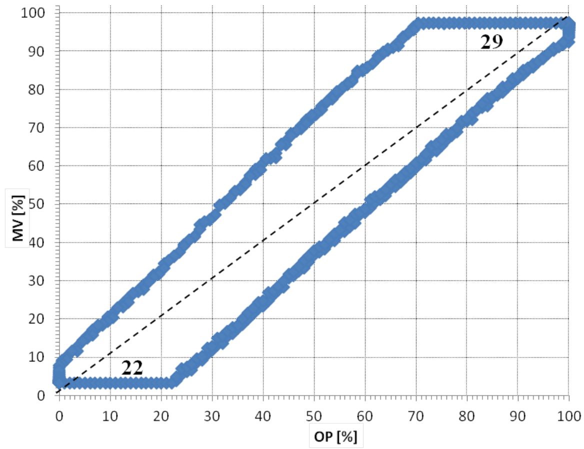

Fig. 6. Input-output plot of the sticky valve.

Table 2. Second experiment: valve stiction and external disturbance.

LIN technique	NL model	S	J	F_{PV}	$F_{PV}^{(id)}$	$F_{PV}^{(val)}$	F_{MV}
ARX	Kano	13.8	2.7	78.26	78.27	78.20	-131.27
	He	13.1	1.3	78.37	78.22	78.54	-116.95
ARMAX	Kano	12.2	2.7	78.75	78.62	78.88	-163.99
	He	10.2	4.8	78.94	78.97	78.86	-189.26
SS	Kano	10.2	2.7	78.88	78.73	79.03	-203.10
	He	10.4	2.8	79.14	78.85	79.50	-181.10
EARX	Kano	20.6	0.9	78.61	79.81	76.95	39.21
	He	20.2	0.5	78.66	79.83	77.04	38.55
EARMAX	Kano	20.2	0.5	78.79	80.01	77.11	36.71
	He	20.3	2.8	78.74	80.06	76.93	24.89

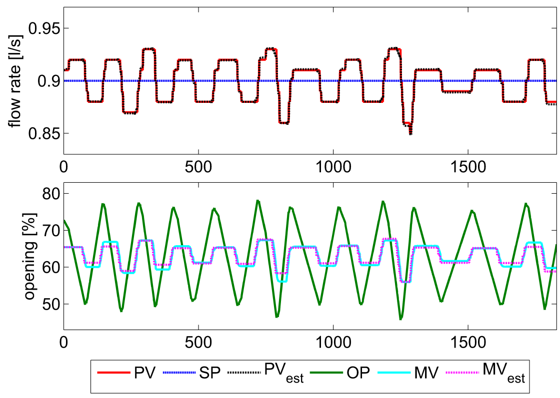

Fig. 7. First experiment: registered time trends.

5. CONCLUSIONS

In this paper, two different stiction models and five linear models have been presented and compared in order to identify the Hammerstein system describing a process controlled with a sticky valve. The identification methods have been validated, firstly, by using closed-loop simulation data in the presence of different faults (low/high stiction, with/without external nonstationary disturbances). Then, practical usefulness has been demonstrated through the application of the considered identification methods to a pilot plant.

For the nonlinear part, both Kano's and He's models are appropriate to model the sticky valve. Simpler models (ARX, ARMAX and SS) seem the best choice for the linear part, describing the process, when stiction is the only source of loop os-

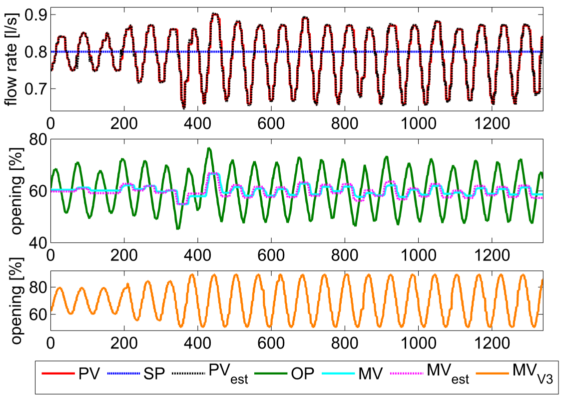

Fig. 8. Second experiment: registered time trends.

cillation. The extended models (EARX, EARMAX), which incorporate the time varying additive nonstationary disturbance, yield a better process identification and a more accurate stiction estimation in the case of disturbance acting simultaneously with stiction. Thus, detecting the presence of external disturbance seems the logic solution to this problem. Recent techniques (Naghoosi and Huang, 2014; Guo et al., 2014) could be used as a preliminary step in stiction estimation in order to choose between simpler or extended process models.

Our current research is devoted to extending the comparison to a large industrial data set, featuring data from loops available in (Jelali and Huang, 2010) and from Italian refinery plants. This evaluation will allow one to further assess the relative merits of the different techniques and the need of using the more complex models in situations where the presence/absence of nonstationary disturbances cannot be confirmed a-priori.

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