Identification for the control of MIMO industrial processes

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Abstract

A procedure for the identification of industrial processes with the intention of control system design is proposed, discussed and illustrated by an application to a full scale production process. The procedure has been developed by directly meeting engineering constraints. The various identification steps are motivated, keeping industrial applicability of the procedure in mind.

The MIMO model set used is the common denominator form or minimum polynomial form. Parameter estimation is performed in several steps, thus adapting to estimation and control requirements.

The proposed general scheme has proved to perform well in various industrial applications. As an indicative example of practical results obtained, the identification and control of a quartz tube glass process is described.

Keywords: identification, parameter estimation, MIMO industrial process.

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Contents

1. Introduction

Identification has become of age ... also in industrial applications. An identification scheme meeting engineering constraints and its capabilities are given in the following.

An industrial production process usually consists of various multi-input multi-output (MIMO) subprocesses, which can be characterised by a high degree of interrelationship, i.e. each output is dynamically influenced by (almost) all inputs. Lower in hierarchy, at the primary control level, PID like controllers keep primary process inputs (e.g. flow, temperature, humidity, force, speed, power, ...) at a preset level: the setpoint. The control discussed in this paper refers to the supervisory control of MIMO subprocesses. Supervisory control implies tuning of the primary controller setpoints based on observed outputs of the MIMO subprocess. Presently, control at this secondary level is mostly done by operators. This is feasible due to the fact that most subprocesses studied show dominating linear and stationary behaviour around their operating points by proper choice of inputs and outputs.

This contribution is focussed on identification techniques for obtaining a proper model of such industrial subprocesses, to be used for automatic and improved supervisory control. Subsequently the concerned subprocess will be indicated by process. The characteristics mentioned allow us to perform off-line identification in open loop.

We concentrate on time invariant controllers, because we generally deal with grossly stationary systems. Improvement by automatic supervisory process control depends significantly on the quality of the process models on which the controller design is based. Conversely, system identification techniques, which produce these models, should be geared to the intended use in the control system design. Straightforward one step ahead prediction models are sufficient, if there is simply a need (and possibility!) for correcting the outputs in a time span which is small compared to the smallest relevant time constants of the process. These one step ahead prediction models can easily be obtained by equation error, least squares

methods. Industrial practice, however, confronts us with the indispensability of models, which perform equally well for both high and low frequencies in the relevant process dynamics. Control for fast changeovers requires a good fit for the higher frequency range, whereas disturbance reduction by feedback focusses on low frequencies, because it is almost always hampered by inevitable time delays. Consequently, models with adequate simulation performance over the full frequency range of the process are indispensable and searched for in the proposed identification scheme. The full frequency range of the process is being considered as all those frequencies, for which output disturbances can reasonably be compensated for by proper input signals in the allowed ranges.

Essentially the full identification procedure includes preliminary probing measurements, data acquisition and primary data processing, followed by parameter estimation steps, model validation and, finally, evaluation of the modelling purpose i.e. control. The ultimate success of the parameter estimation and the application of the obtained model is completely dependent on the preparation steps. Although this should be well known, we nevertheless experienced some quantitative unbalance in theoretical details and treatment of practical protocols in contemporary and past literature and even in textbooks. This can easily misguide industrial control engineers (e.g. cf. [Ljung, 1987; Söderström and Stoïca, 1988]). Also in this paper, in section 2, we have to confine ourselves to some superficial remarks on these topics, although in practice they require the dominant part of project time and effort.

Section 3 motivates and discusses modelling and estimation. In sections 4 and 5 a case study on a full scale production process shows the usefulness of the proposed method. Finally, section 6 presents the attained improvement by a controller designed on the basis of the estimated model.

2. Preliminary process measuring, data acquisition and primary signal processsing

After preliminary study of the process and extensive interviews with various groups of specialists (process engineers, control engineers, maintenance engineers and operators) the first step in the modelling of an industrial process is the selection of process inputs, which enable sufficiently accurate control of the selected outputs. The set of such process inputs has to have the following properties:

- the inputs must enable sufficient compensation of encountered disturbances both in amplitude and in frequency range over the permitted operating range;
- those inputs are preferred which enable more or less independent control of the outputs;
- reliable manipulation of the inputs has to be feasible;
- input/output transfers, possibly including (PID) control of primary process signals, have to be almost linear or linearizable (i.e. preferably no thresholds, dead zones, hystereses and the like). We were mainly confronted with processes where control had to improve quality by decreasing product tolerances. In these cases the assumption with respect to linearity is or can be satisfied. Even if processes have to be operated at the intersection of constraints, which may not be violated and thus represent non-linearities, the reduction of variances in a linear setup may decrease the allowed distance between operating point and these constraints (e.g. cf. [Åström, 1985])

When candidate process inputs and outputs have been found, preliminary experiments have to be done that are directed to the rough modelling of the process. In general three types of experiments are required:

- experiments designed for finding disturbance characteristics of the process outputs;

- experiments to test the (range of) linearity of the process, to find steady state gains and to get a rough estimate for the largest relevant time constant;
- experiments to determine the smallest relevant time constant and data acquisition for parameter estimation and model validation.

In the first set of experiments the inputs selected are kept constant. Analysis of the spectrum of the measured process outputs gives insight in the required bandwidth and in the range the control system has to have in order to reduce the disturbances.

In the second set of experiments, test signals of a symmetric staircase-type are applied to the selected process inputs. Steady state responses of the process to these inputs may be used to test steady state linearity of the process. Furthermore, rough estimates for the largest relevant time constant and steady state gains may be obtained on the basis of the measured process responses and an analysis can be done on the presence of hysteresis in the various process transfers.

In the third set of experiments, Pseudo Random Binary Noise Sequence (PRBNS) test signals of proper length (defined by the estimated largest time constant) and high clock frequency are applied to the process inputs. During these experiments all inputs are excited simultaneously with mutually independent PRBN sequences. These fast, large bandwidth PRBNS experiments are indispensable for the determination of process bandwidth and for the estimation of delay times.

A first impression of the bandwidth of the various process transfers is obtained by computation of the ratios of the spectra of the output responses and the spectra of the input signals for the large bandwidth PRBNS experiments. This information is used to determine the required clock frequency of the PRBNS test signals used in the final data acquisition. These final experiments are directed to parameter estimation and to model validation.

Pre-processing of the collected process data involves:

- peak shaving

Removal of outliers, which are mostly caused by measurement errors and by induction in sensor leads.

- trend correction

  Removal of trends, which are caused by all kinds of low frequency and tracable disturbances.

- delay time compensation

  Compensation of delay times by shift of the collected process data, as far as possible, preparatory to parameter estimation. The delay times are obtained from crosscorrelation estimates between inputs and outputs.

- offset correction

  Subtraction of average signal values in order to enable linearization arround the selected working point.

- scaling

  All measured physical quantities should be scaled in order to avoid numerical anomalies due to greatly different ranges.

- filtering

  Prevention of aliasing and improvement of signal to noise ratios

The trend correction, as an example, deserves more explanation. Very low frequency components, characterized by just a few periods in the data sets, are filtered out by applying an appropriate low pass filter to the data set. This is done consecutively both forwards and backwards in time, thereby avoiding phase shifting. These trends are mainly caused by disturbances. A small fraction, contributed by system transfer, bears too little information in the data set to be useful for identification. If not filtered out, the disturbance part would highly deteriorate estimation results. This requires careful adjustment of the applied trendfilter on the basis of a-priori knowledge. An alternative could be the use of CARIMAX models [Box and Jenkins, 1976] where input/output data is filtered by simple differentiation. Consequently, this is not a flat bandfilter and the higher frequencies get disproportionate weight. For that reason we do not choose this approach.

A more detailed discussion on experiment design and primary signal processing can be found in [Backx, 1987; Backx and Damen 1989].

3. Estimation of a simulation model

The procedure, developed for the estimation of a well fitting, compact MIMO simulation model, is motivated and elaborated in the next four subsections.

The statements made are based on experience in industrial practice. An attempt has been made to present explanation in the context of theories familiar from literature. For identification of SISO systems good textbooks are available [Ljung and Söderström, 1983; Ljung, 1987; Söderström and Stoïca, 1988], but MIMO system analysis need extra attention and discussion. Concepts of proofs are provided in the Appendices. Further theoretical elaboration of the framework is given in [Backx, 1987]. In our opinion the nice industrial results obtained so far indicate the applicability and the engineering justification of the developed scheme.

3.1 Rationale

The causal discrete time model to be estimated will be the basis for the control system design. Consequently, the following aspects put constraints on the characteristics of the estimated model, as will be explained in section 6:

- For shortening the process settling time in startup situations or changeovers, feedforward control based on the nominal model characteristics is necessary. A feedback solution would be too slow, because commonly present delays, in the order of magnitude of at least the shortest relevant time constant, prohibit high frequency feedback.
- Often disturbances are caused by effects like changes in properties of raw materials and changes in environmental conditions. These

effects influence the process outputs; they are hard to be characterized or measured in order to be used for feedforward control. Only amplitude bounds on additive output disturbances in the frequency domain seems an appropriate description to us. In industrial processes studied so far, predominantly flat disturbance spectra have been encountered.

- Disturbance reduction can only be based on a feedback loop which, because of the delays, is necessarily low-pass. This feedback loop has to enable a maximum compensation of the disturbances acting on the controlled process outputs. Consequently the nominal model has to fit well for a frequency band, determined by the time delays.

These control design constraints and disturbance characteristics require a good simulation model of the dynamic transfer characteristics of the process for the full process frequency band, i.e. for all frequencies for which the output disturbances can be compensated by control inputs within allowed amplitude ranges. Such a simulation model has to be identified on the basis of data of the process in open loop. Of course primary control loops are functioning during these experiments.

Effectively, system identification ultimately comes down to minimizing some error between data sets and model representations; this error accounts both for disturbances and for modelling errors. Under favourable circumstances the frequently used ARX models and equation error minimization will provide models that are only suited for short horizon prediction [Damen et al., 1986, Van den Hof and Janssen, 1987], that show bad behaviour for low frequencies [Ljung, 1987] and that are far from well defined for MIMO systems [Janssen, 1988, Van den Hof, 1989]. Based on assumptions on disturbances prediction error methods are usually proposed as improvement, where disturbance characteristics are modelled by noise filters, which are to be identified too. In using this approach one has to consider that:

- The noise filters may not be too complicated, otherwise data sequences will be too short to render sufficient information, resulting in high variances of the estimates.

- The disturbances should indeed be of a stochastic character as required: i.e. white, gaussian, zero mean, stationary noise filtered by time invariant linear filters.
- Appropriate modelling of both process and noise filters can be cumbersome a task for MIMO systems.
- Reliability of the results depends on suitability of the model set in describing the process and noise filter dynamics.

If these conditions are not sufficiently satisfied, reliability of the resulting models for both process dynamics and disturbances will be questionable. We choose to assume as little as possible concerning the disturbances. We only suppose that the disturbances can be modelled as being additive to the outputs and that they essentially have a flat spectrum and are independent of the inputs. Good experiment design and proper choice of the outputs to be used for feedback, choice of sensors and scaling will enable disturbances on the various outputs to be, to some extent, mutually independent and approximately of the same power after scaling. A priori this choice is not restricted to the direct output variables to be controlled, but e.g. reasons of easy and reliable measurement may cause other, related variables to be preferred.
Resuming, the noise characteristics, average value and crosscorrelation with applied input testsignals, are supposed to tend to zero. Under these assumptions adequate simulation behaviour of the system dynamics can be estimated by applying an output error Least Squares method if, in addition, the inputs have a flat spectrum in the relevant frequency range.

Least squares minimization of the output error implies minimization of the average power of the output error signal. If a Finite Impulse Response (FIR) model is chosen, it is easy to prove that the estimated model will converge to the actual impulse response for the concerned sample moments, if the process under study is indeed linear (see Appendix). If a general linear model set is being used, it can be shown that for extensive data sequences a

model is obtained, which minimizes the criterion J_e:

$$J_e = \text{trace}((F - \hat{F})^T(F - \hat{F})) \qquad (3.1)$$

This is the Frobenius norm of a matrix containing the differences between the real Markov parameters F and the estimation $\hat{F}$ in block vector form (see Appendix).

Summarizing, an output error criterion is chosen to be minimized, while taking care that the input signals are sufficiently rich compared to the frequency band of the transfer dynamics. The resultant output errors, after estimation, can be analysed e.g. in the frequency domain. In most cases this gave no indication for particular modifications of the low pass feedback dictated by the delay times. In fact the inevitable delays restricted the frequency band in which suppression of the disturbance could be accomplished, and in this band the estimated output disturbance was generally found to be predominantly flat.

Having decided to apply Least Squares minimization of output errors, the choices for the deterministic model set are now discussed. Model sets like finite impulse response (FIR), ARMAX, State Space representations and Matrix Fraction Descriptions are all based on difference equations. One can distinguish parameters as coefficients of the input differences which, for the sake of convenience, will be indicated here by Moving Average (MA) parameters and coefficients of the output (state) differences denoted as Auto Regressive (AR) parameters. Since the input samples are known, the outputs are linearly dependent on the MA parameters, hence such minimization of Least Squares of output errors is very straightforward. AR parameters, on the contrary, are more difficult to estimate in an output error criterion. Consequently we prefer a minimum number of AR parameters in the modelset. This consideration would advocate the use of a FIR model, which has no AR part. (In this particular case the output error least squares coincides with the equation error least squares, which makes the parameter estimation extremely simple.) The drawback, however, is a large number of parameters to

be estimated and a correspondingly high McMillan degree. Apart from the resulting big variance of the estimated model parameters, a high McMillan degree is disadvantageous for the design of a low order controller. Consequently, a FIR model set is not suitable for a final estimate but, nevertheless, we will use the FIR model set for an initial estimate, rendering sufficient accuracy in a first step, as explained later.

Concluding on the requirements for the nominal model we need a low order model with good simulating qualities and few autoregressive parameters.

Guided by literature on theoretical basics, one is inclined to start with canonical state space representations of low McMillan degree. A severe drawback of the use of these model sets is the required structure selection procedure. In order to avoid this structure selection overlapping parametrizations (multistructural models) have been proposed. For facilitating estimation these overlapping state space representations are transformed to matrix fraction descriptions (MFD's) (cf. e.g. [Guidorzi, 1975, 1981; Gevers and Wertz, 1984, 1985; Correa and Glover, 1984]). It is claimed that any overlapping parameterization can represent almost all MIMO systems of the proper order. If the entries of state space matrices are randomly chosen then this claim will indeed be fulfilled, because then all states are highly interrelated and all outputs depend on all states. Industrial processes, however, do not necessarily have this high degree of internal interrelationships, but are designed to have some special internal structure, which can easily be one of the set of processes that is not covered by the overlapping parameterization used. Besides, the MFD model, once estimated, may partly represent noncausal systems, which are irrealistic and cannot be retransformed to causal state space models again. Consequently heuristic retransformation deforms part of the information. The use of a parametrisation suggested by Correa [Correa and Glover, 1984; Janssen, 1987, 1988] indeed eliminates the noncausal aspects, but in the estimation this leads to consecutive steps, which in turn deteriorate the estimation criterion originally wanted [Janssen, 1987; Janssen and Damen, 1987]. Consequently, output error least squares minimization should then be done with constraints, which highly complicates the minimization procedure.

Apart from the drawbacks mentioned already, both canonical and overlapping parametrizations still contain nominally n*q autoregressive parameters, where n equals the McMillan degree and q denotes the number of inputs or outputs depending on the type of overlapping/canonical form chosen.

There is a way out, where we deal with only r (the degree of the minimum polynomial) autoregressive parameters and where we can avoid any structure selection. This is offered by a model set indicated as the common denominator form [Kailath, 1980] or minimum polynomial form [Gerth, 1972; Backx, 1987]. In the sequel we will call this model set the Minimum Polynomial and Start Sequence of Markov parameter model abbreviated by MPSSM, which is given by the following definition:

Definition of the MPSSM model set:

Let the minimum polynomial (cf. [Gantmacher, 1959]) of a discrete time, causal system be given by:

$$z^r + a_1 z^{r-1} + \ \dots \ + a_{r-1} z + a_r = 0 \qquad (3.2)$$

Let the first r Markov parameters be given by M_j (j=1,2, ... r) and the direct feed through by D. Then the output vector y of p outputs generated by an input vector u of m inputs is given by a convolution:

$$y_k = \sum_{j=0}^{\infty} F_j u_{k-j} \qquad \dim[F] = pxm \qquad (3.3)$$

$$F_j = \begin{cases} D & j=0 \qquad (3.4) \\ M_j & j=1,2, \dots ,r \qquad (3.5) \\ -\sum_{i=1}^{r} a_i F_{j-i} & j>r \qquad (3.6) \end{cases}$$

The parameter set such defined consists of the r minimum polynomial coefficients and the first r Markov parameters extended with the direct feed through term D. This sums up to r+rmp+mp parameters. The majority of these parameters, the (r+1)mp entries in M_j and D, are in fact moving average parameters.

A disadvantage of the MPSSM model set is the presence of multiplicity of poles, which can be illustrated by transformation of the MPSSM model to corresponding state space representations. If $p \leq m$ the following observability canonical form (A,B,C,D) can easily be verified:

$$A = \mathrm{diag}(A_1, A_2, \ldots, A_p) \qquad \dim A: rpxrp \qquad (3.7)$$

with:

$$A_i = \begin{bmatrix} 0 & & \\ \vdots & & I_{r-1,r-1} \\ 0 & & \\ -a_r & -a_{r-1} \cdots & -a_1 \end{bmatrix} \qquad i=1,2, \ldots ,p \qquad \dim A_i: rxr$$

$$C = [C_1, C_2, \ldots, C_p] \qquad \dim C: pxrp \qquad (3.8)$$

with:

$$C_i = \begin{bmatrix} 0 & 0 & \ldots & 0 \\ . & . & & . \\ 0 & 0 & \ldots & 0 \\ 1 & 0 & \ldots & 0 \\ 0 & 0 & \ldots & 0 \\ . & . & & . \\ 0 & 0 & \ldots & 0 \end{bmatrix} \leftarrow i \qquad i=1,2, \ldots ,p \qquad \dim C_i: pxr$$

$$B = [B_1^T,\ B_2^T,\ \ldots\ ,\ B_p^T]^T \qquad \text{dim } B: \text{ rpxm} \qquad (3.9)$$

with:

$$B_i = \begin{bmatrix} M_1(i,1) & \ldots & M_1(i,m) \\ . & & . \\ . & & . \\ M_r(i,1) & \ldots & M_r(i,m) \end{bmatrix} \qquad \begin{array}{l} i=1,2,\ \ldots\ ,p \\ \text{dim } B_i\text{: rxm} \end{array}$$

$M_i(j,k)$: entry (j,k) of Markov parameter M_i

For $m \leq p$ the <u>controllability canonical form</u> is the appropriate representation:

$$A = \text{diag}(A_1,\ A_2,\ \ldots\ ,\ A_m) \qquad \text{dim } A: \text{ mrxmr} \qquad (3.10)$$

with:

$$A_i = \begin{bmatrix} 0 & \ldots & 0 & -a_r \\ & & & -a_{r-1} \\ & I_{r-1,r-1} & & . \\ & & & -a_1 \end{bmatrix} \qquad \begin{array}{l} i=1,2,\ \ldots\ ,m \\ \text{dim } A_i\text{: rxr} \end{array}$$

$$B = [B_1^T,\ B_2^T,\ \ldots\ ,\ B_m^T]^T \qquad \text{dim } B: \text{ rmxm} \qquad (3.11)$$

with:

$$B_i = \begin{bmatrix} 0 & .. & 0 & 1 & 0 & .. & 0 \\ 0 & & 0 & 0 & 0 & & 0 \\ . & & . & . & . & & . \\ . & & . & . & . & & . \\ 0 & .. & 0 & 0 & 0 & .. & 0 \end{bmatrix} \qquad \begin{array}{l} \text{(1 in column } i\text{)} \\ i=1,2,\ \ldots\ ,m \\ \text{dim } B_i\text{: rxm} \end{array}$$

$$C = [C_1, C_2, \ldots, C_m] \qquad \dim C: pxrm \qquad (3.12)$$

with:
$$C_i = \begin{bmatrix} M_1(1,i) & \ldots & M_r(1,i) \\ . & & . \\ . & & . \\ M_1(p,i) & \ldots & M_r(p,i) \end{bmatrix} \qquad i=1,2, \ldots ,m$$

$$\dim C_i: pxr$$

For generic values of M_i i=1,2,..,r these representations will be minimal. Consequently the McMillan degree equals r*min(m,p). This can easily be concluded from the rank of an extensive Hankel matrix built up by Markov parameters F_k. Because of (3.7) respectively (3.10) this rank will generically be equal to r*min(m,p), which is the McMillan degree.

These state space representations clearly show that all poles, indicated by the zeros of the minimum polynomial, have multiplicity q=min(m,p). Furthermore, they are all distinct (corresponding to distinct Jordan cages; corresponding to different eigenvectors) because the off-diagonal blocks A_{ij} of state matrix A are all equal to zero. In practical terms one might say that these multiplicities just refer to "parallel" modes, which happen to be exactly equal. In industrial practice such a coincidence is highly unlikely. Surely multiplicity of poles as e.g. in z=0 for delays and in z=1 for multiple integrations may occur, but these kind of multiplicities are not distinct and can be described as "cascaded" modes. Of course these "common" multiplicities are incorporated in MPSSM as well, but will be reflected in each diagonal block matrix A_i.

This multiplicity of distinct poles leads to the following effects and remedies. The MPSSM model set used for estimation has to have a minimum polynomial degree r=n, if the process under estimation is expected to have a McMillan degree n. But this implies that the models in the MPSSM model set themselves have a McMillan degree equal to r*min(m,p)=n*min(m,p). This excess in McMillan degree is due to the unavoidable multiplicity of poles.

Very rarely do practical systems show any multiplicity of distinct poles in the above sense and, consequently, if we adjust the model parameters for the fit to a practical data set, this freedom will hardly be needed. Consequently this negligibly small part of the estimated model can easily be removed afterwards by some model reduction technique as will be indicated in subsection 3.4.

This degression on the allowing of multiplicity of poles in the model set and the final elimination by model reduction might seem very detailed, but, nevertheless, it is quite crucial as control asks for low order models in order not to complicate reliable controller design and implementation.

Finally, one more problem has to be overcome. Output error criteria combined with autoregressive parameters force us to make use of numerical optimization techniques for minimization of the criterion function (i.e. an output error least squares). In order to avoid local minima and for speeding up the minimization process a good initial estimate of the parameters is essential. This initial estimate can be obtained by subsequent use of the following steps:

- Fit a FIR model in an output error criterion to the dataset, which is very easy and straightforward
- Fit an MPSSM model to this FIR model according to the method of Gerth as explained in subsection 3.3. In fact this is a kind of model reduction technique.

Then the MPSSM model obtained in the previous step can be used as an initial estimate in the final minimization process, which fits an MPSSM model to the dataset by minimization of an output error criterion.

Having motivated and outlined the main steps in the identification we will now briefly comment on the various steps in the following subsections.

3.2 Estimation of the FIR model

The length of the FIR model can easily be fixed based on the knowledge obtained from the preliminary measurements as described in section 2.

The least squares estimation of the FIR is very well known and does not need any further description (cf. e.g. [Niederlinski and Hajdasinski, 1979]).

If the dataset is sufficiently large, if the disturbances can be considered as independent and zero mean, and if the input signals are white (sufficiently rich) then it is easy to prove that the estimated Markov parameters are unbiased and that the influence of a truncated tail of the impulse responses is negligibly small (see Appendix). As we have many independent parameters in the FIR model, the variances of the parameters will be relatively big compared to the variances of the succeeding MPSSM model parameters.

3.3 Model reduction of the FIR model to an MPSSM model

Let the Markov parameters of the estimated FIR model from subsection (3.2) be given by $\tilde{F}_j$, $j=1,2, \ldots ,L$, then a sufficiently reliable estimation of the degree r of the minimum polynomial can be based on the singular values of the following block Hankel matrix:

$$\tilde{H}_v = \begin{bmatrix} \mathrm{vec}(\tilde{F}_1) & \mathrm{vec}(\tilde{F}_2) & \ldots & \mathrm{vec}(\tilde{F}_j) \\ \mathrm{vec}(\tilde{F}_2) & \mathrm{vec}(\tilde{F}_3) & \ldots & \mathrm{vec}(\tilde{F}_{j+1}) \\ \circ & \circ & & \circ \\ \circ & \circ & & \circ \\ \mathrm{vec}(\tilde{F}_i) & \mathrm{vec}(\tilde{F}_{i+1}) & \ldots & \mathrm{vec}(\tilde{F}_L) \end{bmatrix} \qquad (3.13)$$

where $\mathrm{vec}(\tilde{F}_i)$ indicates that all columns of $\tilde{F}_i$ are put below one another into one vector. The reason is that we want to obtain the minimum polynomial degree instead of the McMillan degree. Since the $\mathrm{vec}(\tilde{F}_k)$ satisfy the minimal polynomial equation (3.2) (like $\tilde{F}_k$), it is easy to see that $\mathrm{rank}(\tilde{H}_v)$ is r. A sharp decrease and/or stabilization to the noise level in the behaviour of the decreasing singular values indicates the appropriate value of r. For details see [Damen et al., 1982].

For a rough fit of an MPSSM model to the FIR model a method proposed by Gerth [Gerth, 1972] may be used. This method gives initial values for the MPSSM model parameters, which are sufficient for the final estimation to converge to the global minimum. Gerth's method can briefly be explained as follows. If we substitute the estimated Markov parameters $\tilde{F}_j$ for F_j in eq. (3.4), (3.5) and (3.6), we can use these parameters for a least squares estimation of the minimum polynomial coefficients a_i or more explicitly:

$$\tilde{G}\, a = \tilde{v} \tag{3.14}$$

with:

$$\tilde{G} = \begin{bmatrix} \mathrm{vec}(\tilde{F}_1) & \mathrm{vec}(\tilde{F}_2) & \dots & \mathrm{vec}(\tilde{F}_r) \\ \mathrm{vec}(\tilde{F}_2) & \mathrm{vec}(\tilde{F}_3) & \dots & \mathrm{vec}(\tilde{F}_{r+1}) \\ \circ & \circ & & \circ \\ \circ & \circ & & \circ \\ \mathrm{vec}(\tilde{F}_{L-r}) & \mathrm{vec}(\tilde{F}_{L-r+1}) & \dots & \mathrm{vec}(\tilde{F}_{L-1}) \end{bmatrix} \tag{3.15}$$

$$\tilde{v}^T = [\mathrm{vec}(\tilde{F}_{r+1})^T \quad \mathrm{vec}(\tilde{F}_{r+2})^T \quad \dots \quad \mathrm{vec}(\tilde{F}_L)^T]^T \tag{3.16}$$

$$a^T = -[a_r,\ a_{r-1},\ \dots\ ,\ a_1]^T \tag{3.17}$$

So we obtain:

$$\hat{a} = (\tilde{G}^T \tilde{G})^{-1} \tilde{G}^T \tilde{v} \tag{3.18}$$

If we take this estimate of the minimum polynomial coefficients as sufficiently accurate, the start sequence of Markov parameters M_i, i=1,2, ...,r, represented in a column vector form in matrix M_s, has to satisfy the following equation:

$$H M_{sv} = \tilde{F}_v \tag{3.19}$$

$$\text{with: } H^T = [I_r \quad AE_r \quad A^2E_r \quad \dots \quad A^{m-r}E_r] \tag{3.20}$$

$$A = \begin{bmatrix} 0 & \dots & 0 & -\hat{a}_r \\ I_{r-1,r-1} & & & \cdot \\ & & & -\hat{a}_1 \end{bmatrix} \tag{3.21}$$

$$E_r = [0, 0, \dots, 0, 1]^T \tag{3.22}$$

$$M_{sv}^T = [\text{vec}(M_1) \quad \text{vec}(M_2) \quad \dots \quad \text{vec}(M_r)] \tag{3.23}$$

$$\tilde{F}_v^T = [\text{vec}(\tilde{F}_1) \quad \text{vec}(\tilde{F}_2) \quad \dots \quad \text{vec}(\tilde{F}_L)] \tag{3.24}$$

Analogously we obtain an estimate $\hat{M}_{sv}$ by taking:

$$\hat{M}_{sv} = (H^T H)^{-1} H^T \tilde{F} \tag{3.25}$$

The MPSSM given by (3.18), (3.25), and a direct feed through estimate $\hat{D}$ directly obtained from the estimated FIR model, appears to be sufficiently

accurate for use as an initial estimate in the iterative fitting process described in the next subsection.

3.4 Adjustment of an MPSSM model to the original dataset

The criterion J to be minimized is defined as a least squares of the output errors. If we apply an MPSSM model, the start sequence of Markov parameters $M_s = \{ M_i;\ i=1,2, \ldots ,r\}$ appears quadratically in the error function. This can easily be understood as this Markov sequence M_s appears in the canonical forms either in the B or in the C matrix (cf. eq. (3.7) - (3.12)). Consequently, it is very easy to minimize J with respect to M_s for a particular value of a, the set of the minimum polynomial coefficients, and the dataset samples:

$$\frac{d\ J(a,M_s)}{d\ M_s} = 0 \quad \rightarrow \quad M_s = M_s(a) \tag{3.26}$$

Substitution of this solution in the error criterion leaves us with the problem of finding the minimum of the criterion only for the r minimum polynomial coefficients a_i:

$$J(a,M_s) = J(a,M_s(a)) = V(a) \tag{3.27}$$

The obtained analytical form $J(a,M_s)$ allows us to compute gradients with respect to a_i so that quasi-Newton methods can be used for minimization of $J(a,M_s)$. Unfortunately the expression $M_s(a)$ cannot be obtained in an explicit analytical form. Therefore minimization of $J(a,M_s)$ is done alternately for M_s and a. This approach is speeding up the iteration process considerably.

The expressions for the functions and gradients are rather complex and do not provide any further insight. As the formulae can be obtained in a straightforward derivation, they are not given here. Details about this approach can be found in [Backx, 1987].

Furthermore, in the Appendix it is shown that the estimated MPSSM model will converge asymptotically to the model in the modelset which is optimal in the sense of eq. (3.1), and thus to the real process if it is contained in the modelset used. Due to the zeroth iteration, available from the previous step, the quasi Newton methods converge to the proper minimum in all our experiments. This zeroth iteration is close to the proper minimum, as it is obtained from a model to model fit on the basis of the earlier obtained FIR model, which has been computed as the minimum of a convex function.

Finally, as explained in subsection 3.1 we have to compensate for the practically nonexisting multiplicity of the poles. This can be done by straightforward model reduction techniques. We applied the Moore-Pernebo-Silverman approximation [Moore, 1981; Pernebo and Silverman, 1982] which simply deletes the irrelevant (with respect to the noise level) singular values in the balanced state space realization.

4. Description of the industrial process

The identification approach described in the previous sections has been applied to various industrial processes like a feeder of a glass furnace, a shaping process of glass bulbs, a telecommunication fiber production process, a shaping process of normal glass tubes.

Here results are presented for the shaping part of a quartz glass tube production process. A sketch of this process is given in Fig. 4.1. Shaping of the tube takes place at and just below the end of the mandril. The shape of the tube is characterized by the average tube diameter and the average tube wall thickness; these are defined as the outputs of the process. Process parameters that directly influence shaping of the tube, are mandril gas pressure, drawing speed, power applied to the furnace, melting vessel

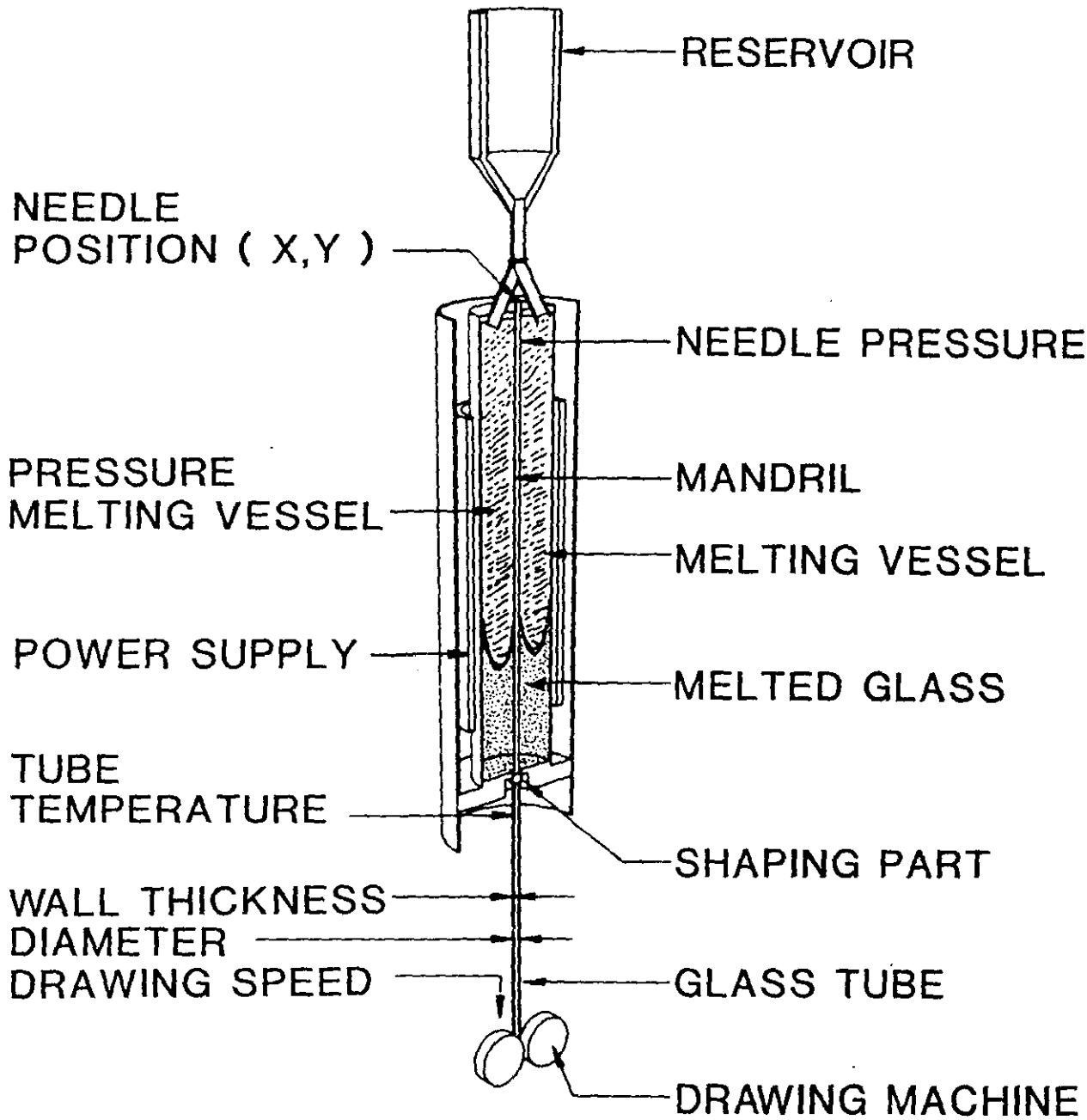

Fig. 4.1 Outline of the quartz tube glass production process

pressure and composition of the raw materials. Some of these have such a small bandwidth (power and composition of raw materials), influence the glass quality badly (composition of raw materials), or have such extremely large delay times involved (power, melting vessel pressure, composition of raw materials); so they are not well suited for control of tube dimensions. Mandril pressure and drawing speed influence the shaping of the tube in a most direct way. Transfers from these inputs to both wall-thickness and diameter have the largest bandwidth, the shortest delay times and permit, to some extent, independent manipulation of the outputs. The permitted ranges for these two process inputs allow a control of tube dimensions over the full amplitude range of output disturbances.

Shaping of the tube truly is a MIMO process with a high degree of interaction. Increase of the mandril pressure results in an increase of the tube diameter and in a decrease of the wall thickness. Increase of the drawing speed causes a decrease of both diameter and wall thickness.

It is clear that the input/output transfer of this process cannot exactly be described with a linear, lumped parameter model as assumed for the process identification method developed. However, that method proved to be adequate for finding a simulation model that properly describes the process dynamics in the operating range around the working points used.

5. Identification results for the quartz tube glass process

The various experiments as indicated in section 2 have been carried out.

The signal to noise ratios have been estimated from 8 data sets of 2500 samples each of the excited (with a PRBNS) and of the non-excited process. The latter columns of Table 5.1 show the results for the ratios of average noise power and the average signal power (N/S) in order to enable comparison later on with estimation results. Computed standard deviations on the basis of the 8 data sets are also shown.

The FIR model, obtained in the first estimation step, consists of 50 Markov parameters. This length has been chosen on the basis of responses of

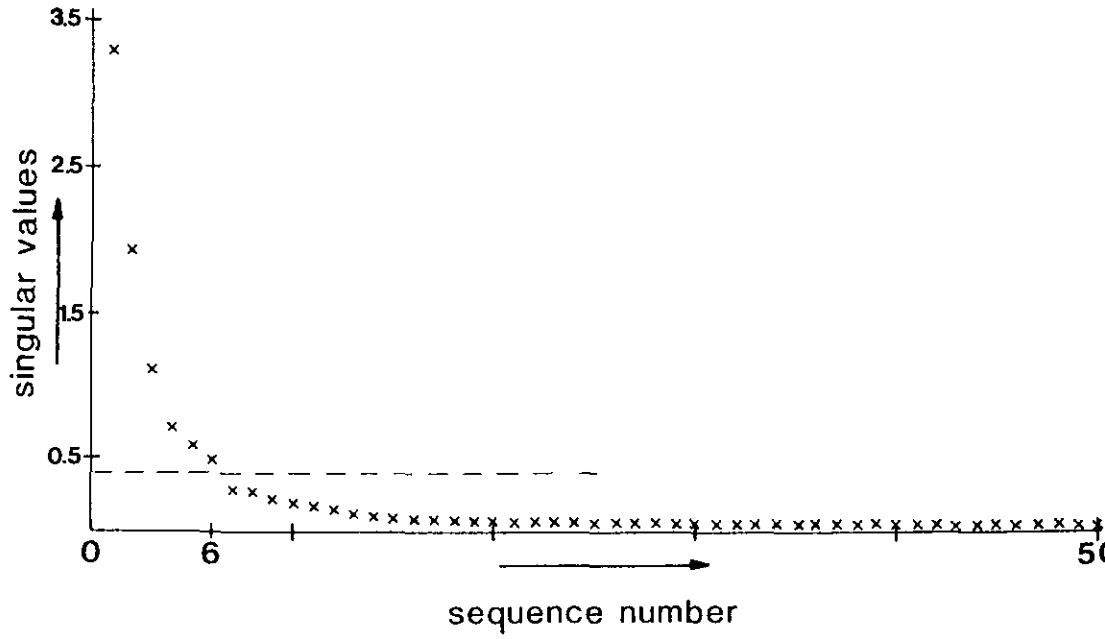

Fig. 5.1 Singular values of the block Hankel matrix eq. (3.13)

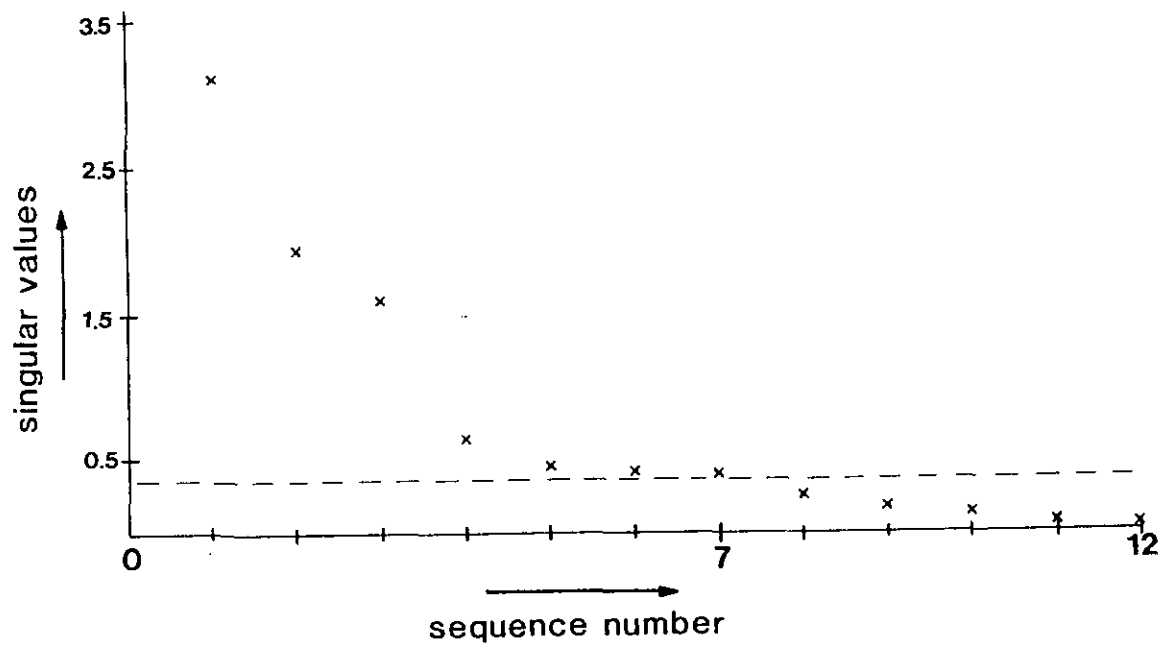

Fig. 5.2 Hankel singular values of the final MPSSM model

the process to applied staircase type input test signals. The estimation has been done on the basis of the first 1000 samples of a PRBN experiment.

An appropriate value r=6 for the degree of the MPSSM model has been determined on the basis of the singular values of the finite block Hankel matrix of the estimated FIR Markov parameters in vector form (cf. equation (3.13) and Fig. 5.1). An estimated noise level, shown in Fig. 5.1, indicates the number of relevant Hankel singular values. Note that the MPSSM model set contains 34 parameters of which 6 are autoregressive. Overlapping parametrization would lead to 28 parameters of which 12 are autoregressive.

Using the MPSSM model parameters obtained with Gerth's algorithm as zero-th iteration, a final MPSSM model has been fitted to the dataset with the direct estimation method discussed in section 3.

Finally, the model reduction technique of Pernebo and Siverman has been applied to remove inherently present, irrelevant modes from the model obtained so far. An appropriate order n=7 of the approximate state space realization of the estimated MPSSM model has been determined on the basis of the Hankel singular values of the balanced state space representation of the MPSSM model in relation to the observed signal-to-noise ratios (cf. Fig. 5.2).

Fig. 5.3 shows the various impulse responses obtained in the subsequent steps and the various delays, which have been estimated beforehand by crosscorrelation techniques.

PRBN sequences, with the same characteristics as the sequences used for identification, have been used for the first validation experiment. The second validation experiment was done with PRBN test signals with a clock frequency of 0.0667 times the clock frequency of the initially used PRBN sequences. The bandwidth of these last input signals corresponds with the bandwidth of the input signals applied to the process during normal operation. Process responses (y_i) have been compared with outputs simulated

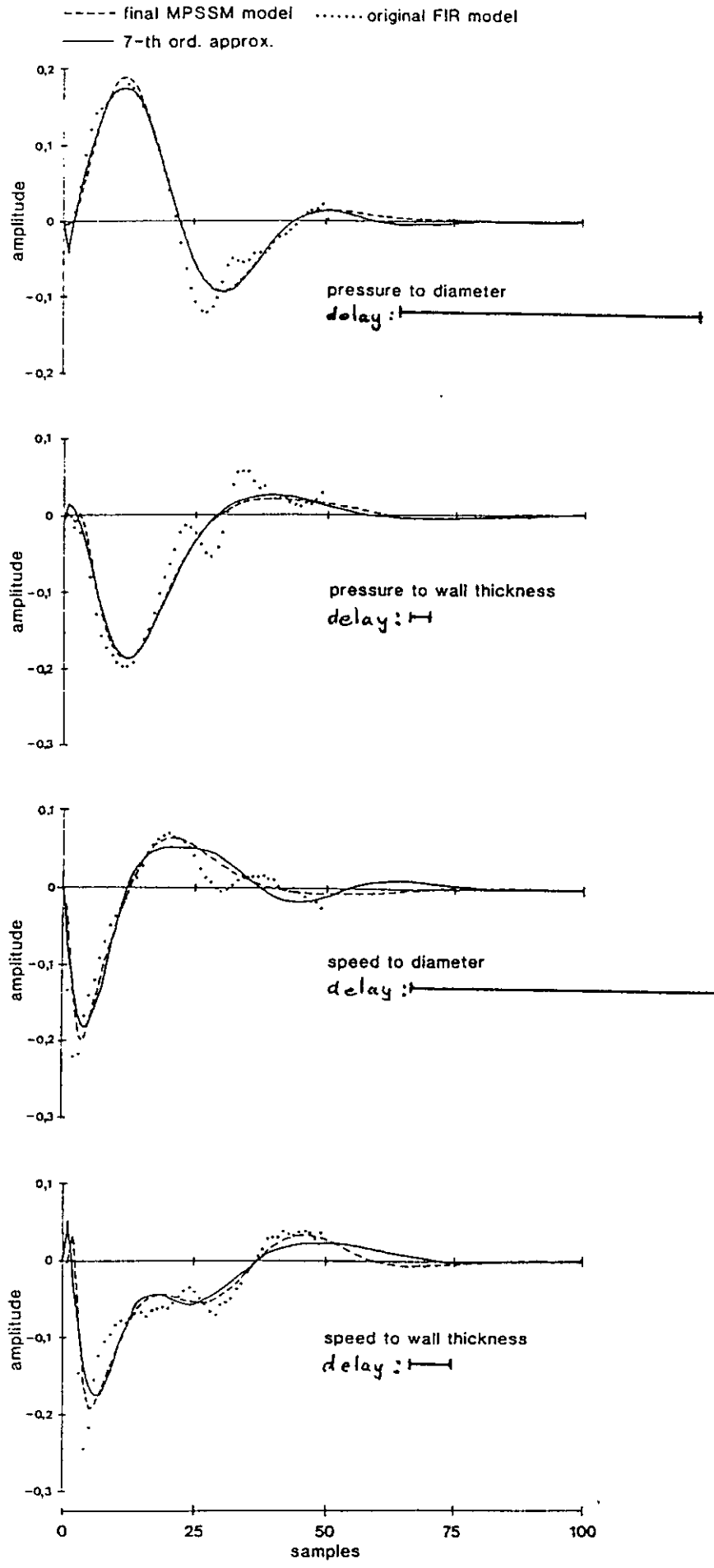

Fig. 5.3 Impulse responses of the estimated FIR model, the final MPSSM model and the approximate realization of the MPSSM model

by the models ($\hat{y}_i$) by using a relative output energy measure (E):

$$E = \frac{\sum_{i=1}^{K} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{K} y_i^2} \qquad (5.1)$$

Plots show that the simulated output signals are almost indistinguishable from the real output signals. Differences are within the noise level (e.g. cf. Fig. 5.4), which is sustained by the validation values shown in Table 5.1. If the models are indeed able to represent the process transfers exactly, the presented ratios E have to correspond with the N/S ratios considering the standard deviations. Wall thickness results approach this limit quite well, while diameter results come close to the limit too, taking into account the low noise level.

Both validation results show that the input/output behaviour of the MPSSM model and of its 7-th order approximate realization very well resemble the input/output behaviour of the shaping part of the process.

Generally speaking, it can be stated that the model simulation fit on the validation data is about as good as the fit on the estimation data. Compared to the computed noise to signal ratios (cf. the latter 2 columns of Table 5.1) the results obtained during validation confirm reliability. For wall thickness the errors are close to the noise to signal ratio. Diameter results are a factor 3 to 5 worse. This may be explained from the fact that wall thickness is hard to be measured and as a result noise in the measured wall thickness signal is much larger than noise in the measured diameter signal. Modelling errors in diameter are therefore expected to be dominant over diameter measurement noise. The balance might be improved by further adjustment of the energy contents of the applied testsignals during the experiments for parameter estimation.

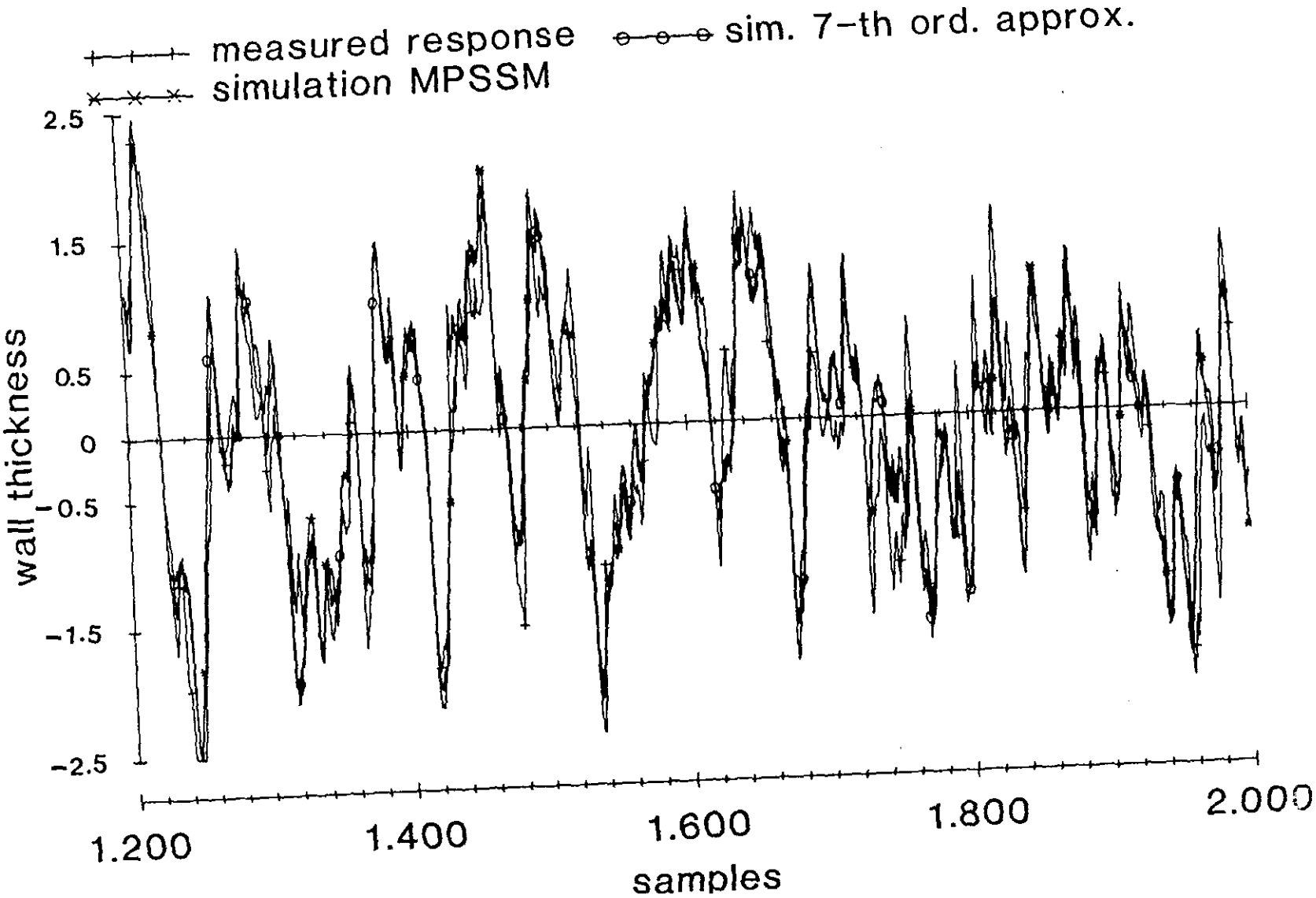

Fig. 5.4 Actual outputs compared with simulated outputs

output	FIR	MPSSM initial	MPSSM final	7-th ord. approx.	average N/S	standard deviation
			Estimation data			
wall thickness	0.1523	0.2156	0.1257	0.1462	0.1519	0.0671
diameter	0.0886	0.2327	0.0621	0.0789	0.0196	0.0066
			First set of Validation			
wall thickness	0.1731	0.2536	0.1437	0.1629	0.1519	0.0671
diameter	0.0996	0.2589	0.0879	0.0997	0.0196	0.0066
			Second set of Validation			
wall thickness	0.2104	0.2967	0.1805	0.1835	0.1519	0.0671
diameter	0.1121	0.1937	0.0567	0.0581	0.0196	0.0066

Table 5.1 The relative output energy measure (E) (eq. 5.1) for the consecutively estimated models on both estimation and 2 sets of validation data. For comparison the last columns show estimated N/S ratios and their standard deviations on the basis of preliminary measurements.

6. Control of the quartz tube glass process

For control of industrial MIMO processes a control system based on an internal model has been developed. The next two subsections describe the control system and present the results attained on the quartz tube glass production process.

6.1 Description of the applied control system

For control of the shaping part of the tube glass production process a control system based on an internal model is applied (e.g. cf. [Åström, 1989; Garcia et al., 1989]). Fig. 6.1 shows the diagram of the MIMO control system.

In the diagram S_p and S_m respectively denote the true MIMO process transfer function and the model. Delay times are part of both the true process transfer and the model. As indicated before, the delay times encountered may be relatively large compared to the process dynamics.

The control system consists of two parts:

- A feedforward control system used to modify the dynamic properties of the process transfers and to realize an approximate decoupling. The feedforward control system involves the blocks S_m (the model), F (a state feedback controller) and H_{cl}^{-1} (the static inverse of the state feedback controlled model). Design of the state feedback controller F is done by means of the implicit model following technique (cf. [Tyler, 1964; Kreindler and Rothchild, 1976; Backx, 1987]). Modification of the system dynamics has to be done such that realized dynamics do not need input signal amplitudes which exceed the permitted input signal ranges.
- A feedback control system directed to the suppression of disturbances on the process outputs (n_k). To allow robust control of the disturbances the measured process outputs are compensated with the simulated deterministic part of the process outputs. The feedback control system involves feedback controller block S_f. Due to the compensation of measured process outputs with the outputs simulated by the model, loop gains remain small although the full process gains are available for noise reduction.

  To cope with large delay times in the process transfers the feedback controller S_f needs to have low pass characteristics in order to

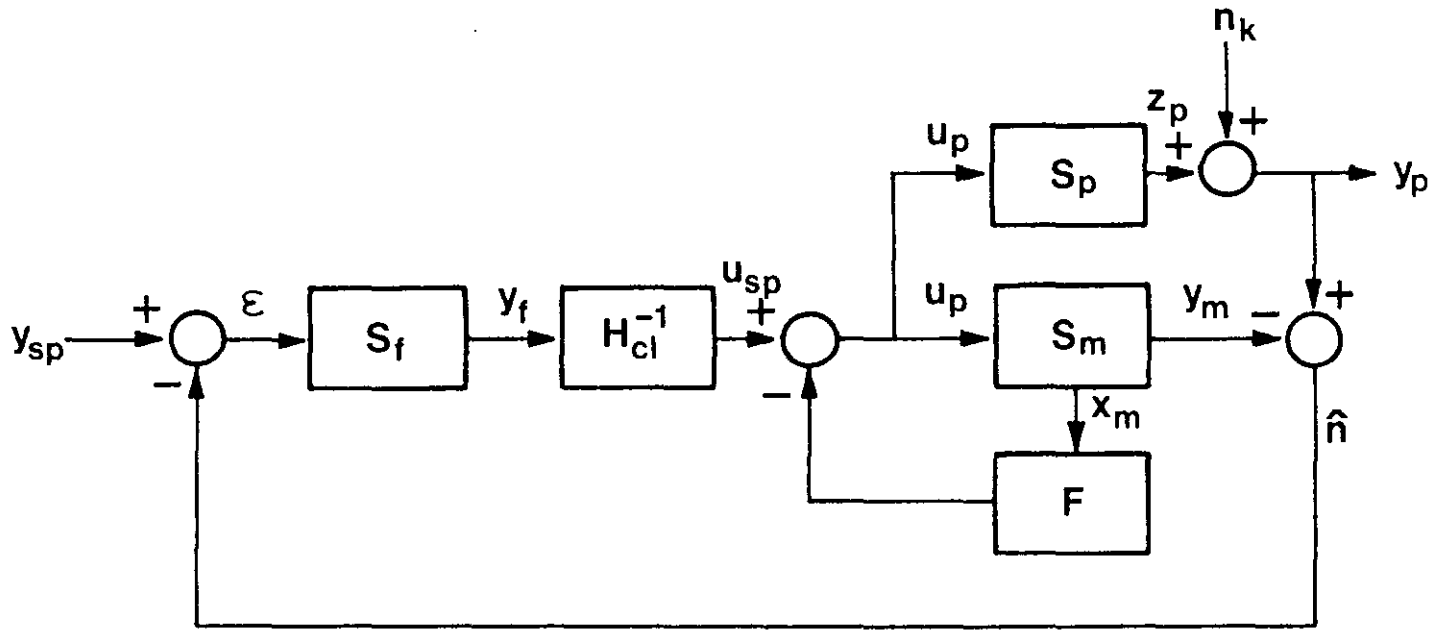

Fig. 6.1 Diagram of the MIMO control system

prevent control actions at frequencies exceeding the frequency corresponding with $1/2\tau_d$ (τ_d is the time delay in a transfer).

6.2 Performance of the control system

The control system discussed in section 6.1 has been applied to the quartz tube glass production process.

Before the estimation experiment was done, the delay times due to sensor positioning were kept to a minimum. After the estimation experiment, some technical overheating problems were overcome and it appeared possible to decrease the delay times for control by adjustment of the position of the diameter sensor. After repositioning of the sensor the delay times in the transfers to the diameter outputs decreased with 50 samples compared to the estimation data (cf. Fig. 5.3).

For design of the feedforward control system a double SISO reference transfer function with eigenvalues at 0.7 is used. These eigenvalues lead to process inputs within the permitted input signal range.

Experiments have been done alternately with the standard operator setpoint control of both PID controlled mandril pressure and drawing speed on the one hand, and the MIMO supervisory control system on the other hand.

Fig. 6.2 shows the improvement obtained by the MIMO controller. The computed distribution of tube wall thicknesses and diameters with the standard control system and with the MIMO control system are convincing. For computation of the distributions 10000 samples of the controlled process have been used. An important improvement of the settling time during changeovers and startup situations, from about 2 hours in standard control to 2 minutes with the discussed supervisory control, has also been accomplished! This improvement could be realized due to the smoothening of process response characteristics by the internal model based feedforward control system. Consequently, the trajectory towards the new operating point can be controlled directly and smoothly, only restricted by physical constraints on the process inputs. This could not be accomplished by

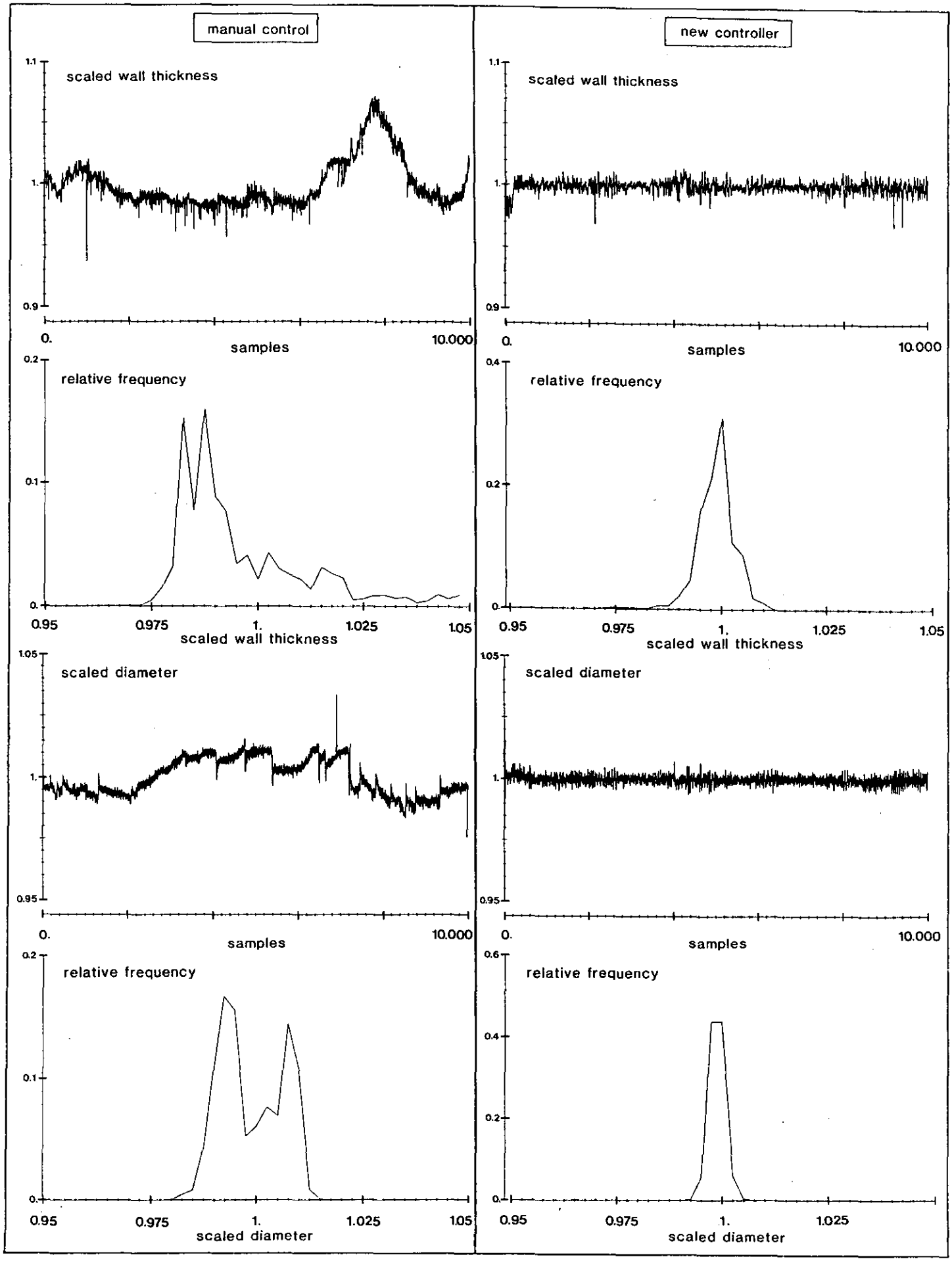

Fig. 6.2 Improvement of the newly developed controller over the normal control system

operators before, as they had to use many consecutive small control steps due to the large overshoots and settling times encountered, especially in diameter responses.

7. Conclusions

A description has been given of the identification strategy developed for the identification of a simulation model of MIMO industrial processes for the purpose of supervisory control system design. For the design of both the identification and control procedure assumptions are made with respect to industrial process behaviour:

- Predominantly linear and stationary behaviour
- Delays of the order of relevant time constants
- Open loop identification is feasible by temporarily prohibiting operator intervention
- Disturbances cannot be compensated for by feedforward control
- Zero correlation between the broad band disturbances and the broad band input signals

The processes under study all showed these characteristics, or slight modifications could bring about this behaviour. In this respect the preliminary study of the process, the orienting measurements, data acquisition and preprocessing appear to be crucial in preparing the conditions for successful identification and control.

Based on available model sets and identification techniques a procedure has been outlined and motivated to arrive at an appropriate simulation model. The procedure essentially consists of output error minimization for a minimum polynomial model, where a zero-th iteration is obtained from the Gerth algorithm applied to a FIR model estimated in a first step.

By adopting the modelset defined by a minimum polynomial model (MPSSM) the following advantages are obtained:

- No cumbersome structural identification is required

- The number of autoregressive parameters is small, being effectively equal to the minimum polynomial degree r
- Estimation of this degree r for the MPSSM model is easy on the basis of an earlier estimated FIR model
- Estimation of MPSSM model parameters requires a numerical minimization algorithm for the computation of the r minimum polynomial coefficients only

The obtained model is used for a MIMO control strategy based on an internal model, which enables accurate control for improvement of process input/output characteristics as well as for disturbance reduction even with (large) time delays involved.

The presented identification and control procedure has been tested on various industrial processes with very positive results indeed. As an example a quartz tube glass production process has been discussed.

Appendix

An outline of proofs

For this proof it is not necessary to assume that the process is in the model set e.g. by letting n (McMillan degree) tend to infinity (cf. [Ljung, 1987]). Assume the true process input/output behaviour to be described by:

$$Y = F_m \Omega_m + F_{tail} \Omega_{tail} + N \qquad (A.1)$$

where: Y - a block vector containing the outputs of the true system

F_m - a block row containing the main Markov parameters, which have to be estimated

F_{tail} - a block row containing the Markov parameters in the truncated tail

Ω_m, Ω_{tail} - proper Toeplitz matrices containing the inputs

N - a block vector containing the additive output disturbances

Since we assume that:

1. The average of the output disturbances N is zero
2. Cross products between inputs and noise samples scaled on the number of samples tend to zero for large datasets, due to the supposed independence of inputs and disturbances

3. The autocorrelation of the inputs is $\sigma^2 I$ (white, sufficiently rich input signals),

for large data sets holds:

$$\frac{1}{l+1} \Omega_m \Omega_m^T \to \sigma^2 I \qquad \frac{1}{l+1} \Omega_{tail} \Omega_m^T \to 0 \tag{A.2}$$

with: l denoting the number of samples used

For the FIR modelling we get for the simulated outputs:

$$\hat{Y} = \hat{F}_m \Omega_m \tag{A.3}$$

Consequently by minimization of a least squares output error criterion J:

$$J = \frac{1}{l+1} \text{trace}\{(Y - \hat{Y}) (Y - \hat{Y})^T\} \tag{A.4}$$

we get:

$$\hat{F}_m = (Y \Omega_m^T) (\Omega_m \Omega_m^T)^{-1} =$$

$$M_m + (M_{tail} \Omega_{tail} \Omega_m^T) (\Omega_m \Omega_m^T)^{-1} + (N \Omega_m^T) (\Omega_m \Omega_m^T)^{-1} \tag{A.5}$$

For sufficiently large data sets the second term vanishes because of assumption 3 and the last term vanishes because of assumption 2. As a result the estimated FIR parameters converge to the true system parameters.

For the MPSSM modelling we get:

$$\hat{Y} = \hat{F}(\hat{a},\hat{M}_s) [\Omega_m; \Omega_{tail}] = \hat{F}(\hat{a},\hat{M}_s) \Omega \tag{A.6}$$

Here the Ω_{tail} is incorporated, because we actually estimate in state space form and tail effects can be ignored for large data sets. Minimizing J we get:

$$\min_{a,M_s} J = \min_{a,M_s} \frac{1}{l+1} \text{trace}\{(F\,\Omega + N - \hat{F}(\hat{a},\hat{M}_s)\,\Omega)\,(F\,\Omega + N - \hat{F}(\hat{a},\hat{M}_s)\,\Omega)^T\} =$$

$$= \min_{a,M_s} \frac{1}{l+1} \text{trace}\{(F - \hat{F}(\hat{a},\hat{M}_s))\,\Omega\,\Omega^T\,(F - \hat{F}(\hat{a},\hat{M}_s))^T + N\,N^T +$$

$$2(F - \hat{F}(\hat{a},\hat{M}_s))\,\Omega\,N^T\} \qquad (A.7)$$

In this expression the last term vanishes because of assumption 2. The second term is irrelevant as it is not a function of the parameters. Since $\frac{1}{l+1}\,\Omega\,\Omega^T$ converges to $\sigma^2 I$ (assumption 3), we see that minimization of J for large data sets comes down to minimization of J_e in equation (3.1):

$$J_e = \text{trace}\{(F - \hat{F}(\hat{a},\hat{M}_s))\,(F - \hat{F}(\hat{a},\hat{M}_s))^T\} \qquad (A.8)$$

Therefore the estimated MPSSM model will be as close as possible to the true systems impulse response in Frobenius norm. The estimated response converges to the true response, if the system is in the model set.

References

Åström, K.J.
Process control - past, present and future.
IEEE Control Systems Magazine, Vol. 5 (1985), No. 3, p. 3-11.

Åström, K.J. and B. Wittenmark
Adaptive control.
New York: Addison Wesley, 1989.

Backx, A.C.P.M.
Identification of an industrial process: A Markov parameter approach.
PhD.-Thesis, Eindhoven University of Technology, 1987.

Backx, A.C.P.M. and A.A.H. Damen
Identification of industrial MIMO processes for fixed controllers, Part 1: General theory and practice.
Journal A, Vol. 30, nr. 1, p. 3-12 (1989a).

Backx, A.C.P.M. and A.A.H. Damen
Identification of industrial MIMO processes for fixed controllers, Part 2: Case studies.
Journal A, Vol. 30, nr. 2, p. 33-43 (1989b).

Box, G.E.P. and G.W. Jenkins
Time Serie Analysis: Forecasting and Control,
San Francisco: Holden Day, 1976.

Correa, G.O. and K. Glover
Pseudo-canonical forms, identifiable parametrizations and simple parameter estimation for linear multivariable systems: Input-output models.
Automatica, vol. 20, p. 429-442, (1984a)

Correa, G.O. and K. Glover
Pseudo-canonical forms, identifiable parametrizations and simple parameter estimation for linear multivariable systems: Parameter estimation.
Automatica, Vol. 20, p. 443-452, (1984b),

Damen, A.A.H., and P.M.J. Van den Hof, A.K. Hajdasinski
Approximate realization based upon an alternative to the Hankel matrix: The page matrix.
Systems and Control Letters, vol. 2 (1982), p. 202-208.

Damen, A.A.H. and R.L. Moses, P.M.J. Van den Hof
Bounds on the simulation power of equation error estimates.
Proc. 25th Conf. on Decision Control
Athens, Dec. 10-12, 1986, p. 1646-1647.

Gantmacher, F.R.
The Theory of Matrices. Vol. I.
New York: Chelsea, 1959.

Garcia, C.E. and D.M. Prett, M. Morari
Model predictive control: Theory and practice - a survey.
Automatica, Vol. 25 (1989), No. 3, p. 335-348.

Gerth, W.
Zur Minimalrealisierung von Mehrgrossenübertragungssystemen durch Markovparameter.
PhD.-Thesis, Fakultät für Maschinenwesen der Technische Universität Hannover, 1972.

Gevers, M. and V. Wertz
Uniquely identifiable state space and ARMA parametrizations for multivariable linear systems.
Automatica, Vol. 20 (1984), p. 333-347.

Gevers, M. and V. Wertz
Techniques for the selection of identifiable parametrizations for multivariable linear systems.
In: Control and dynamic systems: Advances in theory and applications.
Ed. by C.T. Leondes. Vol. 24. New York: Academic Press, 1985.

Goldberger, A.S.
Econometric theory.
New York: Wiley, 1964.

Guidorzi, R.P.
Canonical structures in the identification of multivariable systems.
Automatica, Vol. 11 (1975), p. 361-374.

Guidorzi, R.P.
Invariants and canonical forms for systems: Structural and parametric identification.
Automatica, Vol. 17 (1981), p. 117-133.

Janssen, P.H.M.
MFD models and time delays: Some consequences for identification.
Int. J. of Control, Vol. 45 (1987), p. 1179-1196.

Janssen, P.H.M. and A.A.H. Damen
Comments on: "MFD models and time delays: Some consequences for identification".
Int. J. of Control, Vol. 46 (1987), p. 1857-1859.

Janssen, P.H.M.
General results on the McMillan degree and the Kronecker indices of ARMA and MFD models.
Int. J. of Control, Vol 48 (1988), p. 591-608.

Janssen, P.H.M.
On Model Parametrization and Model Structure Selection for Identification of MIMO systems.
PhD-Thesis, Eindhoven University of Technology, 1988.

Kailath, T.
Linear Systems
Englewood Cliffs: Prentice Hall, 1980.

Kreindler E. and D. Rothchild
Model following in a linear quadratic optimization.
AIAA Journal, Vol. 14, No. 7, 1976, p. 835-842

Ljung, L. and T. Söderström
Theory and practice of recursive identification.
Massachusetts: MIT Press, 1983.

Ljung, L.
System identification: Theory for the user.
London: Prentice Hall, 1987.

Moore, B.C.
Principal component analysis in linear systems: Controllability, observability and model reduction.
IEEE Trans. A.C., Vol AC-26 (1981), p. 17-32.

Niederlinski, A. and A.K. Hajdasinski
Multivariable system identification: A survey.
Proc. of the 5-th IFAC Symposium on Identification and System Parameter Estimation, Darmstadt, 24-28 Sept. 1979. Ed. by R. Iserman.
New York: Pergamon, 1980.

Pernebo, L. and L.M. Silverman
Model reduction via balanced state space representations.
IEEE Trans. A.C., Vol. AC-27 (1982), p. 382-387.

Söderström, T. and P. Stoïca
System identification.
London: Prentice Hall, 1988.

Tyler, J.S.
The characteristics of model-following systems as systhesized by optimal control.
IEEE Trans. A.C., Vol. AC-9 (1964), p. 427-436.

Van den Hof, P.M.J. and P.H.M. Janssen
Some asymptotic properties of multivariable models identified by equation error techniques.
IEEE Trans A.C., Vol. AC-32 (1987), p. 89-92.

Van den Hof, P.M.J.
Criterion based equivalence for equation error models.
IEEE Trans. A.C., Vol. AC-34 (1989), p. 191-193.

Eindhoven University of Technology Research Reports
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ISSN 0167-9708
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(226) Dahiya, R.P. and E.M. van Veldhuizen, W.R. Rutgers, L.H.Th. Rietjens
EXPERIMENTS ON INITIAL BEHAVIOUR OF CORONA GENERATED WITH ELECTRICAL PULSES SUPERIMPOSED ON DC BIAS.
EUT Report 89-E-226. 1989. ISBN 90-6144-226-5

(227) Bastings, R.H.A.
TOWARD THE DEVELOPMENT OF AN INTELLIGENT ALARM SYSTEM IN ANESTHESIA.
EUT Report 89-E-227. 1989. ISBN 90-6144-227-3

(228) Hekker, J.J.
COMPUTER ANIMATED GRAPHICS AS A TEACHING TOOL FOR THE ANESTHESIA MACHINE SIMULATOR.
EUT Report 89-E-228. 1989. ISBN 90-6144-228-1

(229) Oostrom, J.H.M. van
INTELLIGENT ALARMS IN ANESTHESIA: An implementation.
EUT Report 89-E-229. 1989. ISBN 90-6144-229-X

(230) Winter, M.R.M.
DESIGN OF A UNIVERSAL PROTOCOL SUBSYSTEM ARCHITECTURE: Specification of functions and services.
EUT Report 89-E-230. 1989. ISBN 90-6144-230-3

(231) Schemmann, M.F.C. and H.C. Heyker, J.J.M. Kwaspen, Th.G. van de Roer
MOUNTING AND DC TO 18 GHz CHARACTERISATION OF DOUBLE BARRIER RESONANT TUNNELING DEVICES.
EUT Report 89-E-231. 1989. ISBN 90-6144-231-1

(232) Sanne, A.D. and M.H.A.J. Herben
DATA ACQUISITION AND SIGNAL PROCESSING/ANALYSIS OF SCINTILLATION EVENTS FOR THE OLYMPUS PROPAGATION EXPERIMENT.
EUT Report 89-E-232. 1989. ISBN 90-6144-232-X

(233) Nederstigt, J.A.
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