Valve friction and nonlinear process model closed-loop identification

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Abstract: Friction in control valves and inadequate controller tuning are two of the major sources of control loop performance degradation. As friction models are needed to diagnose abnormal valve operation or to compensate such undesirable effects, process models play an essential role in controller design. This paper extends existing optimization-based methods that jointly identify the process and friction model parameters, so that a nonlinear process model structure is considered. The procedure is based on data generated from closed-loop experiments with an external test signal. A simulation example indicates that the method accurately quantifies the valve friction, the process dynamics and the nonlinear steady state characteristics, even when the system is subjected to different level of disturbances.

Keywords: Control valves; Nonlinear models; Identification algorithms; Friction.

1. INTRODUCTION

Among several process variability sources (e.g., inadequate controller structure/ tuning, equipment malfunction, poor design, lack of maintenance) valve friction is supposed to be one of the most prevalent (Desborough and Miller, 2001). For this reason, friction quantification methods are highly desirable, since they can be applied in the development of model-based compensators or to diagnose valves that need repair. Moreover, quantification methods based only on controller output (*op*) and process output (*pv*) measurements from closed-loop experiments, are preferable for practical reasons.

Choudhury et al. (2004) dealt with friction quantification by means of the *pv*-*op* plot, but the results produced by this technique depend on the controller tuning. In a method proposed by Srinivasan et al. (2005), an optimization approach is used to jointly estimate the process dynamics and the friction model parameters. This method can be seen as a Hammerstein model identification, since the valve friction is treated as a nonlinear static block ($\mathcal{N}$) followed by a linear dynamic block ($\mathcal{L}$) that represents the process. As the process dynamics is also estimated, the joint procedure previously mentioned can be used for controller retuning. However, in that work, an inappropriate friction model structure that is unable to reproduce important sticky valve characteristics is employed. In a recent work (Choudhury et al., 2008), this drawback was eliminated through the adoption of another friction model structure.

An additional extension to the method originally proposed by Srinivasan et al. (2005) is to model the process with a Wiener structure (Figure 1), built up with a linear dynamic block connected to a nonlinear static function ($\mathcal{L} \rightarrow \mathcal{N}$). In this approach the Hammerstein structure is extended to a Hammerstein-Wiener one ($\mathcal{N} \rightarrow \mathcal{L} \rightarrow \mathcal{N}$), i.e., the valve friction is associated with the first nonlinear block, while the remainder blocks represent the process. The Hammerstein-Wiener structure is shown in Figure 2.

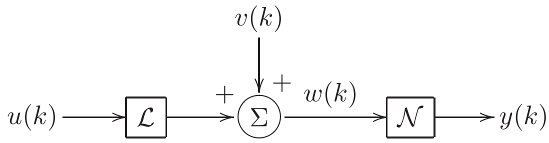

Fig. 1. Wiener model structure with nonlinear disturbance.

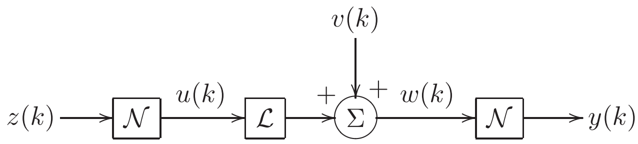

Fig. 2. Hammerstein-Wiener model structure with nonlinear disturbance.

This extension intends to provide some features: (*i*) to avoid that process nonlinearities be erroneously incorporated in the friction model, (*ii*) to prevent bias problems in the process model identification and (*iii*) to turn the estimation method suitable to wider operating ranges.

This work proposes a procedure to jointly estimate nonlinear process dynamics and friction model parameters from closed-loop experiments. Actually, it is an extension from previous works (Choudhury et al., 2008; Srinivasan et al., 2005). The paper is organized as follows: the structure that models the valve friction is described in section 2. The parameterization of the nonlinear process, as well as an estimation algorithm suitable for closed-loop data are treated in section 3. The friction and process model joint estimation procedure is presented in section 4. This procedure is tested through a simulated example in section 5. At last, the conclusions are drawn.

2. VALVE FRICTION MODEL

Several friction models were evaluated using ISA standard tests in Garcia (2008). The best trade-off between accuracy and simplicity was achieved by the data-driven model proposed by Kano et al. (2004). This is a modified version of the model employed in the friction quantification algorithm proposed in Choudhury et al. (2008) and it is characterized by two parameters: S that represents the cummulative input signal $z(k)$ amplitude change necessary to revert the valve movement direction and J that is the size of the stem slip, also referred as slip-jump, observed when the valve starts to move.

Besides the parameters S and J, the friction model uses three auxiliar variables: stp that indicates if the valve is moving ($stp = 0$) or if it is stuck ($stp = 1$), z_s that is updated with $z(k)$ every time the valve sticks and $d = \pm 1$ that denotes the direction of the friction force.

The relationship between the command signal $z(k)$ and the valve stem position $u(k)$ is described in the flowchart shown in Figure 3. After testing whether the valve stopped, so that z_s and stp are eventually updated, a new value is assigned to $u(k)$ if: (i) the valve is moving ($stp = 0$), (ii) the valve changes its direction and overcomes S or (iii) the valve moves in the same direction and overcomes J. On the contrary, the position remains the same.

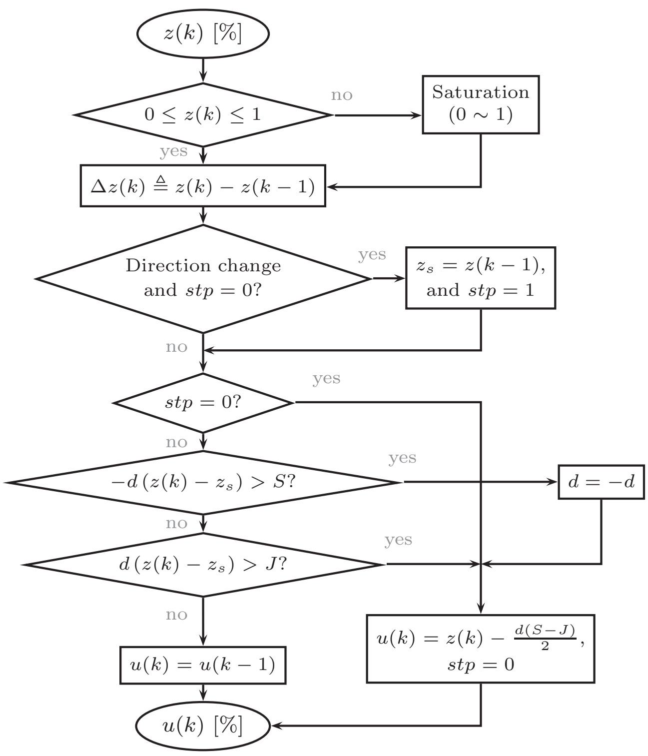

Fig. 3. Flowchart of the data-driven model parameterized by S and J (Kano et al., 2004).

3. NONLINEAR PROCESS MODEL

3.1 *Model parameterization*

Consider the Wiener model depicted in Figure 1, where the input signal is denoted by $u(k)$, the output signal by $y(k)$ and $v(k)$ represents the process disturbances. Notice that $v(k)$ is applied before the nonlinear block. In this case, the disturbances are also subject to the process nonlinearity. This scheme, proposed by Zhu (1999), is more realistic from a process operation point of view.

The linear dynamic block can be represented by a rational transfer function of order n:

$$G(q) = \frac{b_1 q^{-1} + \ldots + b_n q^{-n}}{1 + a_1 q^{-1} + \ldots + a_n q^{-n}} = \frac{B(q)}{A(q)} \tag{1}$$

where q^{-1} is the backward operator.

When prior knowledge about the process nonlinearity is not available, piecewise polynomials of third degree (cubic spline) provide advantages in respect of polynomials and piecewise linear functions to model the nonlinear block. For a set of m different knots:

$$w_{\min} = w_1 < w_2 < \ldots < w_{m-1} < w_m = w_{\max} \tag{2}$$

A cubic spline can be expressed by (Lancaster and Šalkauskas, 1986):

$$\begin{aligned} y(k) &= f\left(w(k)\right) \\ &= \sum_{i=2}^{m-1} \xi_i \left|w(k) - w_i\right|^3 + \xi_m + \xi_{m+1} w(k) \end{aligned} \tag{3}$$

where $\Xi \triangleq (\xi_2, \ldots, \xi_{m+1})^T$ is the cubic spline parameter vector and $w(k)$ denotes the Wiener model intermediate signal.

3.2 *Wiener model parameter estimation*

In the closed-loop identification of Wiener models, the prediction error approach yields unbiased estimates, provided the process and the disturbance models are built simultaneously and the process model contains at least a delay of one sampling period (Forssell, 1999). To satisfy this condition, the disturbance term is modeled using an Auto Regressive Moving Average (ARMA) structure:

$$\begin{aligned} v(k) &= H(q)e(k) = \frac{C(q)}{D(q)} e(k) \\ &= \frac{1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-nc}}{1 + d_1 q^{-1} + \ldots + d_{n_d} q^{-nd}} e(k) \end{aligned} \tag{4}$$

where $e(k)$ is white noise with zero mean and variance σ^2.

Suppose that the function which describes the process nonlinearity is monotonic and invertible. Hence, analogously to (3), the inverse of the process nonlinearity $f^{-1}(\cdot)$ can be denoted by:

$$w(k) = \sum_{i=2}^{p-1} \gamma_i \left|y(k) - y_i\right|^3 + \gamma_p + \gamma_{p+1} y(k) \tag{5}$$

Furthermore, as the intermediate signal $w(k)$ is unmeasurable, the gain of the Wiener model can be arbitrarily distributed between the dynamic and the static block. For this reason, the constraint $\gamma_{p+1} = 1$ is introduced in (5), so that the parameters can be uniquely determined.

The Wiener model parameters can be obtained from the minimization of the prediction error criterion:

$$V = \sum_k \left(H^{-1}(q)\left(w(k) - G(q)u(k)\right)\right)^2 \tag{6}$$

In order to estimate the Wiener and disturbance model parameters, besides the assumption that the process nonlinearity is invertible, the algorithm considers that the process is open loop stable. Both assumptions are commonly found in many practical situations, e.g., CSTRs, distillation columns and pH neutralization processes. Hence, $G(q)$ can be approximated by a finite impulse response (FIR) model, so that the intermediate signal is expressed by:

$$w(k) = \beta_1 u(k-1) + \ldots + \beta_r u(k-r) + v(k) \tag{7}$$

For more compact notation, consider the regression $\psi(k)$ and the parameter θ vectors:

$$\psi(k) \triangleq \Big(-|y(k) - y_2|^3, \ldots, -|y(k) - y_{p-1}|^3, -1, u(k-1), \ldots, u(k-r)\Big)^T \tag{8}$$

$$\theta \triangleq (\gamma_2, \ldots, \gamma_{p-1}, \gamma_p, \beta_1, \ldots, \beta_r)^T \tag{9}$$

Considering (8) and (9), (6) can be rewritten as:

$$V = \sum_k \left(H^{-1}(q)\left(y(k) - \psi^T(k)\theta\right)\right)^2 \tag{10}$$

Since the criterion (10) is a nonlinear least-squares problem, the following algorithm is employed to calculate $G(q)$, $f(\cdot)$ and $H(q)$:

***Algorithm** 1.* Wiener and ARMA disturbance model parameter estimate.

i. Initialize the disturbance model $H(q)$ with:

$$\hat{C}(q) = \hat{D}(q) = 1 \tag{11}$$

ii. Calculate filtered version of the output and the regression vectors:

$$y_f(k) = \frac{D(q)}{C(q)} y(k)$$

$$\psi_f(k) = \frac{D(q)}{C(q)} \psi(k)$$

iii. Estimate the parameter vector θ from:

$$\hat{\theta} = \left(\sum_k \psi_f(k)\psi_f^T(k)\right)^{-1} \left(\sum_k \psi_f(k) y_f(k)\right) \tag{12}$$

iv. Calculate the residuals $\zeta(k)$ of the Wiener model obtained from the previous step:

$$\zeta(k) = y(k) - \psi^T(k)\hat{\theta} \tag{13}$$

v. Estimate an ARMA model for $\zeta(k)$, i.e., a filter to uncorrelate the residuals:

$$\hat{D}(q)\zeta(k) = \hat{C}(q)e(k) \tag{14}$$

vi. While convergence of $\hat{H}(q)$ does not occur, go to step (ii). Otherwise, go to the next step.

vii. The parameters of $A(q)$ and $B(q)$, defined in (1), are estimated by minimizing the error between the outputs of the FIR model and the transfer function $G(q)$:

$$V_{red} = \sum_k \left(\sum_{i=1}^{r} \hat{\beta}_i u(k-i) - \frac{B(q)}{A(q)} u(k)\right)^2 \tag{15}$$

viii. The nonlinear block parameter vector Ξ estimate is given by:

$$\hat{\Xi} = \arg\min_{\Xi} \sum_k \left(y(k) - \phi^T(k)\Xi\right)^2 \tag{16}$$

where:

$$\phi(k) \triangleq \Big(|\hat{w}(k) - w_2|^3, \ldots, |\hat{w}(k) - w_{m-1}|^3, 1, \hat{w}(k)\Big)^T$$

$$\hat{w}(k) \triangleq \hat{f}^{-1}(y(k))$$

Correspondingly to the iterative calculation of θ, the linear model reduction (15) and the nonlinear function determination (16) are formulated as linear least squares problems. For this reason, the procedure is considered to be numerically simple and suitable for practical situations.

4. FRICTION AND PROCESS MODEL JOINT IDENTIFICATION ALGORITHM

Consider the process control loop depicted in Figure 4. Since in most of the practical situations only the controller output and the process output are known, the problem to be treated is to identify the friction and process model by means of $z(k)$ and $y(k)$.

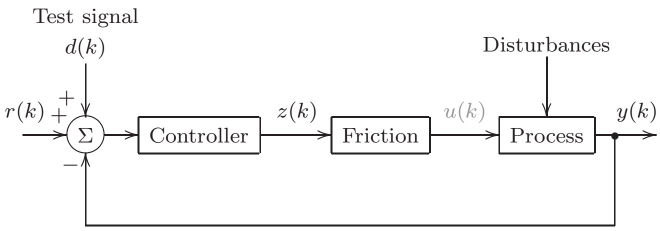

Fig. 4. Process control loop subject to valve friction.

In this work, the friction block is represented by the data-driven model of section 2, while the process dynamics is modeled by a Wiener structure. These parameterizations originate the control loop model shown in Figure 5.

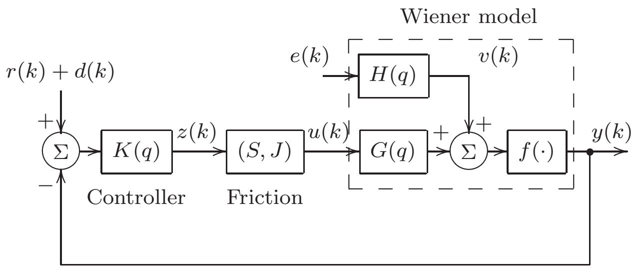

Fig. 5. Control loop where the valve friction and the process are modeled by a Hammerstein-Wiener structure.

In a first moment, suppose that the friction model parameters S and J are known. With this in mind, as the controller output $z(k)$ is considered to be measurable, it is possible to estimate $u(k)$ with:

$$\hat{u}(k) = \mathcal{F}\left(z(k), \hat{u}(k-1), S, J\right) \quad (17)$$

where $\mathcal{F}(\cdot)$ is the nonlinear transformation described in the flowchart of Figure 3. Hence, the Wiener model parameters can be estimated, using the measured output $y(k)$ and $\hat{u}(k)$ instead of $u(k)$, by means of the algorithm presented in section 3. However, S and J are unknown. To deal with this fact, the following algorithm is proposed:

***Algorithm** 2.* Algorithm that simultaneously estimate the parameters of the friction and nonlinear process model.

i. Generate a set of candidate values for the pair (S, J). Two aspects are considered in order to restrict the set of candidate values: (a) the behavior of most real valves is reproduced by the data-driven model with $\max(J) \leq S$; (b) it is obvious that without stem movement, to estimate the valve friction is an impossible task. If an appropriate excitation $d(k)$ is employed, it is reasonable to consider that the stem velocity reversions are produced by the test signal. Therefore, the controller output imposes an upper bound for S:

$$\max(S) < \max(z(k)) - \min(z(k)) \quad (18)$$

Such constraints yield the geometric locus shown in Figure 6.

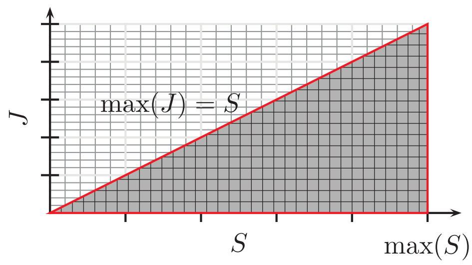

Fig. 6. Geometric locus of the friction model parameter candidate values.

ii. Choose a pair (S_i, J_j) from the set described in the previous step.
iii. Calculate the sequence of values $\hat{u}(k)$ from (17).
iv. Estimate the process model parameters using algorithm *1*, described in section 3.
v. Compute the prediction error of the intermediate signal $w(k)$ through the criterion:

$$\mathcal{C} = \sum_k \left(\hat{H}^{-1}(q)\left(\hat{f}^{-1}(y(k)) - \hat{G}(q)\,\hat{u}(k)\right)\right)^2 \quad (19)$$

vi. Until all the candidate values have been tested, back to step (ii). Otherwise, the values of S, J, $G(q)$ and $f(\cdot)$ are supposed to be the ones for which $\mathcal{C}$ is minimum.

Furthermore, note in Figure 4 that a test signal $d(k)$ is introduced into the set-point. Although external interferences are highly undesirable, the test signal guarantees sufficiently informative experiments. A well-known result from the closed-loop identification literature (Ljung, 1999) is that prediction error approach is not consistent if the data have been collected exclusively under feedback. In fact, the variance on the parameter estimate increases with disturbances and decreases the higher $d(k)$ is.

5. SIMULATIONS

To verify the applicability of the friction and process joint identification algorithm, the process loop in Figure 4 is simulated with a PI controller $C(q)$, a process dynamics reproduced by a continuous linear dynamic model $G(s)$ followed by a nonlinear block $f(w(k))$ and a disturbance $v(k)$ given by:

$$C(q) = \frac{0.5\left(1 - 0.5q^{-1}\right)}{\left(1 - q^{-1}\right)}$$

$$G(s) = \frac{5}{(0.5s+1)(s+1)(10s+1)}$$

$$y(k) = f\left(w(k)\right) = \frac{w(k)}{\sqrt{0.1 + 0.9w^2(k)}}$$

$$v(k) = \frac{\rho}{1 - 2.65q^{-1} + 2.335q^{-2} - 0.684q^{-3}}e(k)$$

The simulated friction model parameters are $S = 10\%$ and $J = 2\%$. The algorithm is tested in two distinct situations: low and high disturbances. In the first case, ρ is adjusted so that the disturbance level in $y(k)$ is 1.44% (in variance), while in the high disturbance scenario $v(k)$ provides a ratio of 12.5%.

A randomly switched multi-level signal, GMN (see Zhu, 2001), with average switch time of 25 sampling intervals and amplitude uniformly distributed between $[-0.15, 0.15]$ is applied in $d(k)$. The set-point $r(k)$ is fixed in 0.75. The input-output data of the high disturbance situation, as well as the excitation signal are shown in Figure 7.

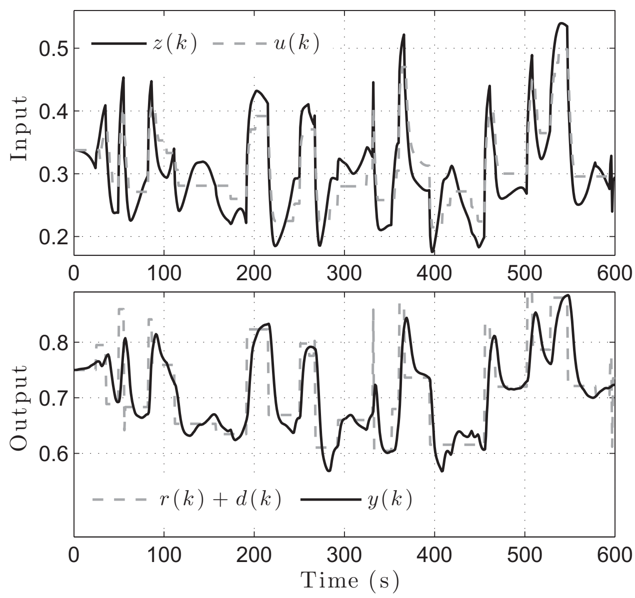

Fig. 7. Input-output data and external test signal of the high disturbance simulation.

The friction and process model parameters are estimated using 600 samples and a 1s sampling period. From (18) one has $\max(S) = 35\%$. A set of candidate values of the pair (S,J) is generated with a resolution of 1% and the process model was estimated using: $m = p = 3$, $r = 35$, $n_c = 0$, $n_d = 6$ and $l = 3$.

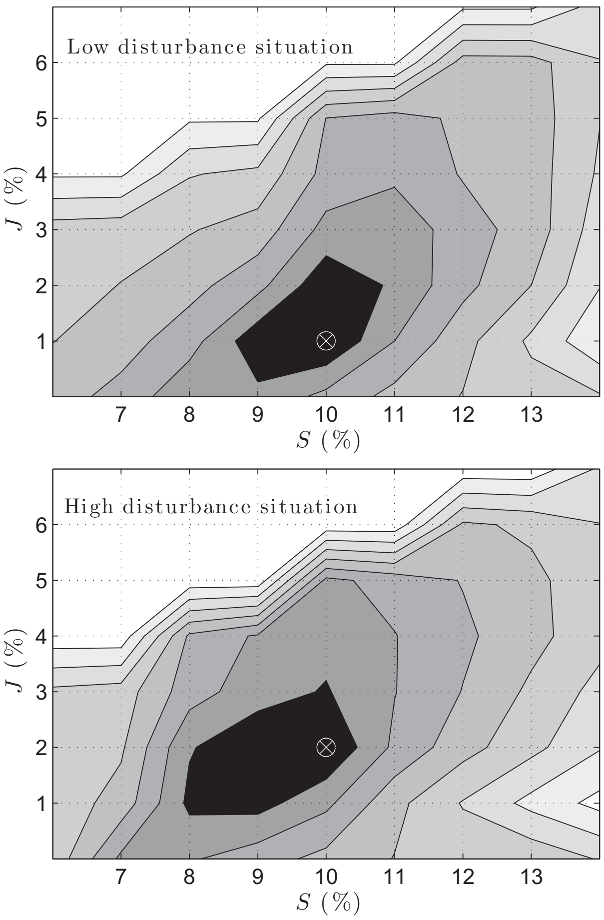

Fig. 8. Level curves of the prediction error $\mathcal{C}$.

The behavior of the prediction error $\mathcal{C}$, in both disturbance situations, is shown in Figure 8. Darker locations indicate lower prediction errors and the symbol "$\otimes$" indicates the minimum. In both disturbance situations, the parameter S is exactly estimated.

On the other hand, $\hat{J} = 1\%$ and 2% for the low and high disturbance scenarios, respectively. The slight misfit obtained in lower disturbance situation has two reasons: (1) the influence of the parameter S is prominent if compared to J and (2) the occurences of slip-jumps in the low disturbance simulation is minor (21 slip-jumps against 26 provided by the major disturbance simulation).

The Nyquist plot of linear block estimate from both disturbances scenarios are compared to the actual one in order to check if the process dynamics were incorporated. From Figure 9 it can be seen that the estimation from the low disturbance dataset provided better results. Therefore, it is clear that the disturbances degrade the accuracy of the identified linear dynamic block.

To get a better insight about frequency domain errors, the Bode plot of the estimates is depicted in Figure 10. Although the Nyquist curves suggest that the dynamic block estimate from the high disturbance simulation data presents a larger misfit, one can see that the errors related to the actual frequency response are acceptable for practical purposes.

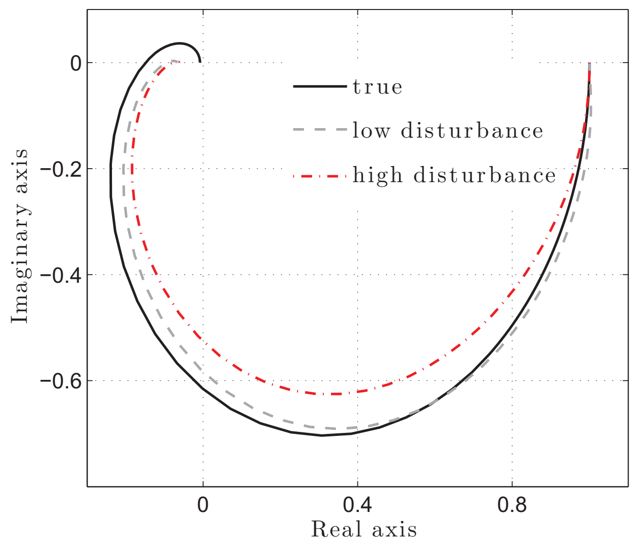

Fig. 9. Nyquist plot of $\hat{G}(q)$ obtained from both disturbance scenarios.

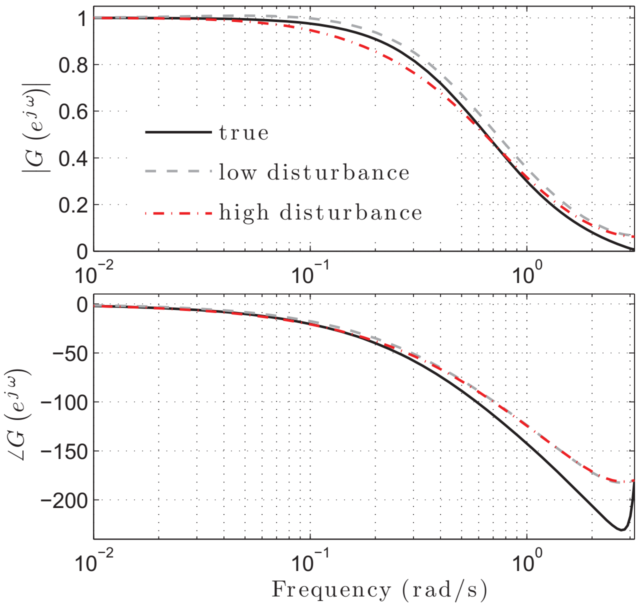

Fig. 10. Bode plot of the estimated dynamic models.

Finally, the nonlinear block fit is investigated. The true process nonlinearity and the estimates from low and high disturbance scenarios, denoted as $\hat{f}_{(low)}(\cdot)$ and $\hat{f}_{(high)}(\cdot)$, are presented in Figure 11. Despite adopting a parameterization different from the cubic splines during the simulations, the process nonlinearity is accurately estimated in both disturbance conditions.

Comparing the results achieved in each of the disturbance situations, one can see that the process steady state curve fit is better when the disturbance level is lower. Nevertheless, the estimation performance deterioration is slight, in spite of the substantial increase (almost 10 times higher) in the disturbance level.

6. CONCLUSIONS

The results provided by the simulated example suggests that the proposed procedure that jontly identifies the

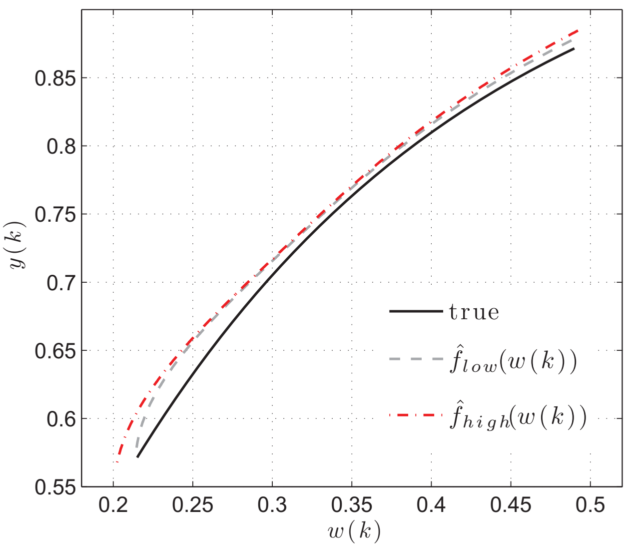

Fig. 11. Actual and estimated process nonlinearity.

friction and the nonlinear process model parameters is promising.

Moreover, the estimation results indicate that the GMN test signal is suitable for the process model identification. On the other hand, this excitation can not be adjusted in order to control the ocurrences of slip jumps. Thus, the GMN is insufficient to guarantee accurate estimates of the parameter J. An alternative to deal with this drawback is to combine a multi-level randon noise with a staircase excitation.

Another aspect that shoud be emphasized is that, when the process nonlinearity is severe, the Wiener model can be used to develop nonlinear controllers, such as gain schedule strategies.

Results of the procedure proposed here applied to industrial data is under development.

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