Identification and estimation of valve stiction by the use of a smoothed model

Riccardo Bacci di Capaci * **Marco Vaccari** * **Gabriele Pannocchia** *,**
Claudio Scali *

* *Department of Civil and Industrial Engineering, University of Pisa, Pisa, Italy*
** *Corresponding author: gabriele.pannocchia@unipi.it*

Abstract: Stiction in control valves is considered one of the most common causes of poor performance in control loops. Thus, non-invasive, reliable and efficient methods which can detect and quantify this malfunction are highly desirable in the process industry. Under the framework of Hammerstein model identification and nonlinear optimization, this paper proposes an approach to estimate stiction amount on the basis of a recently proposed smoothed model. One of the motivations of the work is to improve the performance of a stiction unaware model predictive controller which exhibits sustained oscillations in the presence of valve stiction. By augmenting process model with the identified valve dynamics, the controller is turn to a stiction embedding formulation which can actually remove fluctuations and then guarantees good set-point tracking. Applications to simulation case studies and industrial loops are used to demonstrate the validity of the proposed method. Results are compared with a standard grid-search approach and other identification techniques of the literature.

Keywords: Process control; control valve; stiction modeling and estimation; model predictive control

1. INTRODUCTION

Stiction is now a well-known source of performance degradation in industrial control loops, caused by excessive static friction between the stem and packing in the control valve. The major consequence is the presence of sustained oscillations in process variables, which lead to shorter life of control valves, and then inferior quality end-products and minor profitability of whole industrial plant (Jelali and Huang, 2010). These limit cycles appear when a traditional controller with integral component is used, as an excessive control action is imposed while the valve is sticking, so that the valve jumps between two extreme positions, above and below the desired operating point.

It is well established that controller retuning, both in PID and MPC configuration, can help to reduce amplitudes and frequencies of oscillation (Ale Mohammad and Huang, 2012), but performance degradation is prone to recur as the process dynamics changes or different operation conditions are set. In addition, it has to be noted that even the standard offset-free formulation of a model predictive controller (MPC) cannot completely address valve stiction, whether the valve malfunction is not expressly considered in the plant model. In these cases, the disturbance estimate is not zero, but shows sustained oscillations which unavoidably propagate to other loop variables.

In a recent work, Bacci di Capaci et al. (2017) observed that stiction embedding MPC is a valid solution which guarantees good set-point tracking ability and stiction compensation. Fair robustness has been demonstrated, but performance tend obviously to deteriorate once stiction is unmodeled or when a parameters mismatch is present. Therefore, a suitable model for valve dynamics and a good estimate for stiction parameters are required.

This paper is hence focused on a reliable and efficient approach to estimate valve stiction amount, on the basis of a recently proposed smoothed model, under the framework of Hammerstein model identification and nonlinear optimization. The remainder of the work is organized as follows. Preliminaries about problem definition, valve stiction modeling and quantification are given in Section 2. The proposed identification and estimation method is described in Section 3. Some numerical examples are then presented in Section 4, while applications to industrial data are shown in Section 5. Finally, conclusions are drawn in Section 6.

2. PROBLEM DEFINITION

The plant under study is formed by the control valve followed by the process dynamics as depicted in Figure 1. In detail, χ is the valve stiction output, that is, process input; y is the process output; u is the output of a generic (e.g. PID or model predictive) controller, and v is a white Gaussian output noise. For the sake of simplicity, the case of SISO system is presented:

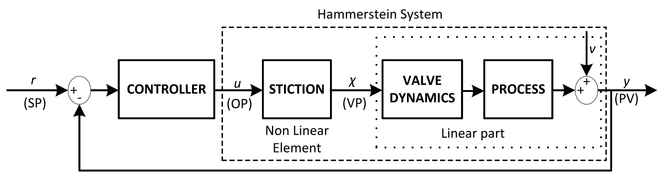

Fig. 1. The closed-loop system with the sticky control valve followed by the process.

a nonlinearity for the valve stiction followed by a linear dynamics for the process, thus forming a Hammerstein structure for the whole plant. Investigation of MIMO systems and nonlinear processes are beyond of our current scope, although a generalization is possible. Valve dynamics is described by a data-driven stiction model, while the linear process dynamics can be expressed by ARX, ARMAX, or state-space model.

For example, the whole plant dynamics in standard state-space formulation can be written as:

$$\begin{aligned} z_{k+1} &= f(z_k, u_k) \\ y_k &= h(z_k) + v_k \end{aligned} \tag{1}$$

The valve output χ represents the first component of the state vector of whole plant $z_k = [\chi_{k-1}, \xi_k]^T$, so that:

$$\begin{aligned} z_{k+1} = \begin{bmatrix} \chi_k \\ \xi_{k+1} \end{bmatrix} &= \begin{bmatrix} \varphi(\chi_{k-1}, u_k) \\ \mathbf{A}\xi_k + \mathbf{B}\varphi(\chi_{k-1}, u_k) \end{bmatrix} \\ y_k &= \mathbf{C}\xi_k + v_k \end{aligned} \tag{2}$$

where $\xi \in \mathbb{R}^n$ is the process state vector, $\mathbf{A} \in \mathbb{R}^{n\times n}$, $\mathbf{B} \in \mathbb{R}^{n\times m}$, $\mathbf{C} \in \mathbb{R}^{p\times n}$, being n the process model dimension, and $m = p = 1$. Note that the first component of state equation is given by the stiction nonlinearity, expressed by the discontinuous function $\varphi(\cdot)$: $\mathbb{R}^m \times \mathbb{R}^m \to \mathbb{R}^m$, later discussed.

2.1 Stiction Modeling

Stiction in pneumatic sliding stem control valves can be described both by detailed physical models and by empirical (data-driven) models (Garcia, 2008). For practical purposes, only the latter are actually useful, as few parameters and relatively simple algebra are involved. The most established data-driven models have been proposed by Choudhury et al. (2005), Kano et al. (2004) and He et al. (2007). Only two parameters are used: the sum of stickband and deadband (S), and the stick-slip jump (J) for first two models; the dynamic (f_D) and static (f_S) friction in the third one. The aforesaid standard empirical model and the semi-physical model (He and Wang, 2010) by He and coworkers have been proved suitable to reproduce the valve response generated by physical stiction models without involving computationally intensive numerical integration. In these models, fast response from the valve is assumed, so that the transient dynamics can be ignored and a static – but with memory – nonlinear function can be used, that is, only the stationary-state values of stem position are considered.

A discontinuous model. In He's standard data-driven model (He et al., 2007), the sticky valve has a nonlinear dynamics $\chi_k = \varphi(\chi_{k-1}, u_k)$ expressed by the following two relations:

$$\chi_k = \begin{cases} \chi_{k-1} + [e_k - \text{sign}(e_k) f_D] & \text{if} \quad |e_k| > f_S \\ \chi_{k-1} & \text{if} \quad |e_k| \le f_S \end{cases} \tag{3}$$

where f_S and f_D are static and dynamic friction parameters, respectively, and $e_k = u_k - \chi_{k-1}$. Note that e_k can be interpreted as the valve position error, while $f_S \ge f_D$ by definition. By substituting e_k, then by expanding the nonlinear *sign* function, and finally by solving the inequalities, the valve dynamics can be rewritten as:

$$\chi_k = \begin{cases} u_k - f_D & \text{if} \quad u_k - \chi_{k-1} > f_S \\ u_k + f_D & \text{if} \quad u_k - \chi_{k-1} < -f_S \\ \chi_{k-1} & \text{if} \quad |u_k - \chi_{k-1}| \le f_S \end{cases} \tag{4}$$

Therefore, the stiction nonlinearity $\varphi(\cdot)$ is formed by a set of three linear and parallel relations, thus constituting a sort of switching "multi-mode" model, which, when identified along with the process dynamics, acts as a *discontinuous* model.

The smoothed model. Due to the presence of *if-else* statements which imply two hard discontinuities in the input-output relation of the valve, He's model involves stiff equations that might represent a difficult task into the optimization problem used in identification. Therefore, the *smoothed* stiction model introduced by Bacci di Capaci et al. (2017) is used in this work in order to get a smoother problem. Model (4) is expressly approximated by using a single smoothing function $\varphi_S(\cdot)$:

$$\chi_k = \eta_1(e_k)\chi_{k-1} + (1 - \eta_1(e_k))u_k + \eta_2(e_k) f_D \tag{5}$$

where $\eta_1(e_k)$ and $\eta_2(e_k)$ are the sum of two hyperbolic functions, defined as below:

$$\begin{aligned} \eta_1(e_k) &= \frac{1}{2}\tanh(\tau(e_k + f_S)) + \frac{1}{2}\tanh(\tau(-e_k + f_S)) \\ \eta_2(e_k) &= \frac{1}{2}\tanh(-\tau(e_k + f_S)) + \frac{1}{2}\tanh(\tau(-e_k + f_S)) \end{aligned} \tag{6}$$

where τ is a smoothing parameter, such that the higher is its value, the larger is the sharpness of the functions. Extensive simulations have verified that, using $\tau \ge 10^4$, the valve signature given by the proposed smoothed model (5) matches exactly the original He's model results. It is to be noted that the proposed identification method can be applied with other smoothed stiction models based on the various discontinuous models available in the literature.

2.2 Stiction Quantification

The ability of providing an estimate of stiction amount is a crucial step for shortlisting the most critical valves, scheduling valve maintenance, or performing on-line compensation. Methods available in the literature can be broadly divided into four main categories: apparent stiction techniques (Choudhury et al., 2006), Hammerstein-based methods (e.g., Srinivasan et al. (2005); Choudhury et al. (2008); Jelali (2008); Bacci di Capaci and Scali (2014); Bacci di Capaci et al. (2016)), nonlinear process model-based methods (e.g., Wang and Wang (2009); Romano and Garcia (2011)), mixed approaches (e.g., Zabiri et al. (2009); Araujo et al. (2012); He and Wang (2014)). Some techniques perform detection and quantification of valve stiction in a single stage, while other methods can be applied only once stiction is clearly detected by suitable methods.

Among others techniques, the methods of Jelali (2008) and Farenzena and Trierweiler (2012) used global and gradient-free optimization approaches. The first one implemented genetic and path search algorithms, but, despite being quite robust, high computational times are required. The second proved to be an improvement as one-stage identification is performed by means of a deterministic algorithm that is no longer dependent on the initial guess, obtained via the ellipse fitting method of Choudhury et al. (2006).

3. THE PROPOSED METHODOLOGY

In this section the proposed stiction identification and quantification method is detailed. The linear part of the Hammerstein model has an ARX structure in discrete-time form:

$$A(q)y_k = B(q)\chi_{k-t_d} + v_k \tag{7}$$

where $A(q)$ and $B(q)$ are polynomials in backward shift operator q^{-1} (i.e. such that $\chi_k = q^{-1}\chi_{k+1}$), v_k is white noise, and t_d is the input time-delay of the process. The two polynomials are expressed as:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_{n_a} q^{-n_a} \\ B(q) &= b_1 q^{-1-t_d} + b_2 q^{-2-t_d} + \ldots + b_{n_b} q^{-n_b - t_d} \end{aligned} \tag{8}$$

where (n_a, n_b) are the orders on the auto-regressive and exogenous terms, respectively. The nonlinear part of process model employs the aforesaid smoothed stiction model (5).

Optimization variables X are static and dynamic friction of (5) and $n_a + n_b$ coefficients of ARX process model (7), that is, $X = [\hat{f}_S, \hat{f}_D, \hat{\theta}^T]^T$, being $\theta = [a_1, \ldots, a_{n_a}, b_1, \ldots, b_{n_b}]^T$. The nonlinear optimizer finds an optimal solution starting from a suitable initial point X_0. In particular, vector coefficients of process dynamics θ is initialized by performing a first-guess identification with an ARX model between controller output u and process variable y, that is, no valve stiction is firstly assumed. Hence, $\hat{\theta}_0$ is calculated by:

$$\hat{\theta}_0 = \text{pinv}(\Phi_0)y = [\Phi_0^T \Phi_0]^{-1} \Phi_0^T y \tag{9}$$

where $\Phi_0 \in \mathbb{R}^{N \times n_a + n_b}$ is the initial regressor matrix of the measurements, computed by stacking singular linear regressor vectors $\phi_{0,k}$ at each sample time k:

$$\phi_{0,k} = [-y_{k-1}, \ldots, -y_{k-n_a}, u_{k-1-t_d}, \ldots, u_{k-n_b-t_d}] \tag{10}$$

where N is the number of data points.

The one-stage nonlinear optimization problem is then formulated as follows:

$$X^* = \arg \min_{f_S, f_D, \theta} \text{SE}(y, \hat{y}) \tag{11a}$$

subject to:

$$f_{\min} \le f_S, f_D \le f_{\max}$$
$$f_S \ge f_D \tag{11b}$$
$$\sigma^2(\hat{\chi}) \ge \sigma^2_{\min}$$

The objective function is the Square Error (SE) between the output of actual process and of identified model $\hat{y}$:

$$\text{SE}(y, \hat{y}) = \tfrac{1}{2}(y - \hat{y})^T (y - \hat{y}) \tag{12}$$

The output of identified model is computed as $\hat{y} = \Phi \hat{\theta}$, where $\Phi \in \mathbb{R}^{N \times n_a + n_b}$ is the regressor matrix built by stacking singular regressor vectors at each sample time, with values of valve position $\hat{\chi}$ estimated from the nonlinear model, i.e.:

$$\phi_k = [-y_{k-1}, \ldots, -y_{k-n_a}, \hat{\chi}_{k-1-t_d}, \ldots, \hat{\chi}_{k-n_b-t_d}] \tag{13}$$

Note that stiction parameters domain has a triangular shape: $f_{\max} \ge f_S \ge f_D \ge f_{\min} = 0$. Indeed, the so-called overshoot stiction cases are excluded, since waveforms generated by these parameters combinations are rarely observed in practice. The largest value of stiction parameters can be assumed equal to the oscillation span of controller output: $f_{\max} = \Delta u$. As known, under boundary conditions, when $f_S + f_D = \Delta u$, the valve jumps between two extreme positions, thus generating an exactly square-shaped signal.

The other constraint is imposed on $\sigma^2(\hat{\chi})$, the variance of identified valve position $\hat{\chi}$. This is done to avoid uncommon waveforms, that is, identified valve position cannot be fully or mostly steady, but is forced to oscillate due to the presence of stiction. A safe choice is considering the controller output variance, e.g. $\sigma^2_{\min} = \alpha \sigma^2(u)$, with $\alpha = 0.1$. Finally, note that time-delay t_d and model orders are assumed as parameters in the proposed formulation. An iterative approach may be derived by repeating the optimization procedure for a set of time-delays and various model orders.

In this work, analysis have been performed on a code written in Python 2.7 with the use of symbolic framework offered by CasADi 3.1. As nonlinear programming solver, the optimization problem implements `IPOPT`, a well-established interior point algorithm (Wächter and Biegler, 2006).

Finally, note that in order to avoid to be stuck in a local minimum, a multiple starting algorithm has been implemented thus improving robustness of the optimization. The proposed approach is hence iterated by setting M initial solutions. A good method is starting from the boundaries of the triangular-shaped domain of stiction parameters, by fixing a suitable step, e.g. $\Delta f_S = \Delta f_D = 0.5$. Further initial points can be obtained from the ellipse-fitting method (Choudhury et al., 2006). An estimate of the so-called *apparent* stiction S_0 on the x-width of polar plot PV(OP), that is, $y(u)$, is computed, and a limited set of combinations which satisfy $S_0 = f_S + f_D$ are added. Finally, the best solution in terms of objective function and infeasibility is evaluated.

4. SIMULATION ANALYSIS

The performance of proposed approach are firstly investigated on numerical data.

Example 1. A third order transfer function for the process model is considered:

$$P(s) = \frac{1}{(4s+1)(6s+1)(2s+1)} \tag{14}$$

which corresponds to the following ARX process in discrete-time form with sample period $T_s = 1$ and $(n_a, n_b) = (3, 3)$:

$$y_k = 2.232 y_{k-1} - 1.645 y_{k-2} + 0.3998 y_{k-3} + 0.00277 \chi_{k-1} + 0.00884 \chi_{k-2} + 0.001752 \chi_{k-3} + v_k \tag{15}$$

Valve stiction is described by original discontinuous He's model, with parameters: $f_S = 7$, $f_D = 4$. The output white noise v is a random sequence with normal distribution, zero-mean and standard deviation $\sigma = 10^{-2}$.

Closed-loop data are generated in Python by using a model predictive controller (Vaccari and Pannocchia, 2016) and imposing some set-point changes. In the considered *stiction unaware* MPC, the Finite Horizon Optimal Control Problem (FHOCP) solved at each time k is defined as following:

$$\min_{\boldsymbol{x}, \boldsymbol{u}} \sum_{i=0}^{N_H - 1} (\xi_i - \xi_{s,k})^T Q (\xi_i - \xi_{s,k}) + (u_i - u_{s,k})^T R (u_i - u_{s,k}) + (\xi_{N_H} - \xi_{s,k})^T V_F (\xi_{N_H} - \xi_{s,k}) \tag{16a}$$

subject to:

$$\xi_0 = \hat{\xi}_k \tag{16b}$$
$$\xi_{i+1} = \mathbf{A}\xi_i + \mathbf{B}u_i \tag{16c}$$
$$y_i = \mathbf{C}\xi_i + \hat{d}_k \tag{16d}$$
$$\xi_i \in \mathbb{X}, \quad u_i \in \mathbb{U}, \quad y_i \in \mathbb{Y} \tag{16e}$$

where N_H is a positive integer representing the horizon length, Q, R, and V_F are the various penalty matrices, $\hat{\xi}$ and $\hat{d}$ are the current state and disturbance estimate of the model (2), the triple $(\xi_{s,k}, u_{s,k}, y_{s,k})$ represent the steady-state values satisfying (2), and the triple $(\mathbb{X}, \mathbb{U}, \mathbb{Y})$ forms the constraints set. For more details see (Bacci di Capaci et al., 2017). Note that in the stiction unaware MPC formulation, the valve dynamics $\varphi(\cdot)$ of (2) is completely neglected and only the process model P in the corresponding state-space form is embedded:

$$\mathbf{A} = \begin{bmatrix} 2.2318 & -1.6450 & 0.7997 \\ 1.0 & 0 & 0 \\ 0 & 0.5 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0.125 \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{C} = [0.0222 \ 0.0707 \ 0.0280] \tag{17}$$

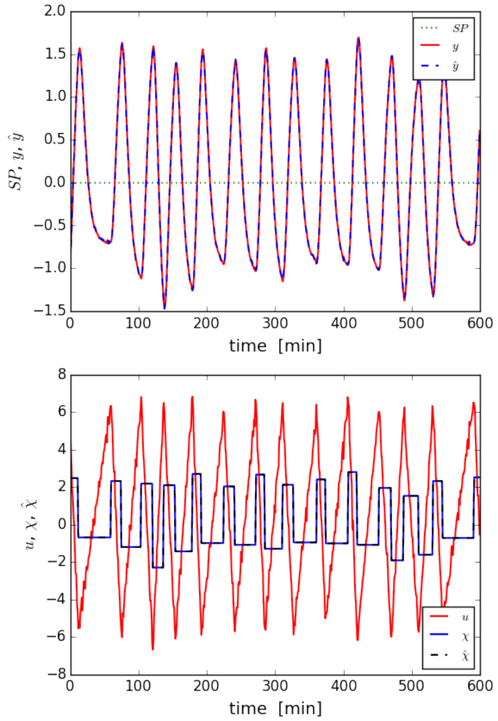

Fig. 2. Example 1. Measured and estimated time trends.

The smoothed stiction model of (5) is used in the identification stage, on the basis of controller output u and process variable y. The time-delay ($t_d = 0$) and ARX model orders are supposed known for the sake of simplicity. The proposed nonlinear optimization method proves to be effective, as it obtains very accurate stiction parameters: $\hat{f}_S = 6.98$, $\hat{f}_D = 4.01$. The corresponding process parameters are identified reasonably close to actual values:

$$\hat{\theta} = [-1.195, -0.204, 0.4353, 0.00375, 0.01094, 0.01767]$$

Note that the computational time required is very short: about 4 s for $M = 7$. Figure 2 shows measured time trends and estimated signals for a data window of sustained oscillation with constant set-point. It is to be observed that the fitting of process variable is high, and also the estimation of valve position is very accurate.

The same data set is then analyzed with a traditional method of grid-search over the space of nonlinear model parameters, as explained by Bacci di Capaci et al. (2016). A triangular grid of stiction parameters (f_S, f_D) is built, and for each possible combination valve output is generated from measured controller output by using the smoothed stiction model (5). Then, ARX model coefficients are identified by least-squares regression on the basis of the generated valve output and the measured process output. The optimal combination of stiction parameter is evaluated as the one that minimizes the SE on process variable (12). The step size of the grid is set to $\Delta f_S = \Delta f_D = 0.5$ and the true combination is included. Not surprisingly, stiction parameters are identified exactly, but at the expense of much higher computational time (about 150 s).

It is evident that the computational time of the proposed optimization is definitely much shorter, thus offering a remarkable advantage in on-line applications. This aspect is further investigated in the following numerical example.

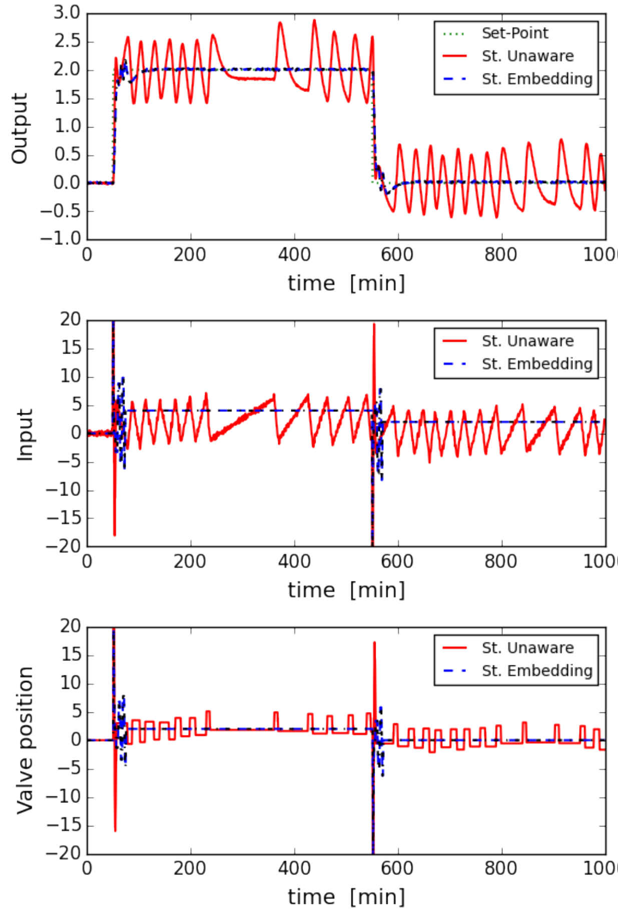

Fig. 3. Example 2. Process variable, controller output and valve position for two different MPC formulations.

Example 2. Another ARX process in discrete-time form with $T_s = 1$ and $(n_a, n_b) = (3, 3)$ is considered:

$$\begin{aligned} y_k &= 2.091 y_{k-1} - 1.375 y_{k-2} + 0.2725 y_{k-3} \\ &+ 0.002445 \chi_{k-1} + 0.007181 \chi_{k-2} + 0.001278 \chi_{k-3} + v_k \end{aligned} \quad (18)$$

He's stiction model with parameters $f_S = 5$, $f_D = 2$ is used for valve dynamics, and the output white noise is a random sequence with normal distribution, zero-mean and standard deviation $\sigma = 10^{-1.5}$. Closed-loop data are obtained by using a stiction unaware MPC, based only on linear process model in the corresponding state-space form (Bacci di Capaci et al., 2017). Once again, the smoothed stiction model is used for the identification stage. The time delay ($t_d = 0$) and ARX model orders are supposed known. The following stiction parameters are obtained $\hat{f}_S = 5.02$, $\hat{f}_D = 1.99$, with a short computational time (about 6 s for $M = 7$). The identified process parameters are not far from actual values:

$$\hat{\theta} = [-1.124, -0.360, 0.5112, 0.002085, 0.011218, 0.010629]$$

Then, the smoothed stiction model with the newly identified parameters is embedded in another formulation of MPC. A *stiction aware* controller is thus derived by augmenting the plant model with the estimated valve dynamics $\varphi(\cdot)$. Process variable, controller output, and valve position for the two different MPC formulations in response to the same set-point trend – a series of two step changes – are shown in Figure 3.

It is evident that the traditional unaware MPC formulation does not remove fluctuations induced by stiction, as the disturbance estimate cannot be brought to zero, but the state estimator keeps sustained oscillations which unavoidably propagate to other loop variables. On the opposite, the embedding formulation shows good set-point tracking ability and allows an effective stiction compensation. Nevertheless, it has to be recalled that best performance for stiction embedding MPC are not achievable only by augmenting plant model with the valve dynamics and accurate stiction parameters. As a matter of fact, also an appropriate warm-start has to be given to the dynamic optimization module of predictive controller, as explained in (Bacci di Capaci et al., 2017).

5. APPLICATION TO INDUSTRIAL DATA

The proposed method is also applied to some industrial data. Three case studies of the dataset of Jelali and Huang (2010), illustrated as a benchmark for stiction detection methods, are used. These loops are clearly indicated as suffering from valve stiction by several detection methods. The obtained results (with $\tau = 2.5 \times 10^2$) are also compared with the estimates given by the grid-search method described in Section 4, with a fixed step size on both parameters: $\Delta f_S = \Delta f_D = 0.1$. In addition, the estimates are compared with values obtained by three well-established techniques of the literature: (Karra and Karim, 2009; Lee et al., 2008; Jelali, 2008). Table 1 summarizes the overall results.

CHEM 10. These data come from a pressure control loop in a chemical process industry. The proposed method is applied to an ARX(2,2) model with fixed time-delay ($t_d = 0$) and two different levels of smoothing factor τ. Figure 4 shows measured time trends and estimated signals. Karra and Karim used Kano's stiction model and an Extended-ARMAX model with $t_d = 1$ and $(n_a, n_b, n_c) = (2,2,2)$. Lee et al. used an ARX$(2,1)$ model and standard He's stiction model. As awaited, different methods obtain different estimates of stiction parameters.

CHEM 25. Also these data are from a pressure control loop in a chemical process industry. The proposed method is applied with different ARX model orders. Figure 5 shows measured time trends and estimated signals for $(n_a, n_b) = (2,2)$. Karra and Karim employed Kano's model and EARMAX model with $t_d = 1$ and $(n,m,p) = (2,2,2)$. Jelali tested the loop twice using an ARMAX model with: (i) $t_d = 2$, $(n,m,p) = (3,2,2)$ and (ii) $t_d = 1$, $(n,m,p) = (2,2,1)$. Lee et al. used an ARX$(2,1)$ model and He's stiction model. Once again, the estimation results are quite heterogeneous.

POW 4. These data are from a level control loop in a power plant. The proposed method is applied with different ARX model orders. Karra and Karim used an EARMAX model with unspecified parameters applied on the initial data window (1 - 1000 samples). Jelali tested the loop using an ARMAX model of unspecified orders, probably on the first 700 samples. Lee et al. used an ARX(2,1) and He's stiction model applied on all available data. The proposed identification method is executed on the first 1000 samples. As in previous two cases, the estimates of stiction parameters are different for the compared methods. Note that the proposed method always requires much lower computational times than the grid-search technique.

As general conclusion from this section, it is worth recalling that the exact stiction estimates depend on several issues. In addition to general aspects, e.g., the dataset used in identification, choice of objective function, solver, and algorithms, in the case of Hammerstein system also the following issues are important: type, order, and time-delay of the linear process model; type of the nonlinear stiction model.

Table 1. Results for industrial data.

Data	Method	St. Model	(n_a,n_b,n_c)	$\hat{f}_S$	$\hat{f}_D$	T_c [s]
CHEM 10	Proposed	smoothed	(2,2)	0.16	0.06	7.0
		smoothed ($\tau = 10^4$)	(2,2)	0.85	0.13	7.0
	Grid	smoothed	(2,2)	1.70	0.00	141
	K & K	Kano	(2,2,2)	0.95	0.90	-
	Lee et al.	He	(2,1)	1.75	0.04	-
CHEM 25	Proposed	smoothed	(2,1)	1.45	0.25	3.7
			(2,2)	0.56	0.41	4.1
			(3,2)	0.76	0.61	5.6
	Grid	smoothed	(2,1)	1.00	0.50	48
	K & K	Kano	(2,2,2)	1.15	0.75	-
	Jelali (i)	Kano	(3,2,2)	1.20	0.60	-
	Jelali (ii)	Kano	(2,2,1)	1.24	0.64	-
	Lee et al.	He	(2,1)	3.84	0.00	-
POW 4	Proposed	smoothed	(2,1)	1.93	0.08	15.1
			(2,2)	0.35	0.28	19.6
			(3,2)	0.53	0.45	16.7
	Grid	smoothed	(2,1)	1.40	0.10	527
	K & K	Kano	-	2.40	1.20	-
	Jelali	Kano	-	3.49	1.00	-
	Lee et al.	He	(2,1)	0.49	0.09	-

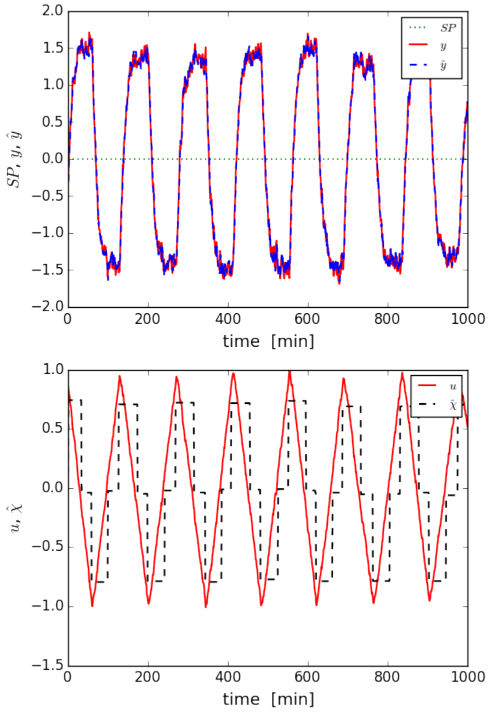

Fig. 4. CHEM 10. Measured and estimated time trends ($\tau = 10^4$).

It is also to be noted that parameters of He's model have their equivalent in Kano's model and vice versa, according to simple relations: $S = f_S + f_D$ and $J = f_S - f_D$, so that, $f_S = \frac{S+J}{2}$ and $f_D = \frac{S-J}{2}$. Nevertheless, these two stiction models can generate very different outputs for a the same input sequence despite equivalent parameters. This is one of the reasons of the different stiction estimates obtained with different methods in Table 1.

Moreover, the way in which the stiction model is initialized must be considered. This issue could seem a negligible aspect, but in reality, as it has been verified by a large number of simulations and applications, it is an important point, as discussed in (Bacci di Capaci et al., 2016) for the specific case of Kano's model. Also the proposed smoothed stiction model could be initialized in several ways. In this paper, we chose to set first valve position as first or as mean value of controller output, that is, $\hat{\chi}(0) = u(0)$ or $\hat{\chi}(0) = \bar{u}$.

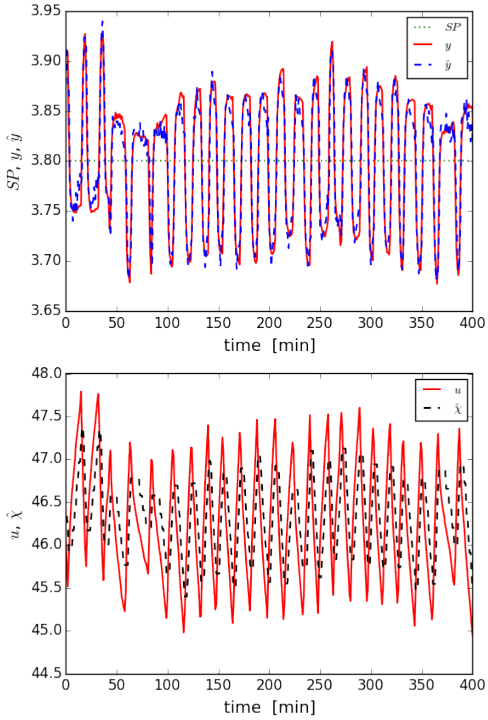

Fig. 5. CHEM 25. Measured and estimated time trends.

6. CONCLUSIONS

This paper has presented a non-invasive, reliable and efficient method to identify stiction in control valves. By the use of Hammerstein model and nonlinear optimization, the proposed approach can estimate the amount of stiction parameters of a recently proposed smoothed model. Applications to simulation case studies and industrial loops have been employed to demonstrate the validity of the proposed method. This technique can be implemented in a on-line routine in order to improve the performance of a stiction unaware model predictive controller, which otherwise would exhibit sustained oscillations in the presence of valve stiction. It has been also shown that by means of the identified stiction model the MPC controller can be eventually turned into a stiction embedding formulation, so that fluctuations removal and good set-point tracking are possible.

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