PERGAMON

Available online at www.sciencedirect.com
SCIENCE DIRECT

Automatica 39 (2003) 417–427

automatica

www.elsevier.com/locate/automatica

Model validation for control and controller validation in a prediction error identification framework—Part II: illustrations[☆]

Michel Gevers[a,*], Xavier Bombois[b], Benoît Codrons[c], Gérard Scorletti[d], Brian D.O. Anderson[e]

[a] Centre for Systems Engineering and Applied Mechanics (CESAME), Université Catholique de Louvain, Avenue Georges Lemaître 4, B-1348 Louvain-la-Neuve, Belgium
[b] Department of Applied Physics, Delft University of Technology, Lorentzweg 1, 2628 CJ Delft, The Netherlands
[c] Laborelec S.C., product line 'Process Control', B-1630 Linkebeek, Belgium
[d] LAP ISMRA, 6 boulevard du Maréchal Juin, F-14050 Caen Cedex, France
[e] Department of Systems Engineering, Research School of Information Sciences and Engineering, Australian National University, Canberra, ACT 0200, Australia

Received 6 June 2000; received in revised form 8 August 2002; accepted 9 October 2002

Abstract

In this paper, we illustrate our new results on model validation for control and controller validation in a prediction error identification framework, developed in a companion paper (Gevers et al., Automatica (2003) 39(3), pii: S005-1098(02)00234-0), through two realistic simulation examples, covering widely different control design applications. The first is the control of a flexible mechanical system (the Landau benchmark example) with a tracking objective, the second is the control of a ferrosilicon production process with a disturbance rejection objective.

© 2002 Elsevier Science Ltd. All rights reserved.

Keywords: System identification; Identification for robust control; Model validation; Controller validation

1. Introduction

In the companion paper (Gevers, Bombois, Codrons, Scorletti, & Anderson, 2003) we have developed a model validation procedure that consists of a prediction error identification experiment with a full order model. This procedure delivers an uncertainty set in transfer function space that we have characterized and baptized generic prediction error (PE) uncertainty set. It is defined as a ratio of linear combinations of known transfer functions, with the coefficient vector constrained to lie in an ellipsoid. We have derived two sets of results for such PE uncertainty sets:

- *Controller validation* results in the form of necessary and sufficient conditions for a specific controller to stabilize—or to achieve a given level of performance with—all systems in such PE uncertainty set.
- *Model validation for control* results in the form of a measure of size of such model uncertainty sets that is connected to the size of a set of robustly stabilizing controllers.

In this paper, we illustrate these technical results with two realistic identification and control design applications. These simulation examples have been chosen to illustrate two typical but very different control design problems. The first one is the widely publicized Landau benchmark transmission system (Landau, Rey, Karimi, Voda, & Franco, 1995b): a tracking problem with a step disturbance rejection objective in an essentially noise-free environment. The second is a typical industrial application: a ferrosilicon production process described in Ingason and Jonsson (1998), in which the main objective is stochastic disturbance rejection.

For each of these two applications, we apply our methodology. A PE identification experiment is performed on the

[☆] This paper was not presented at any IFAC meeting. This paper was recommended for publication in revised form by Associate Editor Brett Ninness under the direction of Editor Torsten Söderström.

* Corresponding author. Tel.: +32-10 47-25-90; fax: +32 10 47-21-80.
E-mail addresses: gevers@csam.ucl.ac.be (M. Gevers), x.j.a.bombois@tnw.tudelft.nl (X. Bombois), benoit.codrons@laborelec.be (B. Codrons), scorletti@greyc.ismra.fr (G. Scorletti), brian.anderson@anu.edu.au (B.D.O. Anderson).

0005-1098/03/$ - see front matter © 2002 Elsevier Science Ltd. All rights reserved.
PII: S0005-1098(02)00235-2

true system leading to a model G_{mod} [1] and an uncertainty region $\mathscr{D}$ containing the true input–output transfer function G_0 at a certain probability level. The worst-case ν-gap is then used to assess the quality of the pair $\{G_{mod}, \mathscr{D}\}$ for robustly stable control design, i.e. one checks whether the worst-case ν-gap $\delta_{WC}(G_{mod}, \mathscr{D})$ is much smaller than the optimal stability margin $b_{opt}(G_{mod})$ of the model G_{mod}. If that is the case, the model G_{mod} is used to design a controller satisfying the performance specifications with this nominal model. The controller validation results are then used to verify if these specifications are also satisfied with all systems in $\mathscr{D}$, and therefore also with the true system G_0.

In the first illustration, we choose the identified model as the model G_{mod} used for control design. In the second illustration, we consider a case where the model G_{mod} used for control design is given a priori. We illustrate the role played by the experimental conditions in our methodology by comparing, for each application, the results delivered by an open-loop PE identification experiment with the results delivered by a closed-loop experiment.

2. The flexible transmission system

2.1. Problem setting

We consider as *unknown true system* the half-load model of the flexible transmission system used as a benchmark in a special issue of the European Journal of Control (Landau et al., 1995b):

$$G_0(z) = z^{-3}\frac{0.10276 + 0.18123z^{-1}}{1 - 1.99185z^{-1} + 2.20265z^{-2} - 1.84083z^{-3} + 0.89413z^{-4}} \triangleq z^{-3}\frac{B(z)}{A(z)}. \quad (1)$$

The sampling period is 0.05 s. The output of the system is subject to step disturbances filtered through $H_0(z) = 1/A(z)$. This means that the plant can be seen as a nonstandard ARX system described by

$$A(z)y(t) = z^{-3}B(z)u(t) + p(t), \quad (2)$$

where $u(t)$ is the input of the plant, $y(t)$ its output and $p(t)$ is a sequence of zero mean step disturbances, modelled as a square wave signal with random transitions. A standard ARX description of such system with step disturbances is given by

$$A(z)\Delta(z)y(t) = z^{-3}B(z)\Delta(z)u(t) + e(t), \quad (3)$$

where $\Delta(z) = 1 - z^{-1}$ and $e(t)$ is a sequence of Gaussian white noise with zero mean and appropriate variance. The effect of the filter $\Delta(z)$ is to put an integrator in the controller such as to reject the step disturbances. The standard prediction error identification algorithm for ARX models can be used to identify the parameters of this system, provided the data are prefiltered by $\Delta(z)$.

Our objective is to apply our PE validation methodology to the flexible transmission system G_0, considered as an unknown system. In order to illustrate the role played by the experimental conditions, we shall compare two validation experiments, one in open loop, one in closed loop. In both cases, we shall estimate a model G_{mod} and an uncertainty set containing the true system G_0 at a probability level of 95%, compute a nominal controller C from the identified model G_{mod} that satisfies some prior specifications with this model, and apply our validation tools to check whether this controller also satisfies the specifications with the "unknown" G_0. The main specifications we shall deal with here are (Landau et al., 1995b):

- stability of the loop $[C\ G_0]$,
- a maximum value of less than 6 dB for the sensitivity function $T_{22}(G_0, C) = 1/(1 + G_0 C)$.

2.2. Open-loop validation experiment

The input signal $u_{ol}(t)$ applied to the stable true system G_0 for open-loop validation is chosen as a PRBS with variance $\sigma^2_{u_{ol}} = 0.1$ and a flat spectrum. The output step disturbances $p(t)$ are simulated as a zero mean random binary sequence with variance $\sigma^2_p = 0.01$ and cut-off frequency at 0.05 times the Nyquist frequency; that is, the mean length of the steps of $p(t)$ is about 20 times longer than that of the steps of $u_{ol}(t)$, while the amplitude of the steps $p(t)$ is $\sqrt{10}$ times smaller than those of $u_{ol}(t)$. The spectra and a realization of $u_{ol}(t)$ and $p(t)$ are shown in Fig. 1. The disturbance signal $p(t)$ is filtered by $1/A_o(z)$ and added to the output of the system. We measure 256 data, and the identification is performed with the same ARX(4,2,3) structure as G_0 after prefiltering these data by $\Delta(z)$. The numerical values attached to this open-loop validation experiment are displayed in Table 1,where $\int_0^\pi \phi_y^p(\omega)\,d\omega / \int_0^\pi \phi_y^u(\omega)\,d\omega$ represents the output noise-to-signal ratio ($\phi_y^u(\omega) = |G_0(e^{j\omega})|^2\sigma^2_{u_{ol}}$ is the spectrum of the part of the output due to the input, and $\phi_y^p(\omega) = |H_0(e^{j\omega})|^2\phi_p(\omega)$ is the spectrum of the part of the output due to the disturbances).

Using these settings, the identified model $G^{ol}_{mod} = G(z, \hat{\delta}_{ol})$ is given by

$$G^{ol}_{mod} = G(z, \hat{\delta}_{ol}) = z^{-3}\frac{0.1052 + 0.1774z^{-1}}{1 - 1.997z^{-1} + 2.23z^{-2} - 1.876z^{-3} + 0.9039z^{-4}}. \quad (4)$$

The parameter vector $\hat{\delta}_{ol}$ is the vector made up of the two numerator coefficients followed by the four denominator coefficients. The covariance matrix of this estimated parameter

[1] The model G_{mod} can also be given a priori.

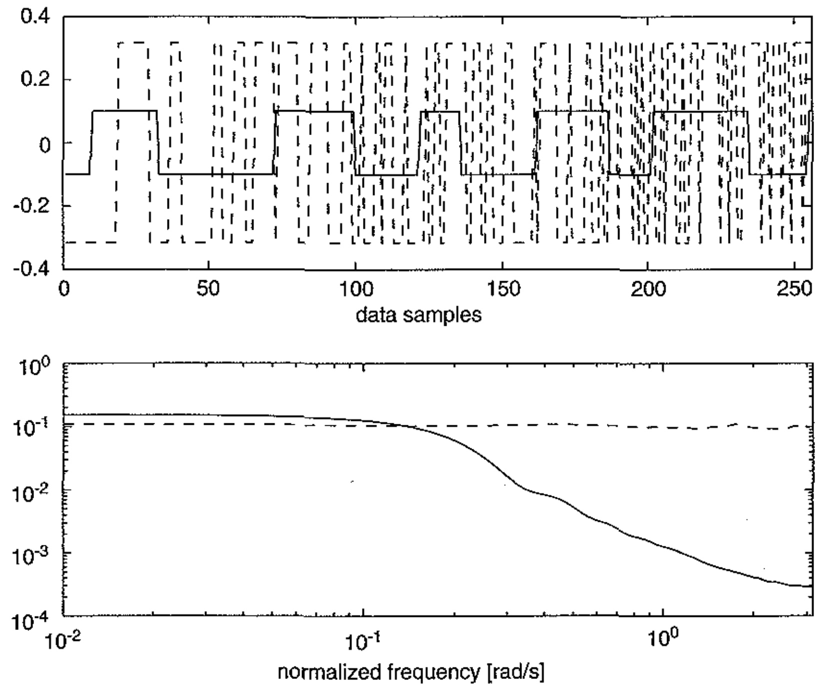

Fig. 1. Open-loop validation. Top: $u_{ol}(t)$ (- -) and $p(t)$ (—). Bottom: $\phi_{u_{ol}}(\omega)$ (- -) and $\phi_p(\omega)$ (—).

Table 1
Open-loop validation

$\sigma^2_{u_{ol}}$	σ^2_p	$\sigma^2_{y_{ol}}$	$\frac{\int_0^\pi \phi_y^p(\omega)\,d\omega}{\int_0^\pi \phi_y^u(\omega)\,d\omega}$
0.1	0.01	0.8932	1.3102

vector is

$$P_\delta^{ol} = 0.001 \begin{pmatrix} 0.2034 & -0.2970 & 0.2411 & -0.1150 & -0.0139 & -0.0027 \\ -0.2970 & 0.5735 & -0.5136 & 0.2397 & 0.0119 & -0.0064 \\ 0.2411 & -0.5136 & 0.5725 & -0.2962 & -0.0130 & 0.0008 \\ -0.1150 & 0.2397 & -0.2962 & 0.2013 & 0.0094 & 0.0020 \\ -0.0139 & 0.0119 & -0.0130 & 0.0094 & 0.0392 & 0.0126 \\ -0.0027 & -0.0064 & 0.0008 & 0.0020 & 0.0126 & 0.0391 \end{pmatrix}.$$

The 95% uncertainty region $\mathscr{D}_{ol}$ around G^{ol}_{mod} can then be expressed as follows:

$$\mathscr{D}_{ol} = \left\{ G(z,\delta) \mid G(z,\delta) = \frac{Z_N\delta}{1+Z_D\delta} \text{ with } \delta \in U_{ol} \right\}, \quad (5)$$

$$U_{ol} = \{\delta \in \mathbf{R}^{6\times 1} \mid (\delta - \hat{\delta}_{ol})^T (P_\delta^{ol})^{-1} (\delta - \hat{\delta}_{ol}) < 12.6\}, \quad (6)$$

where

$$Z_N(z) = (\,0 \quad 0 \quad 0 \quad 0 \quad z^{-3} \quad z^{-4}\,),$$

$$Z_D(z) = (\,z^{-1} \quad z^{-2} \quad z^{-3} \quad z^{-4} \quad 0 \quad 0\,).$$

The size χ of the ellipsoid U_{ol} is equal to 12.6 since $Pr(\chi^2(6) < 12.6) = 0.95$. This uncertainty region $\mathscr{D}_{ol}$ does actually contain the true system since we have

$$(\delta_0 - \hat{\delta}_{ol})^T (P_\delta^{ol})^{-1} (\delta_0 - \hat{\delta}_{ol}) = 5.7555 < 12.6,$$

where $\delta_0 = (-1.99185\ 2.20265\ -1.84083\ 0.89413\ 0.10276\ 0.18123)^T$ denotes the parameter vector of the true system:

$$G_0 = \frac{Z_N\delta_0}{1+Z_D\delta_0}. \quad (7)$$

2.3. Closed-loop validation experiment

In order to perform a validation experiment in closed loop, we need to connect a controller K in feedback with G_0.

The controller K chosen here is the controller obtained by Landau et al. using a combined pole placement/sensitivity function shaping method (Landau, Karimi, Voda, & Rey, 1995a). Its feedback part is described by

$$K(z) = \frac{0.401602 - 1.079378z^{-1} + 0.284895z^{-2} + 1.358224z^{-3}}{1 - 1.031142z^{-1} - 0.995182z^{-2} + 0.752086z^{-3}} \frac{-0.986549z^{-4} - 0.271961z^{-5} + 0.306937z^{-6}}{+0.710744z^{-4} - 0.242297z^{-5} - 0.194209z^{-6}}. \quad (8)$$

It also has a feedforward part that we shall not consider here.

The closed-loop system $[K\ G_0]$ is excited by means of a reference signal $r(t)$ injected at the input of G_0, while the disturbance $p(t)$ is the same as in the previous subsection. In order to establish a fair comparison with the results obtained in open-loop validation, $r(t)$ is a PRBS with a variance $\sigma_r^2 = 0.5541$ that is chosen such that the total output variance is the same in closed loop as in open loop: $\sigma_{y_{cl}}^2 = \sigma_{y_{ol}}^2 = 0.8932$. Other choices could have been made, but from an industrial user's point of view, it is usually the total output variance that matters. Other numerical values attached to this closed-loop validation experiment are displayed in Table 2. $\phi_y^r(\omega)$ and $\phi_y^p(\omega)$ are the part of the output spectrum due to the reference and the disturbance, respectively; thus $\frac{\int_0^\pi \phi_y^p(\omega)\,d\omega}{\int_0^\pi \phi_y^r(\omega)\,d\omega}$ represents the output noise-to-signal ratio. Observe that in closed-loop identification, the disturbance contribution in the input signal does not contribute to the estimation of the plant model G_0 (Gevers, Ljung, & Van den Hof, 2001).

The controller K has unstable poles and nonminimum phase zeros. Therefore, the indirect closed-loop identification method *cannot* be used for validation, as it would deliver a model G_{mod}^{cl} that would be destabilized by K (see Codrons, Anderson, & Gevers, 2002; Codrons, 2000). We therefore use a direct approach to perform the closed-loop identification. Once again, 256 data samples $\{y_{cl}(t), u_{cl}(t)\colon t = 1, \ldots, 256\}$ are measured, and a model G_{mod}^{cl} with the same ARX(4,2,3) structure as G_0 is identified after prefiltering these data by $\Delta(z)$.

Table 2
Closed-loop validation

σ_r^2	$\sigma_{u_{cl}}^2$	σ_p^2	$\sigma_{y_{cl}}^2$	$\frac{\int_0^\pi \phi_y^p(\omega)\,d\omega}{\int_0^\pi \phi_y^r(\omega)\,d\omega}$
0.5541	0.6475	0.01	0.8932	0.2389

The model identified under those closed-loop experimental conditions is

$$G_{mod}^{cl} = G(z, \hat{\delta}_{cl}) = z^{-3} \frac{0.1016 + 0.1782z^{-1}}{1 - 1.986z^{-1} + 2.187z^{-2} - 1.824z^{-3} + 0.8897z^{-4}}.$$

The estimated covariance matrix of the identified parameter vector is

$$P_\delta^{cl} = 10^{-3} \begin{pmatrix} 0.0840 & -0.1166 & 0.1024 & -0.0532 & -0.0062 & -0.0027 \\ -0.1166 & 0.2145 & -0.1966 & 0.1009 & 0.0057 & 0.0008 \\ 0.1024 & -0.1966 & 0.2184 & -0.1197 & -0.0074 & -0.0041 \\ -0.0532 & 0.1009 & -0.1197 & 0.0853 & 0.0063 & 0.0037 \\ -0.0062 & 0.0057 & -0.0074 & 0.0063 & 0.0064 & 0.0021 \\ -0.0027 & 0.0008 & -0.0041 & 0.0037 & 0.0021 & 0.0061 \end{pmatrix}.$$

The 95% uncertainty region $\mathcal{D}_{cl}$ around $G_{mod}^{cl} = G(z, \hat{\delta}_{cl})$ can then be expressed as follows:

$$\mathcal{D}_{cl} = \left\{ G(z,\delta) \mid G(z,\delta) = \frac{Z_N \delta}{1 + Z_D \delta} \text{ with } \delta \in U_{cl} \right\}, \quad (9)$$

$$U_{cl} = \{\delta \in \mathbf{R}^{6\times 1} \mid (\delta - \hat{\delta}_{cl})^T (P_\delta^{cl})^{-1} (\delta - \hat{\delta}_{cl}) < 12.6\}, \quad (10)$$

where Z_N and Z_D are defined in (5). This uncertainty region $\mathcal{D}_{cl}$ contains the true system since we have

$$(\delta_0 - \hat{\delta}_{cl})^T (P_\delta^{cl})^{-1} (\delta_0 - \hat{\delta}_{cl}) = 4.7050 < 12.6,$$

where δ_0 denotes the parameter vector of the true system.

2.4. Robust stability measure of $\mathcal{D}_{ol}$ and $\mathcal{D}_{cl}$

In the previous section, we have performed two different validation experiments leading to two uncertainty regions ($\mathcal{D}_{ol}$ and $\mathcal{D}_{cl}$) with different nominal models (G_{mod}^{ol} and G_{mod}^{cl}). Each validation experiment has delivered a possible pair "model for control design-uncertainty region" i.e. $\{G_{mod}^{ol}\ \mathcal{D}_{ol}\}$ and $\{G_{mod}^{cl}\ \mathcal{D}_{cl}\}$. Let us first assess the quality of both pairs with respect to robustly stable control design. For this purpose, the results of Sections 5 and 6 in (Gevers et al., 2003) are used in order to verify whether all models in $\mathcal{D}_{ol}$ (resp. $\mathcal{D}_{cl}$) are stabilized by a large set of controllers designed with the identified model G_{mod}^{ol} (resp. G_{mod}^{cl}). This is done by computing the worst-case ν-gap $\delta_{WC}(G_{mod}^{ol}, \mathcal{D}_{ol})$ (resp. $\delta_{WC}(G_{mod}^{cl}, \mathcal{D}_{cl})$) and comparing it with the optimal stability margin $b_{opt}(G_{mod}^{ol})$ (resp. $b_{opt}(G_{mod}^{cl})$). The optimal

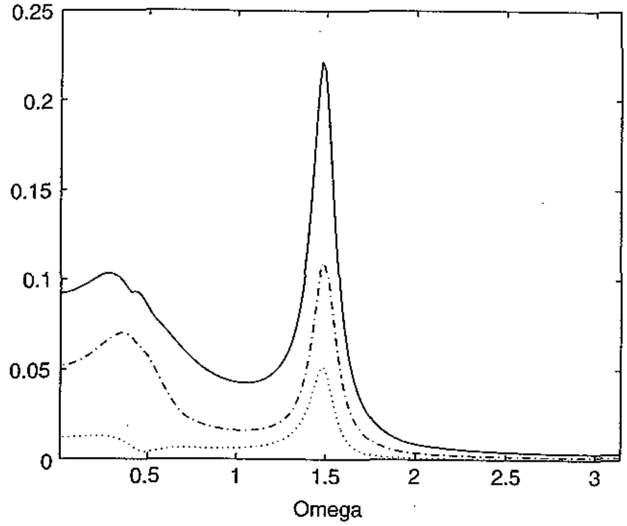

Fig. 2. $\kappa_{WC}(G^{ol}_{mod}(e^{j\omega}), \mathscr{D}_{ol})$ (solid), $\kappa_{WC}(G^{cl}_{mod}(e^{j\omega}), \mathscr{D}_{cl})$ (dashdot) and $\kappa(G^{cl}_{mod}(e^{j\omega}), G_0(e^{j\omega}))$ (dotted) at each frequency.

stability margin can be computed using expression (19) in (Gevers et al., 2003) and the worst-case ν-gap can be derived from the LMI-based computation of the worst-case chordal distances at each frequency. The worst-case chordal distances $\kappa_{WC}(G^{ol}_{mod}(e^{j\omega}), \mathscr{D}_{ol})$ and $\kappa_{WC}(G^{cl}_{mod}(e^{j\omega}), \mathscr{D}_{cl})$ are represented in Fig. 2 where they are compared with the actual chordal distance $\kappa(G^{cl}_{mod}(e^{j\omega}), G_0(e^{j\omega}))$ between the model G^{cl}_{mod} identified in closed loop and the true system G_0. We have not represented $\kappa(G^{ol}_{mod}(e^{j\omega}), G_0(e^{j\omega}))$ in order to keep the figure sufficiently readable.

Using Lemma 1 and expression (19) of Gevers et al. (2003), we obtain the following values for $\delta_{WC}(G^{ol}_{mod}, \mathscr{D}_{ol})$, $\delta_{WC}(G^{cl}_{mod}, \mathscr{D}_{cl})$, $b_{opt}(G^{ol}_{mod})$ and $b_{opt}(G^{cl}_{mod})$:

$$\delta_{WC}(G^{ol}_{mod}, \mathscr{D}_{ol}) = \max_{\omega} \kappa_{WC}(G^{ol}_{mod}(e^{j\omega}), \mathscr{D}_{ol}) = 0.2214,$$

$$b_{opt}(G^{ol}_{mod}) = 0.4685, \tag{11}$$

$$\delta_{WC}(G^{cl}_{mod}, \mathscr{D}_{cl}) = \max_{\omega} \kappa_{WC}(G^{cl}_{mod}(e^{j\omega}), \mathscr{D}_{cl}) = 0.1097,$$

$$b_{opt}(G^{cl}_{mod}) = 0.4650. \tag{12}$$

As $\delta_{WC}(G^{cl}_{mod}, \mathscr{D}_{cl})$ is much smaller than $b_{opt}(G^{cl}_{mod})$, we conclude that the set $\mathscr{C}_{\delta}(G^{cl}_{mod}, \mathscr{D}_{cl})$ of G^{cl}_{mod}-based controllers that are guaranteed by the ν-gap theory to robustly stabilize $\mathscr{D}_{cl}$ is relatively large: see Sections 5.3 and 6.2 of (Gevers et al., 2003). The difference between $\delta_{WC}(G^{ol}_{mod}, \mathscr{D}_{ol})$ and $b_{opt}(G^{ol}_{mod})$ is much smaller. Therefore, there is a strong incentive to give preference to the pair $\{G^{cl}_{mod}\ \mathscr{D}_{cl}\}$ for robust control design. Nevertheless, for the sake of illustration and comparison, we will also keep this pair $\{G^{ol}_{mod}\ \mathscr{D}_{ol}\}$ for further analysis.

2.5. Control design based on the identified model

The identified model G^{ol}_{mod} (resp. G^{cl}_{mod}) would normally be used in order to design a controller C^{ol} (resp. C^{cl}) such that the nominal closed-loop system satisfies the specifications presented at the end of Section 2.1. However, for comparison purposes, we will consider here the same controller C for both models. This controller is the robust controller for the Landau benchmark that was obtained by Nordin and Gutman using quantitative feedback theory (QFT) design (Nordin & Gutman, 1995):

$$C(z) = \frac{0.0355 + 0.0181z^{-1}}{1 - z^{-1}} \times \frac{18.8379 - 43.4538z^{-1} + 26.4126z^{-2}}{1 + 0.6489z^{-1} + 0.1478z^{-2}} \times \frac{0.5626 - 0.7492z^{-1} + 0.3248z^{-2}}{1 - 1.4998z^{-1} + 0.6379z^{-2}} \times \frac{1.0461 + 0.5633z^{-2}}{1 + 0.4564z^{-1} + 0.1530z^{-2}} \times \frac{1.3571 - 1.0741z^{-1} + 0.4702z^{-2}}{1 - 0.6308z^{-1} + 0.3840z^{-2}}.$$

This controller has not been designed from either G^{ol}_{mod} or G^{cl}_{mod}, but it satisfies all specifications with both models.

We now verify whether this controller satisfies these specifications with all plants in $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$, respectively (and therefore also with the true system G_0). Let us begin by the validation of C for stability.

2.6. Controller validation for stability

Following the procedure of Section 3 in Gevers et al. (2003), we build the dynamic vectors $M_{\mathscr{D}_{ol}}(e^{j\omega})$ and $M_{\mathscr{D}_{cl}}(e^{j\omega})$ corresponding to the candidate controller C and the uncertainty sets $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$, respectively, and we compute their stability radius at each frequency according to Theorem 1 in Gevers et al. (2003). These stability radii are represented in Fig. 3.

The maximum values of the stability radii are, respectively,

$$\max_{\omega} \mu(M_{\mathscr{D}_{ol}}(e^{j\omega})) = 0.3244.$$

$$\max_{\omega} \mu(M_{\mathscr{D}_{cl}}(e^{j\omega})) = 0.2375.$$

Since this maximum value is smaller than one in both cases, we may conclude that the controller C stabilizes all plants in both uncertainty sets $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$. Consequently, we can also guarantee that the "to-be-validated" controller $C(z)$ stabilizes the true flexible transmission system G_0 with probability 95%. The first specification presented at the end of Section 2.1 (i.e. the stability of the achieved loop $[C\ G_0]$) is thus satisfied.

2.7. Controller validation for performance

The second requirement presented at the end of Section 2.1 was that the designed controller should ensure *a*

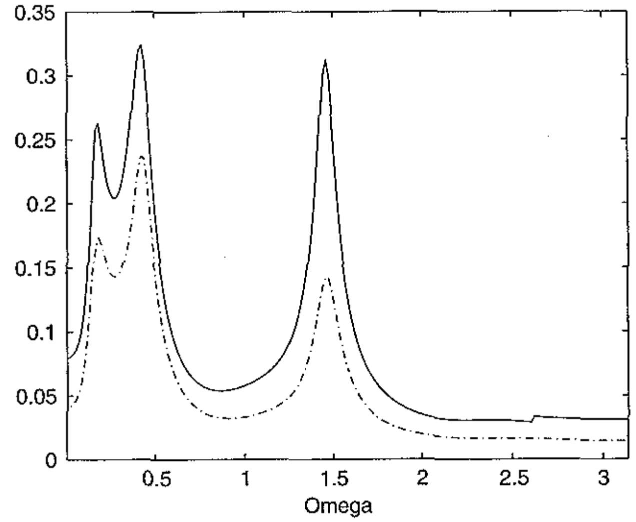

Fig. 3. $\mu(M_{\mathscr{D}_{ol}}(e^{j\omega}))$ (solid) and $\mu(M_{\mathscr{D}_{cl}}(e^{j\omega}))$ (dashdot) at each frequency.

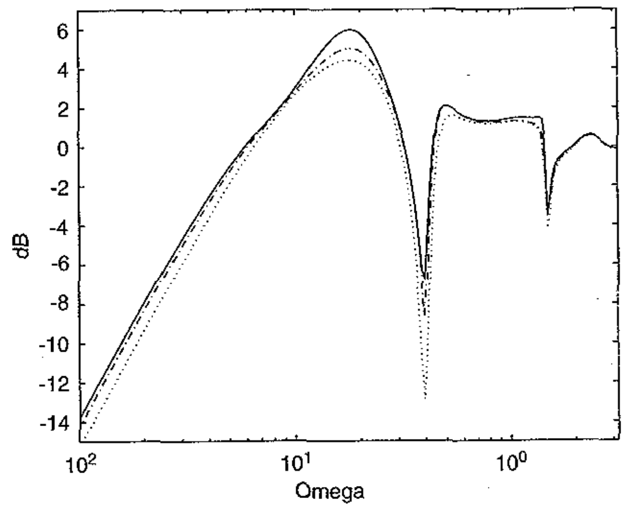

Fig. 4. $t_{\mathscr{D}_{ol}}(\omega, T_{22})$ (solid), $t_{\mathscr{D}_{cl}}(\omega, T_{22})$ (dashdot), and $|T_{22}(G_0, C)|$ (dotted) at each frequency.

maximum value of less than 6 dB *for the sensitivity function.* Since the true system is assumed unknown, we verify whether the controller C achieves these requirements with all systems in $\mathscr{D}_{ol}$ and/or $\mathscr{D}_{cl}$. For this purpose, we choose the following worst-case performance criterion: the largest modulus of the sensitivity function T_{22} over all models in $\mathscr{D}$, denoted by $t_{\mathscr{D}}(\omega, T_{22})$. This worst-case performance criterion can be computed using the LMI procedure presented in Theorem 2 of Gevers et al. (2003) using the following weights: $W_l = W_r = diag(0,1)$. Using this worst-case performance criterion, the controller C is termed validated for performance if

$$\max_{\omega} t_{\mathscr{D}}(\omega, T_{22}) < 6 \text{ dB}.$$

We compute this criterion for the uncertainty sets $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$ delivered by our two validation experiments. Fig. 4 presents $t_{\mathscr{D}_{ol}}(\omega, T_{22})$, $t_{\mathscr{D}_{cl}}(\omega, T_{22})$, and compares them with the actual sensitivity $|T_{22}(G_0, C)|$. We observe that

$$\max_{\omega} t_{\mathscr{D}_{ol}}(\omega, T_{22}) = 5.97 \text{ dB},$$

$$\max_{\omega} t_{\mathscr{D}_{cl}}(\omega, T_{22}) = 5.00 \text{ dB} < 6 \text{ dB}.$$

This means that the open-loop validation procedure nearly leads to rejection of the controller, while the closed-loop validation procedure leads to its acceptance.

With the controller validation procedures for stability and for performance, we have thus been able to establish that the "model-based" controller C achieves the specifications presented at the end of Section 2.1 with the true system G_0 since it achieves *these specifications with all systems in* $\mathscr{D}_{cl}$. Furthermore, we have also shown that, whereas the controller C is clearly validated with the uncertainty set $\mathscr{D}_{cl}$ delivered by a closed-loop PE identification experiment, it is nearly rejected when we apply our controller validation procedure with the uncertainty set $\mathscr{D}_{ol}$ delivered by open-loop identification. This fact illustrates the important role played by the experimental conditions in our validation procedure.

3. Ferrosilicon production process

The first illustration was representative of a mechanical engineering control problem, in which there was no stochastic noise, and where the control objective was one of tracking and of rejection of step disturbances. In order to illustrate the generality of our validation theory, we now present an application that is representative of industrial process control applications, in which the control objective is one of reducing the effects of stochastic disturbances. In this second illustration, we will assume that the model G_{mod} for control design has been given a priori.

3.1. Problem setting

The plant model and the controllers used in this simulation example are taken from a paper by Ingason and Jonsson (Ingason & Jonsson, 1998). Ferrosilicon is a two-phase mixture of the chemical compound $FeSi_2$ and the element silicon. The balance between silicon and iron is regulated around 76% of the total weight in silicon, 22% in iron and 2% in aluminium by adjusting the input of raw materials to the furnace. Those are charged batchwise to the top of the furnace, each batch consisting of a fixed amount of quartz (SiO_2) and a variable quantity of coal/coke (C) and iron oxide (Fe_2O_3). The quantity of coal/coke which is burned in the furnace does not influence the silicon ratio in the mixture, hence the control input is the amount of iron oxide.

The authors of Ingason and Jonsson (1998) have obtained the following ARX model for the process:

$$y(t) + ay(t-1) = bu(t-1) + d + e(t), \qquad (13)$$

where the sampling period is 1 day, $y(t)$ is the percentage of silicon in the mixture that must be regulated around 76%, $u(t)$ is the quantity of iron oxide in the raw materials (expressed in kilogrammes), d is a constant and $e(t)$ is a stochastic disturbance. The nominal values of the parameters and their standard deviations are:

$$a=-0.44,\quad b=-0.0028,\quad d=46.1,$$
$$\sigma_a=0.07,\quad \sigma_b=0.001, \sigma_d=5.6. \tag{14}$$

Here, for the sake of illustrating our theory, we make the assumption that the true system is [2]

$$G_0(z)=\frac{-0.0032z^{-1}}{1-0.34z^{-1}}=\frac{b_0z^{-1}}{1+a_0z^{-1}},$$
$$H_0(z)=\frac{1}{1-0.34z^{-1}}=\frac{1}{1+a_0z^{-1}},\quad d_0=44.$$

The nominal model chosen for control design is the one obtained by Ingason and Jonsson (Ingason & Jonsson, 1998):

$$G_{\text{mod}}(z)=\frac{-0.0028z^{-1}}{1-0.44z^{-1}}=\frac{bz^{-1}}{1+az^{-1}},$$

$$H_{\text{mod}}(z)=\frac{1}{1-0.44z^{-1}}=\frac{1}{1+az^{-1}},\quad d=46.1.$$

This model G_{mod} was used by the authors of Ingason and Jonsson (1998) to compute a GPC controller. The control law that minimizes the cost function

$$J_u=E\left[\sum_{j=1}^{2}(y(t+j)-r(t+j))^2 + \sum_{j=1}^{2}\lambda(\Delta u(t+j-1))^2\right] \tag{15}$$

with $\Delta(z)=1-z^{-1}$, is given by

$$u(t)=[\,1\quad 0\,](H^{\mathrm{T}}H+F^{\mathrm{T}}\Lambda F)^{-1} \times(H^{\mathrm{T}}(w(t)-v(t))-F^{\mathrm{T}}\Lambda g(t)), \tag{16}$$

where

$$H=\begin{bmatrix} b & 0\\ -ab & b\end{bmatrix}, \tag{17}$$

$$F=\begin{bmatrix} 1 & 0\\ -1 & 1\end{bmatrix}, \tag{18}$$

$$v(t)=\begin{bmatrix} -ay(t)+d\\ a^2y(t)-ad+d\end{bmatrix}, \tag{19}$$

$$w(t)=[\,r(t)\quad r(t+1)\,]^{\mathrm{T}}, \tag{20}$$

$$g(t)=[\,u(t-1)\quad 0\,]^{\mathrm{T}}, \tag{21}$$

$$\Lambda=\lambda I. \tag{22}$$

λ is a tuning parameter. The resulting controller, $C_\lambda(z)$, is made up of three parts:

$$u(t)=C_\lambda(z)\begin{pmatrix} r(t)\\ -y(t)\\ d\end{pmatrix} =(\,C_\lambda^r(z)\quad C_\lambda^y(z)\quad C_\lambda^d(z)\,)\begin{pmatrix} r(t)\\ -y(t)\\ d\end{pmatrix}, \tag{23}$$

where

$$C_\lambda^r(z) =\frac{b^3+2b\lambda-ab\lambda}{(b^4+3b^2\lambda+a^2b^2\lambda+\lambda^2-2ab^2\lambda)-(b^2\lambda+\lambda^2)z^{-1}},$$

$$C_\lambda^y(z)= -\frac{ab^3+ab\lambda-a^2b\lambda+a^3b\lambda}{(b^4+3b^2\lambda+a^2b^2\lambda+\lambda^2-2ab^2\lambda)-(b^2\lambda+\lambda^2)z^{-1}},$$

$$C_\lambda^d(z)= -\frac{b^3+b\lambda+b\lambda(1-a)^2}{(b^4+3b^2\lambda+a^2b^2\lambda+\lambda^2-2ab^2\lambda)-(b^2\lambda+\lambda^2)z^{-1}}.$$

The controller $C_\lambda^d(z)$ aims at rejecting the constant disturbance d. The feedback controller $C_\lambda^y(z)$ is the only part that has an impact on closed-loop stability. The reference signal $r(t)$ is generally constant and given by $r(t)=76$.

Our objective is to use the validation tools developed in Gevers et al. (2003) to check whether the controller $C_\lambda(z)$, with $\lambda=0.0007$, that is based on the model G_{mod}, can be applied *with confidence* to the true system G_0, that is to say with the assurance that the closed loop $[C_{\lambda=0.0007}\ G_0]$ will satisfy the following specifications: [3]

- stability of the loop $[C_{\lambda=0.0007}\ G_0]$,
- rejection of the stochastic noise $v(t)=H_0e(t)$.

To check this, we have used the surrogate true plant model (G_0,H_0) as a simulator on which validation experiments have been performed. As with the first illustration, we have performed two validation experiments: one in open loop and the other in closed loop.

3.2. Open-loop validation experiment

The "true plant" model (G_0,H_0) was excited with $u(t)$, chosen as a PRBS with variance $\sigma^2_{u_{ol}}=20$, which is the maximum input variance admissible for this process (Ingason &

[2] Since we have no access to the real plant, we have randomly selected one system in the two-standard-deviation confidence interval around the nominal model and used it as a surrogate true system.

[3] The controller of course achieves these specifications with the nominal model G_{mod}.

Jonsson, 1998). The noise $e(t)$ was chosen as a Gaussian white noise sequence with variance $\sigma_e^2 = 0.078$, which corresponds to the noise acting on the real process, as shown by experiments made by the authors of Ingason and Jonsson (1998). The variance of the output was then $\sigma_{y_{ol}}^2 = 0.0884$. Recall that the validation experiment, i.e. the construction of a validated uncertainty set $\mathscr{D}_{ol}$, consists of performing a PE identification using a full order model structure. Therefore, 300 input–output data samples were collected, corresponding approximately to 1 year of measurements. These data were used to identify an ARX model with exact structure

$$G(z,\delta_{ol}) = \frac{\delta_2 z^{-1}}{1+\delta_1 z^{-1}}, \quad H(z,\delta_{ol}) = \frac{1}{1+\delta_1 z^{-1}}. \tag{24}$$

Recall that this model is only a vehicle for the construction of an uncertainty region $\mathscr{D}_{ol}$ since the model G_{mod} used for control design has been given a priori. We found

$$\hat{\delta}_{ol} = \begin{pmatrix} \hat{\delta}_1 \\ \hat{\delta}_2 \end{pmatrix} = \begin{pmatrix} -0.3763 \\ -0.0073 \end{pmatrix},$$

$$P_\delta^{ol} = \begin{pmatrix} 2.8131 \times 10^{-3} & -1.2784 \times 10^{-5} \\ -1.2784 \times 10^{-5} & 1.4887 \times 10^{-5} \end{pmatrix}. \tag{25}$$

The 95% uncertainty region $\mathscr{D}_{ol}$ around $G(z,\hat{\delta}_{ol})$ is then given by

$$\mathscr{D}_{ol} = \left\{ G(z,\delta) \mid G(z,\delta) = \frac{Z_N \delta}{1+Z_D\delta} \text{ with } \delta \in U_{ol} \right\},$$

$$U_{ol} = \{\delta \in \mathbf{R}^{2\times 1} \mid (\delta - \hat{\delta}_{ol})^T (P_\delta^{ol})^{-1} (\delta - \hat{\delta}_{ol}) < 5.99\},$$

where

$$Z_N(z) = (\,0 \quad z^{-1}\,) \quad \text{and} \quad Z_D(z) = (\,z^{-1} \quad 0\,).$$

The size χ of the ellipsoid U_{ol} is equal to 5.99 since $Pr(\chi^2(2) < 5.99) = 0.95$. The validated uncertainty region $\mathscr{D}_{ol}$ contains both the "unknown" surrogate true system G_0 and the model G_{mod} used for controller design.

3.3. Closed-loop validation experiment

The closed-loop validation was performed with a sub-optimal GPC controller obtained by setting $\lambda = 0.001$ in (23). We added a PRBS signal to the constant reference $r(t) = 76$, with variance $\sigma_r^2 = 0.014$ so as to obtain the same input variance as in the open-loop experiment, i.e. $\sigma_{u_{cl}}^2 = 20$. The white noise $e(t)$ had the same properties as in open-loop validation. With these settings, the output variance was $\sigma_{y_{cl}}^2 = 0.0880$, very close to that of the open-loop experiment. Again, 300 input–output data samples were collected and used to identify an ARX model with the same structure as in open-loop validation (24), using a direct prediction error method. We found

$$\hat{\delta}_{cl} = \begin{pmatrix} \hat{\delta}_1 \\ \hat{\delta}_2 \end{pmatrix} = \begin{pmatrix} -0.3575 \\ -0.0067 \end{pmatrix},$$

$$P_\delta^{cl} = \begin{pmatrix} 2.8323 \times 10^{-3} & -8.7845 \times 10^{-6} \\ -8.7845 \times 10^{-6} & 6.2416 \times 10^{-6} \end{pmatrix}. \tag{26}$$

We then designed a 95% uncertainty region $\mathscr{D}_{cl}$ around $G(z,\hat{\delta}_{cl})$ defined by

$$\mathscr{D}_{cl} = \left\{ G(z,\delta) \mid G(z,\delta) = \frac{Z_N \delta}{1+Z_D\delta} \text{ with } \delta \in U_{cl} \right\},$$

$$U_{cl} = \{\delta \in \mathbf{R}^{2\times 1} \mid (\delta - \hat{\delta}_{cl})^T (P_\delta^{cl})^{-1} (\delta - \hat{\delta}_{cl}) < 5.99\},$$

with the same Z_N and Z_D as in $\mathscr{D}_{ol}$. As with $\mathscr{D}_{ol}$, this uncertainty region $\mathscr{D}_{cl}$ contains both the true system G_0 and the model G_{mod}.

3.4. Comparison of $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$

The worst-case ν-gap is now used to compare the two uncertainty sets deduced from the two validation experiments. For this purpose, we first compute the worst-case chordal distances at each frequency for $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$ using the LMI tools developed in Section 5 of the companion paper (Gevers et al., 2003). According to Lemma 1 of that paper, and since G_{mod} lies in both uncertainty sets, we can derive the worst-case Vinnicombe distances from the worst-case chordal distances as follows:

$$\delta_{WC}(G_{mod}, \mathscr{D}_{ol}) = \max_\omega \kappa_{WC}(G_{mod}(e^{j\omega}), \mathscr{D}_{ol}) = 0.0225,$$

$$\delta_{WC}(G_{mod}, \mathscr{D}_{cl}) = \max_\omega \kappa_{WC}(G_{mod}(e^{j\omega}), \mathscr{D}_{cl}) = 0.0156.$$

Observe that the worst-case gap is again smaller for the set validated under closed-loop experimental conditions than it is for the set validated in open loop. Since the optimal stability margin $b_{opt}(G_{mod})$ is equal to 0.99, the sets $\mathscr{C}_\delta(G_{mod}, \mathscr{D}_{ol})$ and $\mathscr{C}_\delta(G_{mod}, \mathscr{D}_{cl})$ of controllers that robustly stabilize $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$, respectively, are both large. Indeed, the worst-case ν-gaps $\delta_{WC}(G_{mod}, \mathscr{D}_{ol})$ and $\delta_{WC}(G_{mod}, \mathscr{D}_{cl})$ are very small with respect to $b_{opt}(G_{mod})$. Consequently, both uncertainty sets are well tuned for robustly stable controller design based on G_{mod}. We can therefore keep both uncertainty sets for further analysis and controller validation procedures.

3.5. Controller validation for stability

We now examine whether the controller $C_{\lambda=0.0007}$ stabilizes all models in $\mathscr{D}_{ol}$ and/or $\mathscr{D}_{cl}$, using the robust stability analysis tools developed for such PE uncertainty sets in Gevers et al. (2003).

3.5.1. Test based on sufficient condition

We first consider the sufficient robust stability condition based on the worst-case ν-gap, in order to show that this

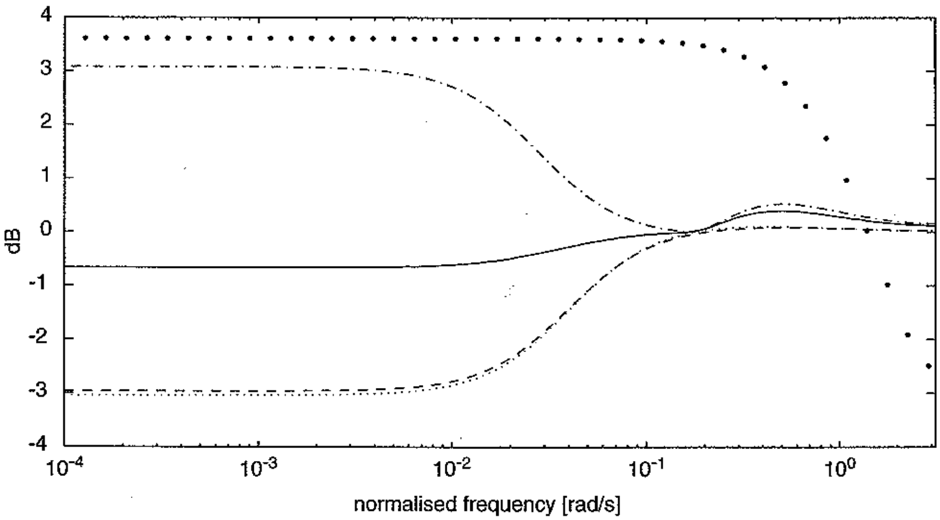

Fig. 5. Open-loop and closed-loop controller validation for performance: $t_{\mathscr{D}_{ol}}(\omega, T_{22})$ (-·), $t_{\mathscr{D}_{cl}}(\omega, T_{22})$ (—), $|T_{22}(G_0, C_{\lambda=0.0007})|$ (- -), $|T_{22}(G_{mod}, C_{\lambda=0.0007})|$ (· · ·) and $|H_0|$ (·).

condition can be conservative with respect to the necessary and sufficient condition developed in Theorem 1 of Gevers et al. (2003).

The nominal stability margin achieved by the controller $C_{\lambda=0.0007}$ with the nominal model G_{mod} is very small: $b_{G_{mod}C^y_{\lambda=0.0007}} = 0.0169$. We conclude that the controller $C_{\lambda=0.0007}$ lies in $\mathscr{C}_\delta(G_{mod}, \mathscr{D}_{cl})$ but not in $\mathscr{C}_\delta(G_{mod}, \mathscr{D}_{ol})$ since

$$\delta_{WC}(G_{mod}, \mathscr{D}_{ol}) > b_{G_{mod}C_{\lambda=0.0007}} = 0.0169 > \delta_{WC}(G_{mod}, \mathscr{D}_{cl}). \quad (27)$$

Therefore, from this sufficiency test, we can conclude that $C_{\lambda=0.0007}$ stabilizes all plants in the set $\mathscr{D}_{cl}$, but we cannot conclude that it stabilizes all plants in $\mathscr{D}_{ol}$. To ascertain this, we need to consider the necessary and sufficient condition for robust stability.

3.5.2. Test based on necessary and sufficient condition

We first check whether $C_{\lambda=0.0007}$ stabilizes the nominal models $G(z, \hat{\delta}_{ol})$ and $G(z, \hat{\delta}_{cl})$. Since this is indeed the case, we build the dynamic vectors $M_{\mathscr{D}_{ol}}(e^{j\omega})$ and $M_{\mathscr{D}_{cl}}(e^{j\omega})$ corresponding to the candidate controller $C_{\lambda=0.0007}$, and we compute their stability radii according to Theorem 1 of Gevers et al. (2003). Their maximum values are, respectively,

$$\max_\omega \mu(M_{\mathscr{D}_{ol}}(e^{j\omega})) = 0.6572 < 1,$$
$$\max_\omega \mu(M_{\mathscr{D}_{cl}}(e^{j\omega})) = 0.2111 < 1. \quad (28)$$

Since these two values are smaller than one, $C_{\lambda=0.0007}$ stabilizes all systems in both uncertainty sets $\mathscr{D}_{ol}$ and $\mathscr{D}_{cl}$. This is remarkable, given that $C_{\lambda=0.0007}$ has a very small nominal stability margin with G_{mod}. This *quantitative* result confirms our earlier *qualitative* observation that both uncertainty sets are well tuned for robustly stable controller design based on G_{mod}, even though that qualitative observation is based on a sufficient condition that would have invalidated the particular controller $C_{\lambda=0.0007}$ when $\mathscr{D}_{ol}$ is considered (see (27)).

We also observe that, just as with the first application, the stability radius is much smaller for the set $\mathscr{D}_{cl}$ obtained by closed-loop validation than for the set $\mathscr{D}_{ol}$ obtained by open-loop validation. Finally, we conclude from these stability tests that the "to-be-validated" controller $C_{\lambda=0.0007}$ is guaranteed to stabilize the surrogate G_0 of the true ferrosilicon production process.

3.6. Controller validation for performance

The second specification presented at the end of Section 3.1 is to reject the noise $v(t) = H_0(z)e(t)$, which is essentially located at low frequencies ($H_0(e^{j\omega})$ is a first-order low-pass filter; see Fig. 5). A performance specification in the frequency domain is therefore that the sensitivity function $T_{22}(G_0, C^y_{\lambda=0.0007}(z)) = 1/(1 + G_0 C^y_{\lambda=0.0007}(z))$ be low at low frequencies in order to attenuate $v(t)$. We thus define the worst-case performance criterion as

$$t_{\mathscr{D}}(\omega, T_{22}) = \max_{G(e^{j\omega},\delta)\in\mathscr{D}} \left| \frac{1}{1 + G(z,\delta)C_{\lambda=0.0007}(z)} \right|. \quad (29)$$

This worst-case performance criterion can be computed using the LMI procedure presented in Theorem 2 of Gevers et al. (2003). We will call the controller $C_{\lambda=0.0007}(z)$ validated if $t_{\mathscr{D}}(\omega, T_{22})$ is high-pass with $\max_\omega t_{\mathscr{D}}(\omega, T_{22}) < 1$ dB. The Bode diagrams of the worst case and achieved sensitivity functions are depicted in Fig. 5. Clearly, the controller is validated by the closed-loop validation experiment yielding $\mathscr{D}_{cl}$ but not by the open-loop experiment yielding $\mathscr{D}_{ol}$.

The main conclusion we can derive from this performance test is that the controller $C_{\lambda=0.0007}$ will achieve the desired performance (i.e. sufficiently decrease the output variance) when applied to G_0. We have indeed proved that, for the uncertainty set $\mathscr{D}_{cl}$ containing G_0, the worst-case modulus of the sensitivity function is a high-pass filter with a resonably small resonance peak allowing rejection of the noise $v(t)$. This application shows once again the important role played by the experimental conditions. Indeed, the controller C designed from G_{mod} is validated with the uncertainty set $\mathscr{D}_{cl}$ delivered by a closed-loop PE identification experiment, but is invalidated with the uncertainty set $\mathscr{D}_{ol}$ delivered by an open-loop PE identification experiment.

Remark. Even though the uncertainty region $\mathscr{D}_{ol}$ is well tuned with respect to robustly stable controller design with G_{mod} (i.e. it has a large set of stabilizing controllers), our analysis shows that the worst-case performance achieved by the controller $C_{\lambda=0.0007}$ with all plants in $\mathscr{D}_{ol}$ is really bad. This is a consequence of the fact that the worst-case ν-gap is only an indicator of robust stability and not an indicator of robust performance. This observation has recently led us to extend our results to an indicator of robust performance for the uncertainty set $\mathscr{D}$ delivered by PE identification (Bombois, Scorletti, Anderson, Gevers, & Van den Hof, 2002).

4. Conclusions

Using two control design applications that are representative of a noise-free mechanical tracking problem and of an industrial problem with a noise rejection objective, respectively, we have illustrated the various model and controller validation results developed in the companion paper (Gevers et al., 2003). In doing so, we have not only illustrated the relevance and practical usefulness of our prediction error framework for model and controller validation, but we have also highlighted the important role of the experimental conditions under which the validation experiments are performed.

Acknowledgements

The authors acknowledge the Belgian Programme on Inter-university Poles of Attraction, initiated by the Belgian State, Prime Minister's Office for Science, Technology and Culture. B.D.O. Anderson also acknowledges funding of this research by the US Army Research Office, Far East, the Office of Naval Research, Washington. The scientific responsibility rests with its authors.

References

Bombois, X., Scorletti, G., Anderson, B. D. O., Gevers, M., & Van den Hof, P. M. J. (2002). A new robust control design procedure based on a prediction error identification uncertainty set. In *CD-ROM Proceedings of the 15th IFAC World Congress*. Barcelona, Spain, pp. 2942–2847.

Codrons, B. (2000). Experiment design issues in modelling for control. Technical report. Ph.D. thesis, Université Catholique de Louvain.

Codrons, B., Anderson, B. D. O., & Gevers, M. (2002). Closed-loop identification with an unstable or nonminimum phase controller. *Automatica*, *38*(12), 2127–2137.

Gevers, M., Bombois, X., Codrons, B., Scorletti, G., & Anderson, B. D. O. (2003). Model validation for control and controller validation in a prediction error identification framework—Part I: Theory. *Automatica*, *39*(3), pii: S005-1098(02)00234-0.

Gevers, M., Ljung, L., & Van den Hof, P. M. J. (2001). Asymptotic variance expressions for closed-loop identification. *Automatica*, *37*(5), 781–786.

Ingason, H. T., & Jonsson, G. R. (1998). Control of the silicon ratio in ferrosilicon production. *Control Engineering Practice*, *6*, 1015–1020.

Landau, I. D., Karimi, A., Voda, A., & Rey, D. (1995a). Robust digital control of flexible transmissions using the combined pole placement/sensititvity function shaping method. *European Journal of Control*, *1*(2), 122–133.

Landau, I. D., Rey, D., Karimi, A., Voda, A., & Franco, A. (1995b). A flexible transmission system as a benchmark for robust digital control. *European Journal of Control*, *1*(2), 77–96.

Nordin, M., & Gutman, P. O. (1995). Digital QFT design for the benchmark problem. *European Journal of Control*, *1*(2), 97–103.

Michel Gevers was born in Antwerp, Belgium, in 1945. He obtained an Electrical Engineering degree from the Université Catholique de Louvain, Belgium, in 1968, and a Ph.D. degree from Stanford University, California, in 1972. He is a Fellow of the IEEE and a distinguished member of the IEEE Control Systems Society, and he holds a Honorary Degree (Doctor Honoris Causa) from the University of Brussels. He has been President of the European Union Control Association (EUCA) from 1997 to 1999, and Vice President of the IEEE Control Systems Society in 2000 and 2001.

Michel Gevers is Professor and Chairman of the Department of Mathematical Engineering at the Université Catholique de Louvain in Louvain la Neuve, Belgium. He is the coordinator of the Belgian Interuniversity Pole on Dynamical Systems and Control funded by the Federal Ministry of Science. He has spent long term visits at the University of Newcastle, Australia, the Technical University of Vienna, and the Australian National University. His present research interests are in system identification and its interconnection with robust control design.

Michel Gevers has been Associate Editor of Automatica and of the IEEE Transactions on Automatic Control, and Associate Editor at Large of the European Journal of Control. He is presently Associate Editor of Mathematics of Control, Signals, and Systems. He has published about 200 papers and conference papers, and two books: "Adaptive Optimal Control — The Thinking Man's GPC", by R.R. Bitmead, M. Gevers and V. Wertz (Prentice Hall, 1990), and "Parametrizations in Control, Estimation and Filtering Problems: Accuracy Aspects", by M. Gevers and G. Li (Springer-Verlag, 1993).

Xavier Bombois was born in Brussels in 1974. He received the Electrical Engineering and Ph.D. degrees from the Universite Catholique de Louvain (Belgium) in 1997 and 2000, respectively. Currently, he is an assistant professor in the Department of Applied Physics at the Delft University of Technology (The Netherlands). His main interests are identification for control and robust control analysis.

Benoît Codrons was born in Brussels, Belgium, in 1972. He obtained an Electrical Engineering degree from the Université Catholique de Louvain, Louvain-la-Neuve, Belgium, in 1995, and a Ph.D. degree from the same university in 2000.

Since July 2000, he has been with Laborelec, the R&D subsidiary of the European electricity company Electrabel. His current professional activities include research and development projects in modelling and advanced control applied to power plants and thermo-hydraulic processes.

Gérard Scorletti received the engineering degree from the Ecole Nationale Supérieure de Techniques Avancees (ENSTA), Paris and obtained his Ph.D. in Automatic Control from Orsay University, France in June 1997. His advisors were Professor Laurent El Ghaoui, Berkeley University and Professor Gilles Duc, Ecole Superiéure d'Electricite, Paris. He was a research associate at Centre for Systems Engineering and Applied Mechanics, Belgium (1997–98) where he collaborated with Professor Michel Gevers and Professor Vincent Wertz. Currently, he is a "maître de conférence" (assistant professor) of Electrical Engineering at Caen University (France) and he holds a permanent joint appointment with the Institut Supérieur de la Matière et du Rayonnement. His research interests include robust (non linear) control theory, gain scheduling control, time-delay system control and linear matrix inequality applications with a special emphasis on CAD. He is an Associate Editor to the IEEE Conference Editorial Board.

Professor Brian Anderson was born in Sydney, Australia. He took his undergraduate degrees in Mathematics and Electrical Engineering at Sydney University, and his doctoral degree in Electrical Engineering at Stanford University in 1966.

Professor Anderson is designate CEO, National ICT Australia. He worked in industry in the United States and at Stanford University before serving as Professor of Electrical Engineering at the University of Newcastle, Australia from 1967–1981. At that time, he took up a post as Professor and Head of the Department of Systems Engineering, at the Australian National University in Canberra, where he was Director of the Research School of Information Sciences and Engineering from 1994–2002. He has held many visiting appointments in the United States, Asia and Europe, including the University of California (Berkeley) Stanford University, Tokyo Institute of Technology, and the Swiss Federal Institute of Technology. Professor Anderson has served as a member of a number of government bodies, including the Prime Minister's Science, Engineering and Innovation Council. He is also a member of the Board of Cochlear Limited, one of the world's major suppliers of cochlear implants. He is a Fellow of his own country's Academy of Science and Academy of Technological Sciences and Engineering, the Institute of Electrical and Electronic Engineers, and an Honorary Fellow of the Institution of Engineers, Australia. In 1989, he became a Fellow of the Royal Society and in 2002 a Foreign Associate of the US National Academy of Engineering. He holds honorary doctorates from the Université Catholique de Louvain, Swiss Federal Institute of Technology (Zürich) and the Universities of Sydney, Melbourne and New South Wales. In 1998 he was elected President of the Australian Academy of Science for a four year term. Professor Anderson received the Quazza Medal at the IFAC 14th World Congress, Beijing, China in 1999 and an Automatica Prize Paper Award at the same time. He has held a number of offices in IFAC, including the Presidency for 1990 to 1993.