Identification of a tube glass production process : point vs. set estimation

IDENTIFICATION OF A TUBE GLASS PRODUCTION PROCESS : POINT vs. SET ESTIMATION

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Abstract : The identification of a tube glass production process is considered applying point as well as set estimation techniques. Classical identification methods, resulting in point estimates, are based on a stochastic description of the noise while set estimation methods use a bounded-error characterization. This paper is focused on the application of these identification techniques to a practical multiple-input multiple-output manufacturing process. Obtaining the required a priori information from the input-output data is described in detail together with several choices during the identification process resulting in a final point and set-model. It is shown that the application of bounded-error techniques in practice is limited due to the conservatism inherent in the method as well as the tendency towards lower order models for low signal-to-noise ratios.

Keywords : System identification; set theory; robustness; manufacturing process.

1 INTRODUCTION

The identification of an industrial MIMO (multiple-input multiple-output) manufacturing process is considered which can be approximated around a working point as being linear and time-invariant. The bounded-error characterization is an alternative to classical identification methods which are based on the assumption that the noise can be statistically modeled. The problem of parameter set estimation when the data points are corrupted by unknown-but-bounded noise mainly consists in characterizing the minimal parameter set consistent with the measurements, the model and the error description.

Obviously, certain a priori knowledge, like model structure and error bounds is required. A detailed noise analysis together with classical identification techniques can provide the required a priori information. To compare both classical and bounded-error estimation methods, an initial (point) estimate has been derived first using classical identification techniques. The initial model is supposed to be a representative candidate of the admissable modelset and it can be checked whether all process data in the bounded- error context is consistent with the assumed model structure and error bounds or not.

However, set estimators are not robust against outliers, i.e. data points which are not consistent with the specified assumptions. Such outliers may result from mistakes made during the acquisition and preprocessing of the data, but also from "overoptimistic" error bounds or unmodeled dynamics. Proper precautions, like data correction [6] or elimenating violating constraints [8], are necessary to avoid an empty parameter set.

For MIMO systems the main problem is that the model can be easily over-parametrized especially for low signal-to-noise ratios which is often the case in practice. The resulting parameter sets then become unbounded. So, for low signal-to-noise ratios the input-output behaviour with unknown-but-bounded errors has to be described using models of low order. It is therefore important for parameter set estimation to select those parameters which contribute most to the input-output behaviour until the difference between the model and the measured process data becomes smaller then the specified error bounds : a complexity-accuracy balance.

For models described by linear differential equations with the coefficients defined as parameters, the feasible parameter region is a convex set which might be very complex particularly for increasing number of

parameters. It is therefore convenient to use simpler although approximate descriptions, like ellipsoidal [7] or orthotopic [10] bounding or combinations [5,6].
In Section 2 a short process description is given. The identification of the manufacturing process including noise analysis together with classical and bounded-error estimation is described in Section 3. Finally, conclusions are given in Section 4.

2 PROCESS DESCRIPTION

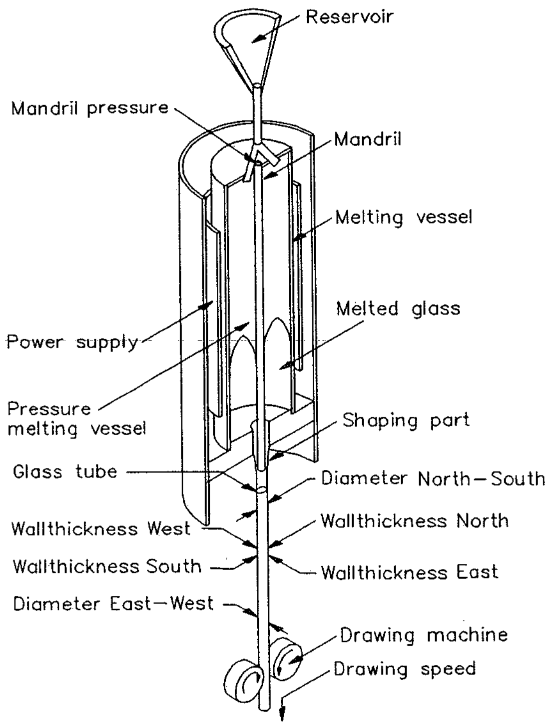

Fig. 2.1 : Tube glass production process.

Fig. 2.1 depicts a schematic outline of the most important part of the tube glass production process. Shaping of the tube takes place at and just below the mandril. The shape of the tube is determined by two output variables : the wall thickness (y_1) and the diameter (y_2) as function of time. The two process parameters that can be influenced most easily and affect the shape of the tube most directly with the shortest delay and over the largest frequency range, are the mandril pressure (u_1) and the drawing speed (u_2). Increasing the mandril pressure results in an increase of the diameter and, simultaneously, in a decrease of the wall thickness, while increasing the drawing speed results in a decrease of both the diameter and the wall thickness.

3 PROCESS IDENTIFICATION

A freerun ($\underline{u}$ = constant) and PRBNS ($\underline{u}$ = Pseudo Random Binary Noise Sequence) experiment have been carried out to analyze the noise and to obtain an estimation data set respectively. After peakshaving and detrending [1], the two output signals, average wall thickness and diameter, have been constructed from the several partially delay corrected (4 wall thickness and 2 diameter) measurements (Fig. 2.1).
The process will be analyzed as two separate MISO systems. Because of the limited space, we will discuss here only the average diameter process. The inputs of the process are the setpoints generated by the control system and therefore exactly known. The noise in the process is assumed to be additive to the output.

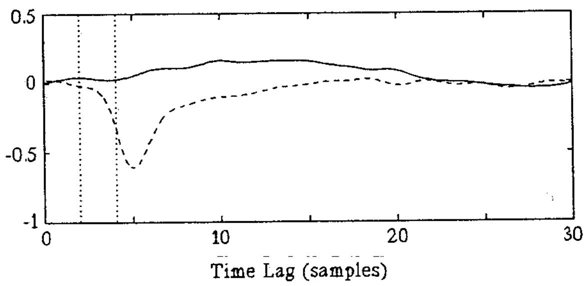

Fig. 3.1 : Cross-correlations : Mandril pressure (solid) and drawing speed (dashed) to average diameter (dotted lines indicate delays).

Fig. 3.1 shows the computed cross-correlations from the mandril pressure and drawing speed to the average diameter. The final noise and estimation data sets have been obtained after delay correction and data reduction. The realized signal-to-noise ratio for the average diameter is 20.3 dB.

3.1 Noise Analysis

The average diameter signal obtained from the freerun experiment after data pre-processing [1] and the corresponding auto-correlation are depicted in Fig. 3.2. The noise affecting the average diameter is clearly coloured. For model estimation, however, it is preferred that white noise affects the data. Therefore, a noise model has to be included or alternatively the data can be pre-filtered with the inverse noise model. In addition for bounded error estimation an accurate upper bound of the noise is required which will be very conservative for coloured noise.
For the noise model an ARMA (Auto-Regressive Moving-Average) structure [9] has been chosen :

$$A(q)y(t) = C(q)e(t) \qquad (3.1)$$

where y is the output, e the noise residual, $A(q) = 1 + a_1q^{-1} + \ldots + a_{na}q^{-na}$ and $C(q) = 1 + c_1q^{-1} + \ldots + c_{nc}q^{-nc}$ with q^{-1} the one sample delay operator.
Testing the whiteness of the residuals for several

orders of the noise model indicated that a second order (na=nc=2) is sufficient to model the noise accurately. The residual of a first order noise model is still clearly correlated while increasing the order of the noise model does not improve the whiteness significantly. The noise filter shows a low-pass behaviour with a low frequent gain of ≈ 15 dB.

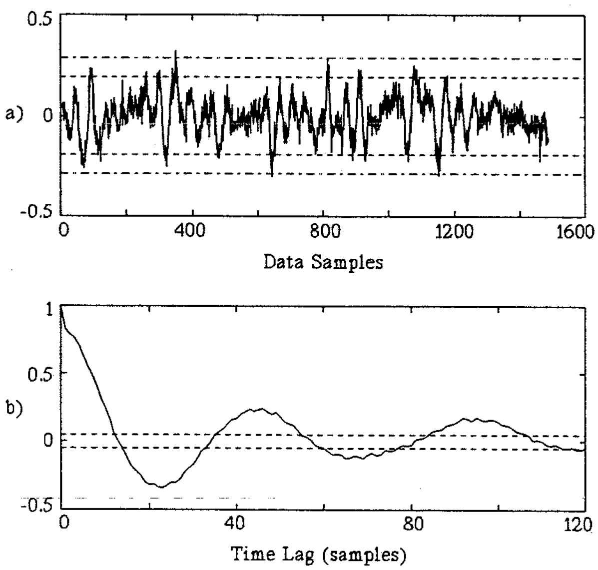

Fig. 3.2 : a) Scaled freerun experiment average diameter with 2σ (dashed) and 3σ (dash-dot) bounds (σ=0.0961). b) Auto-correlation with 95% confidence intervals (dashed).

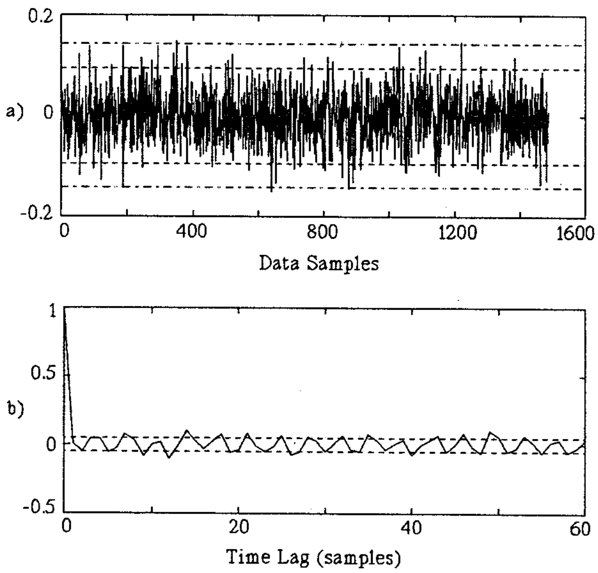

Fig. 3.3 : a) Filtered freerun experiment average diameter with 2σ (dashed) and 3σ (dash-dot) bounds (σ=0.0476). b) Auto-correlation with 95% confidence intervals (dashed).

The standard deviation of e(t) compared to y(t) for the average diameter has been reduced with a factor 2, resulting in a much more accurate bound for set estimation.

3.2 Point Estimation

Because our final goal is to estimate an output-error model [9] which is suitable for long horizon control design, the estimation data set has been filtered in a first approach with the inverse noise model such that :

$$y_f(t) = \frac{B(q)}{F(q)}\underline{u}_f(t) + e(t) \qquad (3.2)$$

where

$$y_f(t) = \frac{A(q)}{C(q)}y(t) \quad , \quad \underline{u}_f(t) = \frac{A(q)}{C(q)}\underline{u}(t) \qquad (3.3)$$

$B_i(q) = b_{1,i}q^{-1} + \ldots + b_{nb,i}q^{-nb}$ and $F(q) = 1 + f_1q^{-1} + \ldots + f_{nf}q^{-nf}$. It turned out however, that due to this high-pass filtering of the estimation data set with the inverse noise model, most low-frequent information has been filtered out. A detailed analysis of this phenomena indicated that the low-pass behaviour of the noise filter is a basic characteristic of the whole process with minor modifications in the several transfers. Therefore, it has been concluded that the process noise is filtered by the low-pass behaviour of the production process. For this reason, the model structure has been adapted to [9] :

$$A(q)y(t) = B(q)\underline{u}(t) + C(q)e(t) \qquad (3.4)$$

where the parameter vector is defined by $\underline{\theta}^T = [\, a_1 \ldots a_{na}\; b_{1,1} \ldots b_{nb,1} \ldots b_{nb,2}\; c_1 \ldots c_{nc} \,]$ in $\mathbb{R}^p$. Effectively a noise model C(q)/A(q) has now been included.

For several orders of the model (Eq. 3.4 with na = nb_i = nc) the standard deviation of the prediction error has been depicted in Fig. 3.4. Because the final model will be used for controller design, the output error of the corresponding models has been included as well. The prediction and output error have been derived from :

$$e_{pe}(t) = \frac{A(q)}{C(q)}y(t) - \frac{B(q)}{C(q)}\underline{u}(t)$$
$$e_{oe}(t) = y(t) - \frac{B(q)}{A(q)}\underline{u}(t) \qquad (3.5)$$

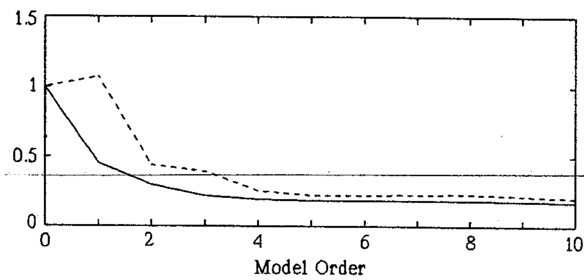

Fig. 3.4 : Order selection ; prediction error (solid) and output error (dashed).

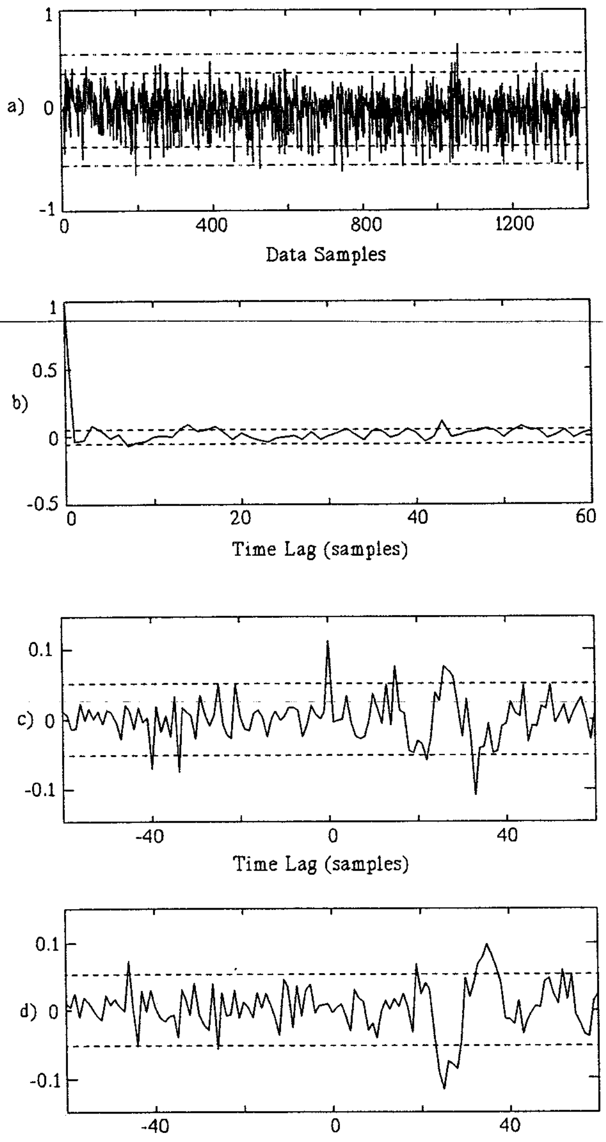

Fig. 3.5 : a) Prediction error 5th order model with 2σ (dashed) and 3σ (dash-dot) bounds (σ=0.1848), b) Auto-correlation, c) X-corr. (u1,e), d) X-corr. (u2,e) with 95% conf. intervals.

The order of the model should be selected from Fig. 3.4 in such a way that the standard deviation does not decrease significantly when increasing the model order. But in addition, the residual of the model, in this case the prediction error, should be white. This can be achieved using a 5th order model ($na=nb_i=nc=5$). For lower order models the auto-correlation is still clearly correlated and increasing the model order does not improve the whiteness of the residuals in the several correlation functions significantly. Analysis showed however that nc=2 is sufficient without affecting the results considerably. Fig. 3.5 depicts the prediction error $e_{pe}(t)$ of the optimal model together with the corresponding auto- and cross-correlations.

The low frequent peaks above the 95% confidence intervals in the cross-correlations are probably caused by non-linear effects in the actuators and the process. It should be noted however, that the standard deviation of the prediction error, σ_{pe} = 0.1848, is significantly larger than the filtered error of the freerun experiment, σ_{fr} = 0.0476. This is probably due to the fact that during the PRBNS experiment more noise is introduced from actuators and non-linear effects of the process itself which do not appear in the freerun experiment.

The validation of this 5th order model has been done using a second PRBNS experiment. The auto-correlation of the prediction error for the validation set is approximately the same as for the estimation set (Fig. 3.5b). However, the peaks in the cross-correlations due to non-linearities become larger.

A last remark should be made about the fact that the prediction error is not significantly smaller than the output error (Fig. 3.4) although much more information is used in the form of previous output samples. However, from Fig. 3.1 it follows that the influence of the mandril pressure and the drawing speed to the average diameter can be separated in a slow (long impulse response) and a fast (short impulse response) part respectively. Because the fast process part which can be easily estimated using either prediction or output error, is clearly dominant and the influence of the slow process part to the input-output behaviour which might be difficult to estimate using output error, is almost negligible, σ_{pe} is not significantly smaller than σ_{oe}.

3.3 Set Estimation

Consider the model described by Eq. 3.4 where the noise bound is defined by :

$$\| e \|_\infty \triangleq \sup_t | e(t) | \leq \gamma \tag{3.6}$$

Then Eq. 3.4 and 3.6 can be rewritten in the form :

$$y(t) = \phi^T(t)\underline{\theta} + e(t) \tag{3.7}$$

subject to the following necessary and almost sufficient conditions :

$$\begin{aligned} H_1 &: (\phi(t)+\Delta\phi(t))^T\underline{\theta} \geq y(t)-\gamma \\ H_2 &: (\phi(t)-\Delta\phi(t))^T\underline{\theta} \leq y(t)+\gamma \end{aligned} \tag{3.8}$$

where $\phi^T(t)$=[$-y(t-1)$ ... $-y(t-na)$ $u_1(t-1)$ ... $u_1(t-nb_1)$ $u_2(t-1)$ ... $u_2(t-nb_2)$ 0 ... 0], $\Delta\phi^T$=[0 ... 0 $\gamma \mathrm{sgn}(c_1)$ ... $\gamma \mathrm{sgn}(c_{nc})$] and $\underline{\theta}$ as defined below Eq. 3.4. This is similar to the extension of output-error and bounded-error-in-variables models described in [3,4]. Whenever C=1, the constraints of Eq. 3.8 reduce to

the well known equation error constraints.
Constructing a constraint set according to Eq. 3.8 with $\gamma = 2\sigma_{pe}$ (Fig. 3.5a) no violating constraints have been detected using the point estimate derived in Section 3.2 as reference. The point estimate also has been used as centre of an orthotope defining an initial parameter set and fixing the sign of the parameters. Applying the orthotopic bounding method [10] (linear programming), the final parameter set is completely defined by the initial orthotope indicating a virtually unbounded set estimation problem and therefore over-parametrization. However, a 5th order model is necessary to obtain an almost white prediction error. Nevertheless, it can be seen from Fig. 3.4 that σ_{pe} decreases hardly for models of order 3 and higher.
So a higher order model is required to make the residuals white but does not result in a significant decrease of the standard deviation. A complexity-accuracy balance has to be found for set estimation. All parameters which do not contribute significantly to the input-output behaviour of the process have to be eliminated. A detailed analysis showed that for set estimation, it is sufficient to model the tube glass production process by :

$$A(q)y(t) = B_2(q)u_2(t) + e(t) \qquad (3.9)$$

where the order has been reduced to 3 ($na=nb_2=3$) and the mandril pressure has been suppressed as input. The point estimate model parameters are $\underline{\theta}^T$ = [-8.3031e-1 3.3740e-1 -2.4116e-1 -8.1158e-2 -4.4093e-1 -1.9560e-1]. The prediction error and auto-correlation of this model have been depicted in Fig. 3.6.

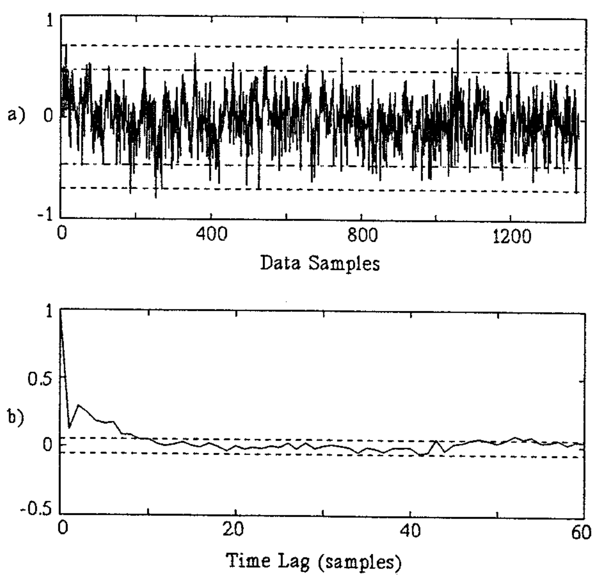

Fig. 3.6 : a) Prediction error 3rd order model with 2σ (dashed) and 3σ (dash-dot) bounds (σ=0.2335). b) Auto-correlation with 95% confidence intervals (dashed).

Comparing Fig. 3.5 and 3.6, we can see that the standard deviation of the prediction error increases slightly ($\sigma_{pe,3}$=0.2335, $\sigma_{pe,5}$=0.1848) although the number of parameters has been reduced significantly (p_3=6, p_5=17).
A new constraint set has been constructed now where the bound γ of the noise can be determined from Fig. 3.6a, because the freerun experiment does not represent sufficiently all noise in the process. Theoretically, $\|e\|_\infty$ should be used as bound. This results however in a very conservative parameter set. To show the influence of this noise bound, $\gamma = 2\sigma_{pe,3}$ as well as $\gamma = 3\sigma_{pe,3}$ are used. For both bounds, all violating constraints with respect to the point estimate, 63 (2.28%) and 7 (0.25%) respectively, have been skipped before applying orthotopic bounding. The results are given in Table 3.1 and 3.2.

Table 3.1 : Orthotopic bounding (γ=2$\sigma_{pe,3}$).

Par.	θ	$\Delta\theta$	%
a_1	-8.3031e-1	1.4595e-2	1.76
a_2	3.3377e-1	1.8877e-2	5.66
a_3	-2.3857e-1	1.2475e-2	5.23
$b_{1,2}$	-8.0593e-2	6.9047e-3	8.57
$b_{2,2}$	-4.3813e-1	7.7955e-3	1.78
$b_{3,2}$	-1.9540e-1	8.1267e-3	4.16

Table 3.2 : Orthotopic bounding (γ=3$\sigma_{pe,3}$).

Par.	θ	$\Delta\theta$	%
a_1	-8.0813e-1	2.4043e-1	29.75
a_2	3.1927e-1	2.4431e-1	76.52
a_3	-2.6478e-1	1.5235e-1	57.54
$b_{1,2}$	-8.1158e-2	8.1158e-2	100.00
$b_{2,2}$	-4.6021e-1	9.8931e-2	21.50
$b_{3,2}$	-2.1305e-1	1.3207e-1	61.99

A 100% uncertainty of parameter $b_{1,2}$ in Table 3.2 indicates that this parameter cannot be estimated using an upper bound $\gamma = 3\sigma_{pe,3}$ and therefore should be eliminated.
These results show clearly the problems and the conservatism of parameter set estimation when applying this method to industrial data. This conservatism is mainly due to the worst case bounded-error approach. The noise should be approximately uniformly distributed to ensure that the upper bound γ is an accurate description and to obtain reasonable parameter sets. This can be achieved using $\gamma = 2\sigma_{pe,3}$ as upper bound and skipping the violating constraints with respect to the reference model.
To illustrate the problems occurring when the noise is normal distributed, Fig. 3.7 depicts the results of a

simulation example with the corresponding exact parameter sets for 2σ and 3σ bounds (1000 data samples, u : uniform white sequence $\sigma = 0.58$, e : normal white sequence $\sigma = 0.12$, SNR $\approx$ 20dB). The violating constraints, 41 (2%) and 4 (0.2%) respectively, have been skipped before applying set estimation. It is obvious that for $\gamma = 2\sigma$ not all outliers, $e(t) > 2\sigma$, have been detected as measurement errors resulting in a too small parameter set (almost a dot in Fig. 3.7b).

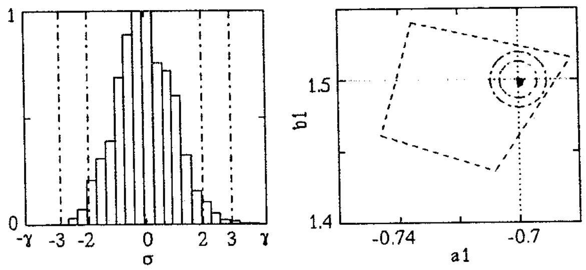

Fig. 3.7 : $y(t)=0.7y(t-1)+1.5u(t-1)+e(t)$, a) Normal dist. noise, b) Parameter space with 2σ (solid), 3σ (dashed) set estimation and 2σ, 3σ (dash-dot) Cramer-Rao bounds.

A balance has to be found between the chosen upper bound, the number of violating constraints and the conservatism of the resulting parameter set. In addition, for the tube glass production process it is obvious that the amplitude of the PRBNS signal to the mandril pressure input has not been designed large enough resulting only in a 3rd order SISO model for parameter set estimation.

4 CONCLUSIONS

It has been shown in this paper that the application of classical identification techniques to industrial data resulting in point estimates of the parameters gives good results in spite of the fact that the signal-to-noise ratio is low and that one input is clearly dominant in the input-output behaviour.

In contradiction to classical identification, set estimation techniques tend to low order models due to the conservatism inherent in the method. Only those parameters which contribute significantly to the input-output behaviour can be estimated. In addition, it has been shown that the choice for the upper bound of the noise is crucial to achieve usefull set estimates. Theoretically, $\|e\|_\infty \leq \gamma$ is a guarantee to obtain a non-empty parameter set under the assumption that the process is in the model set, the results however are very conservative and of no use in practice. A more practical solution is to choose a lower upper bound, for example $\gamma = 2\sigma_e$, and skipping all violating constraints with respect to a reference model. The resulting parameter sets do not define the 100% uncertainty bounds of the model anymore. Nevertheless, this is still not feasible in practice because 1) the number of data samples is limited, 2) industrial processes (non-linear, time-varying) can only be approximated around a working point and therefore the process is never in the model set, and 3) data outliers disturbing the measurements which have not been detected during the data pre-processing phase should not determine the upper bound of the noise.

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