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Practical aspects of process identification with PRIMAL : a tool for process identification

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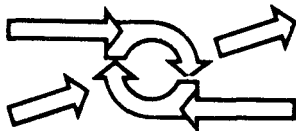
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PRACTICAL ASPECTS OF PROCESS
IDENTIFICATION WITH PRIMAL;
A TOOL FOR PROCESS IDENTIFICATION

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SUMMARY

This rapport treats practical aspects of process identification with PRIMAL; a tool for mathematical model building.

Process identification is an iterative procedure in which knowledge about the dynamic behaviour of the process is gathered by means of experiments, signal analysis, estimation and validation.

In an identification project the preparatory - pre-analysis - phase plays a very important role. Different aspects of the analysis and especially the conditioning of raw measured process data have been given attention in this work.

As a 'partial' result a general signal conditioning application, named FILTER, is added to the PRIMAL package. A protocol has been written to solve some of the questions occurring in the pre-analysis of a practical process with PRIMAL.

It is concluded that proper conditioning of 'raw' process data is one of the most important steps in process identification. If this step is not performed properly, no matter sophisticated the parameter estimation method used might be, an identification method will generally not function adequately.

* : PRIMAL; Package for Real-Time Interactive Modelling, Analyses and Learning.

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List of SYMBOLS

Symbol	Formula/ Paragraph	Size	Description
t	§1. 1	1	Sample time instant
p		1	Number of process inputs
q		1	Number of process outputs
$y(t)$	§1. 1	$q \times 1$	Measured output signals
$u(t)$	§1. 1	$p \times 1$	Measured input signals
Θ	§1. 1	$nAq^2 + (nB+1)pqx1$	Process parameter vector
$x(t)$	§2. 3	$q \times 1$	Undisturbed process output signals
$w(t)$	§2. 3	$q \times 1$	Output signals disturbances
$G(q^{-1})$	§2. 3	$q \times p$	Process transfer function matrix
N	§2. 3	1	Number of data records
K	§2. 3	1	Steady state gain
τ	§2. 3	1	Time constant
τ_d	§2. 3	1	Delay time
A	§2. 3	1	Amplitude input test signal
T_0	§2. 3	1	Sampling rate
$v(t)$	A. 1. 4	$q \times 1$	Equation error
$\varphi(t)$	§2. 3	1	Auto/cross-correlation function
$A(q^{-1}, \Theta)$	5. 3. 3	$q \times q \times nA+1$	Autoregressive part process model
$B(q^{-1}, \Theta)$	5. 3. 3	$q \times p \times nB+1$	Moving average part process model
nA	§5. 3	1	Order matrix polynomial $A(q^{-1}, \Theta)$
nB	§5. 3	1	Order matrix polynomial $B(q^{-1}, \Theta)$
B	§4. 3	1	Bandwidth process
$\Phi(f)$	4. 3. 2	1	Power spectral density
ω	§4. 3	1	Frequency (rad/s)
λ	§4. 3	1	Minimum pulse duration factor
T	§4. 3	1	Minimum pulse duration time

f	§4. 3	1		Frequency (1/s)
H(ω)	5. 2. 6	1		Frequency characteristic, Transfer function
ω_s	5. 2. 6	1		Sample frequency
ω_c	5. 2. 6	1		Cut-off frequency
h(k)	5. 2. 7	1		Finite impulse response sequence
w(k)	5. 2. 7	1		Window function sequence
M	5. 2. 7	1		Filter order
$\Delta y(t)$	5. 3. 5	q	x 1	Simulation outputs residuals

Chapter 1. INTRODUCTION

§ 1.1 Preliminaries

This report is the result of my work at the System & Control group of the Physics Department at the University of Technology in Eindhoven. This work has been performed to obtain a Master of Science degree in Physical Engineering.

One of the main research items in the group is the Methodology of Experimental Modelling. My work is carried out within this context.

For automatic acquisition and analysis of experimental data a tool is needed which supports activities in this field. The centre of attention therefore lies in the development and application of the PRIMAL package (Package for Real-time Interactive Modelling, Analyses and Learning). PRIMAL supports experimenting, data acquisition, signal processing, signal analysis, system identification, modelling and controller design. A more detailed description of the special features of PRIMAL is given in chapter 1.3. Two major aspects in process identification, experiment design (chapter 4) and data conditioning (chapter 5) have been studied. The conditioning of process data has been given most attention. With respect to the design of experiments for identification only a first study has been performed.

In this report I have tried to describe my experiences in the analysis of (measured) process data and model building in the identification of several practical processes. Throughout this report these experiences are formulated in a 'rule of thumb' manner or by means of a protocol. The reader should be aware that -strictly speaking- these rules are only valid for the studied data sequences. Nevertheless I hope that these experiences may be of use for future identification projects.

§ 1.2 Process Diagnostics: the Purpose of Mathematical Model Building

The problems occurring in System & Control Engineering may be divided into 4 main categories:

- 1 Diagnostics & Monitoring: estimation of one or more specific process coefficients which can not be measured directly.
- 2 Prediction: prediction of a process output signal based on past output and past and present input signals.

$$\hat{y}(t+1;\theta) = M_p(U^t, Y^t; \theta)$$

- 3 Simulation: modelling of the dynamic behaviour of a process to explain the output of the process based on the past and present input signals.

$$\begin{aligned}\hat{y}(t+1; \theta) &= M_S(U^t, \hat{y}^t; \theta) \\ &= M_S(U^t; \theta')\end{aligned}$$

- 4 Control: control system design to achieve better dynamical behaviour, e.g. minimization of the influence of disturbances in process variables and changes in process dynamics.

For all these problem areas a model of the dynamical behaviour of the process under study is necessary.

The model is an abstract representation of a part, or certain aspects of interest, of a complex real-world process. Such a system can be thought of as being composed of an observable and unobservable part and a controllable and uncontrollable part. With a model a better understanding of the process can be obtained. Also a model permits us to manipulate the real process for reaching certain goals. It is clear that an important aspect of modelling is its intended use. The construction, the form and the complexity of a model should mainly be determined by those aspects of the "reality" or the studied object which are believed relevant for the intended use of the model. This implies of course that the validity and usefulness of a model is restricted.

§ 1.3 The PRIMAL Project

In literature much attention is paid to the theoretical aspects of identification methods of multivariable processes and design of (adaptive) controllers. In practice however these methods are rarely used. Reliability, robustness and usefulness of the results of these methods have had too little attention in theory.

In practice the path to results is seldomly straight. It is a matter of trial, learning and re-trial. This interactive learning process has been put central in the design of the package PRIMAL, which implies an interactive structure in which the experimenter has a free choice on any moment between all the facilities of the package (see Renes /22/,/26/).

PRIMAL is a tool for mathematical model building meant to close the gap between theory and practice in the field of model building and process identification.

PRIMAL has the following interesting features:

- an interactive structure. The train of thought of the experimenter determines the path followed in identification.
- PRIMAL contains a number of so-called application modules for all the different stages in experimentation and model building.
Applications are available for experimentation, real-time observation of the 'raw' measured process data, correlation and frequency analysis, data conditioning, parameter estimation for parametric and non-parametric models, model validation and model simulation. Also Kalman filtering, extended kalman filtering and controller design will be available in near future.
- New applications can be added easily to the package.
- Applications operate in parallel and independent from one another. Intermediate -temporarily- results of an application are available for other applications and inspection by the experimenter, see figure 1.1.
- A comfortable powerful graphical application is available for visual monitoring of high quantities of data and application results.
- With PRIMAL all kinds of testsignals can be generated for superposition on process inputs to enhance the information in a requested frequency range. With this interactive experimentation can be performed easily.

- Experimentation and processing of the, sofar, gathered data can be performed simultaneously.
- A logbook is being kept of experiment conditions, activities of the experimenter and messages from the package. With this logbook all actions that have been undertaken by the experimenter are tractable.
- PRIMAL has been written in a proper standardized programming language (FORTRAN77). Together with a special software structure and the usage of a number of special written libraries implementation of PRIMAL on different hardware structures in different industrial surroundings is rather easy.

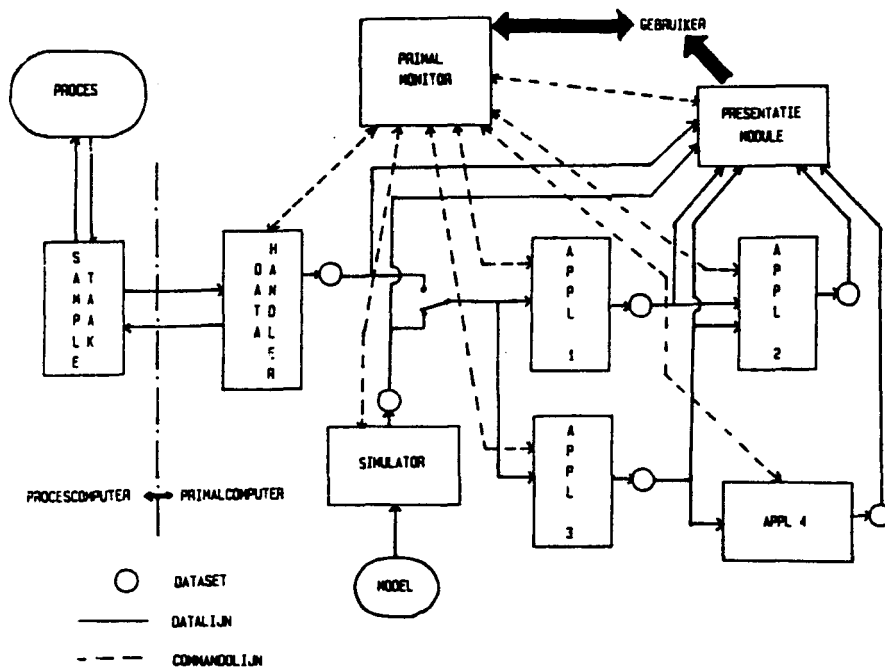


Figure 1.1 Structure of the PRIMAL package

Before commercial industrial application of PRIMAL, the package has to be tested and evaluated in a number of identification applications to real processes under industrial circumstances. In this work PRIMAL has been used as a tool for identification of a laboratory process and an industrial pilot process (see chapter 3). Especially the practical aspects of process identification and the usage of PRIMAL in this have been given attention.

Chapter 2. PRACTICAL ASPECTS OF PROCESS IDENTIFICATION

§ 2.1 Introduction

Mathematical models of the dynamic behaviour of a process can be derived in two ways:

- 1. One possibility is to derive a theoretical model from basic physical laws and construction data. This analytical modelling, of a complex real-world process, is often very difficult. Important process coefficients, often varying with time and place, are very hard to determine.
- 2. With experimental analysis -identification- the (noisy) signals (=time sequences) of interest of an existing process are measured. Using an estimation procedure a model may be obtained describing the input-output behaviour of the process. The driving input signals can be artificial - specially designed- test signals.

§ 2.2 A Methodology in Process Identification

Information sources for the mathematical modelling process

Modelling is an ongoing sequence of activities only limited by practical constraints like cost and time. To achieve a satisfactory a-posteriori result, information is 'tapped' from the process under study from different sources. Three major sources of information feeding the model building process can be distinguished, see figure 2.1.

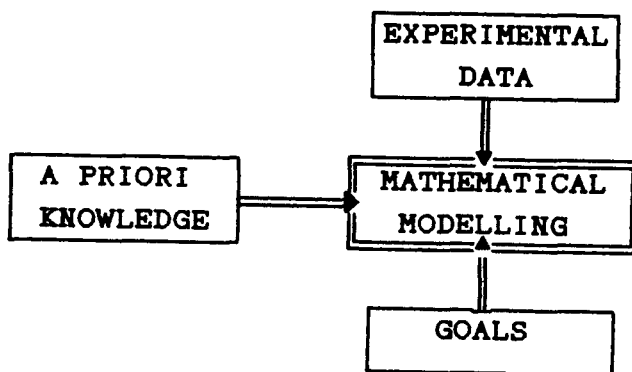


Figure 2.1 Information sources for mathematical modelling

- 1. Goals
The modelling is guided by the goals and purposes of the identification project.
- 2. A priori process Knowledge
Knowledge available about the dynamic properties of the process are used in further steps like the design of experiments and the analysis of the process.
- 3. Experimental data
Information about the process may be gathered through measurements of the process signals.

In identification projects a-priori knowledge is important, but the main information source is data obtained from experiments on the process. Advanced techniques are necessary to define experiments and to gather and analyse the data because of the sensitivity of the result of the analysis with respect to the information content of the measurement data. The goal of the modelling plays an important role during each stage. At any question to be answered during an identification project the intended use of the a-posteriori model has to be kept in mind.

Characterization of the identification problem

An useful characterization of the identification problem has been given by Söderström /15/. The following four notions characterize the identification problem.

- 1. The experimental condition X referring to the manner in which the signals are determined. It describes how the identification experiment is carried out.
- 2. The model structure M referring to the mathematical representation of a process. A restricted modelset of candidate models is selected. In this stage a substantial amount of a-priori knowledge or a-priori guesses with respect to the process is introduced. The set of mathematical models used for identification within PRIMAL can be described with the following list of adjectives:
 - dynamic
 - causal
 - time-invariant
 - discrete-time
 - linear dynamics
 - finite order
 - stochastic
 - lumped parameters
 - SISO (single input single output) or MIMO (multiple input multiple output)

The model set is chosen by selection of a representation form together with a set of parameter vectors. A model structure then is a set of models (or in an isomorphic way) a set of parameter vectors $\{\theta\}$. Together with the concept of generalized models, Eykhoff /13/, a model error form can be chosen for each representation, that is linear in the parameters.

Not only the relation between the dependent (output) and independent (input) variables is linear but also the relation between the dependent variables and the parameters in the parametrization of the chosen model set. Evaluation of a performance criterion - based on such a definition of model error- with respect to the parameters is simple.

-3. The process refers to a mathematical description of the process to be identified. Such a description is an idealization. It describes the mechanism of the process that generates the data. To define and apply identification methods there is no need to assume a certain system description. It is, however, useful for analysis of the results.

We assume, see Söderström /15/, that the system S that generates the data can be described by a deterministic transfer function and an output disturbance signal. The disturbances are described by means of an additive output noise (superposition principle for linear systems).

The system S is linear, finite order, asymptotically stable and stochastic. The output can be written as:

$$S: \begin{aligned} y(t) &= x(t) + w(t) \\ x(t) &= G(q^{-1})u(t) \end{aligned} \quad \text{with}$$

$y(t)$: measured outputs at time instant "t",

$x(t)$: undisturbed outputs,

$w(t)$: output disturbances,

$u(t)$: inputs,

q^{-1} : the backward shift operator

$$q^{-1}u(t) = u(t-1),$$

$G(q^{-1})$: the transfer function matrix.

In practice not only stationary stochastic noise with zero mean enters the system but also disturbances like:

- outliers
- slow "drifts" (trends)
- non-additive noise components like quantisation noise
- static and dynamic non-linearities
- other measurement errors

These disturbances have a large influence on the performance of the identification methods. They have to be taken care of before application of identification methods to the measured process data.

- 4. The criterion J referring to the estimation method used to select in the predefined modelset the element that fits best the available data.
The parameter estimates at time instant N for given X, M, S, J are denoted by $\hat{\theta}(N; X, M, S, J)$.

A global description of the model structure, estimation method and criterion of the parameter estimation applications in PRIMAL is given in paragraph 2.3.

A global scheme in identification

The construction of a model in identification is an iterative learning process. Gained knowledge of the process dynamics is used to adapt one or more intermediate steps in the identification scheme.

Generally 3 main phases can be distinguished in the identification procedure:

- 1. preparation / pre-analysis,
- 2. estimation,
- 3. validation.

In the pre-analysis phase the pre-requisites for the estimation phase are organized.

In the estimation phase a modelset and a suitable parametrization have to be chosen. Then, if a parametric model structure is selected, the structural parameters like model order, or structural invariants, and a possible time delay of the model have to be determined. An estimation method and a criterion have to be selected and finally the parameters are estimated.

In the model validation phase it has to be determined whether an estimated model should be accepted or not.

A scheme of the identification procedure with the mentioned phases in mutual relation is given in figure 2.2. It is my experience is that 4 main loops exist.

PRACTICAL ASPECTS OF PROCESS IDENTIFICATION

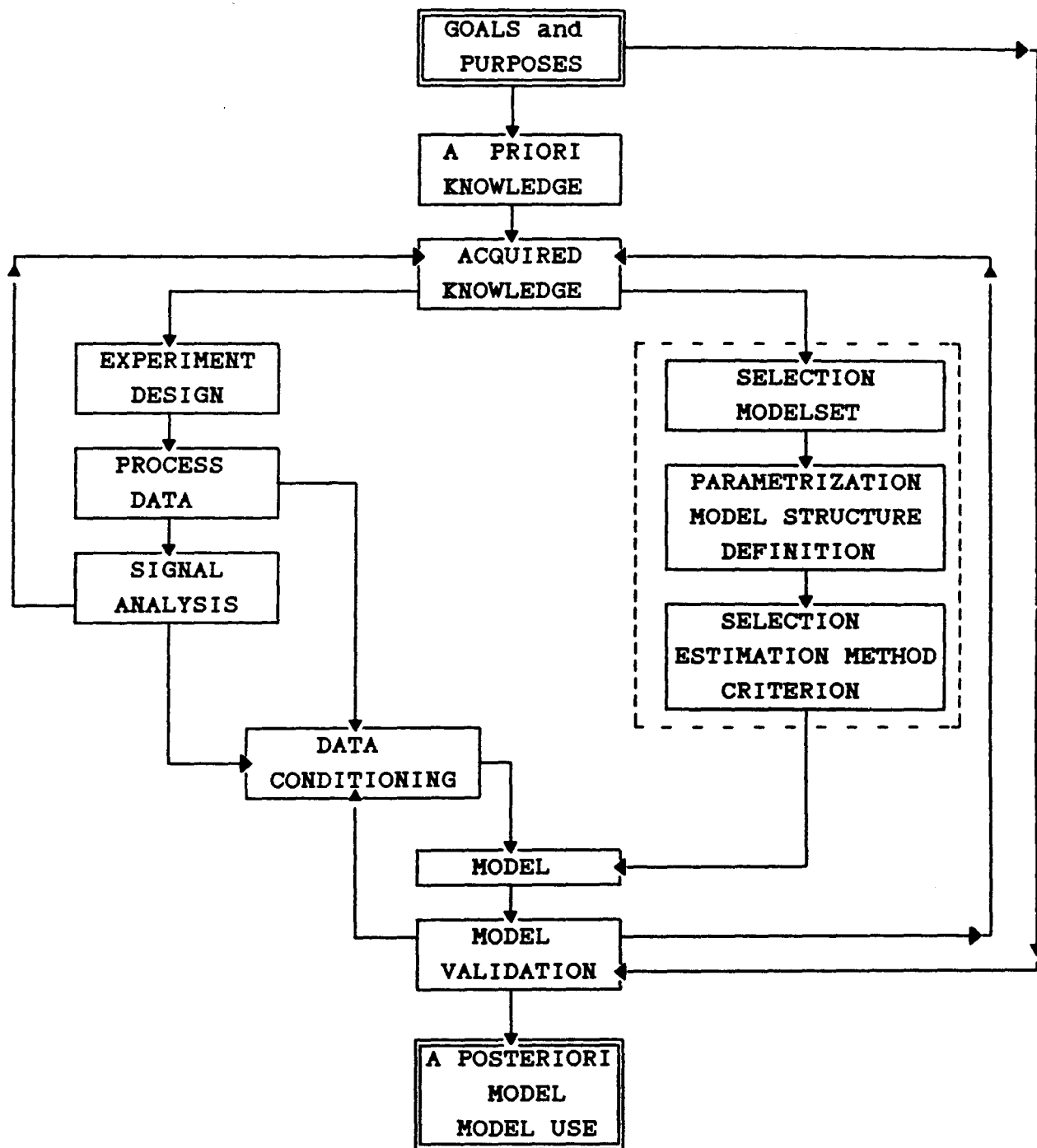


Figure 2.2 Identification procedure

The work has focussed on the pre-analysis phase. This phase takes generally a large amount of time in the total project. Some 'tools' to answer the questions occurring in this phase might therefore be very useful. Most of the questions however can only be answered in an 'ad hoc' manner. I have tried to formulate some 'rules of thumb' and a protocol to solve some of these questions. The reader should remember that the rules presented throughout this report are based on my experiences on the studied processes. Rules formulated by others, Isermann /1/ and Eykhoff /13/, are also mentioned.

The elements of the scheme presented will be discussed detailed now. It is partly based on my experiences in identification of a laboratory process and participation of the System & Control Group with PRIMAL in an identification project concerning a glass-feeder (see chapter 3). Although the various sub-problems are discussed separately many interrelations exist.

-1. Problem definition

The project starts with a detailed description of the goals and purposes of the project:

- Intended use of the model to build
- limited use, e.g. dynamical behaviour around an pre-described operating point or a more generally applicable model. (These aspects determine the need for information in the measured data and the required accuracy of the model to be developed).
- Investigate possible problems and bottlenecks

-2. Preliminary process investigation

At the beginning of the project available existing knowledge of the process has to be gathered.

- Investigate technical properties (dynamics ; non-linearities) and possible constraints of the actuators and the sensors
- Select the process inputs and outputs of interest. The inputs chosen must be able to vary the outputs over the range of interest.
- Determine possible dynamic ranges and accuracy demands for the signals to measure.

In practice it is advisable to measure as much variables as possible. This enables facilitates tracking down the possible reasons for signal disturbances and enlarges the available amount of information on the process and its environment.

- Normal operating points and operating conditions have to be known.
- gather (if possible) some information on the already measured (logged) signals of the process, aspects like natural signal variances and bandwidths of the spectra of the process signals are of interest.
- Characteristics of the disturbances that enter the process S/N ratio of the the process signals.
- Investigate the stability of the process.
- The existence of operative control loops has to be known.

-3. Configuration & Installation Equipment

In this step the necessary hardware and software has to be installed:

- Additional sensors, transformers and actuators must be mounted on the process (if admitted) and gauged.
- Investigate instrument linearity.
- Equipment for signal generation, data storage, on-line analog signal conditioning, for instance scaling and anti-aliasing filters, have to be placed.
- The software for measurement and excitation of the process inputs has to be configured.

-4. Detailed investigation of elementary process dynamics

In this step information on the dynamical behaviour of the process must be gathered.

To design appropriate experiments¹ for process identification, information is needed on the following process features:

- Causal relations between the measured process signals.
- Sensivities (steady state gains K for each interesting input-output relation in combination with
- A range of allowed variations for the input test signals in the experiments.
- An estimation of the S/N ratio for the various process signals measured in the experiments.

The S/N ratio's are very important with respect to the performance of the different parameter estimators. In practice this ratio is often determined by low frequency noise ("trends") (see chapter 5.3).

¹: Application of test signals, to enhance the information content of the input and output signals, is not always allowed at industrial processes. The experimenter is restricted to the natural signals in normal steady state operating conditions. Often these signals do not contain sufficient information for determination of an appropriate model of the dynamical behaviour of the process. In the next steps we assume that application of test signals on the process inputs is allowed.

- Elementary dynamical process properties of each input-output relation of interest, like:
 - dominant time constants τ of the first order process approximations,
 - possible time delays τ_d ,
 - static and dynamic linearity / non-linearity of process and instrumentation, for instance dependency of K (or other process properties) on the amplitude A of a test signal superimposed on a process input: $K = f(A) = \text{constant} ?$ or the occurrence of hysteresis in one or more process signals or possible saturation of the measured process signals.
 - Time-invariant/variant process behaviour like aging, for instance pollution or drifting of the process.
 - An estimate of the order of the different (sub-) processes.

If not enough information on the elementary process dynamics is available, some premeasurements must be performed. A description of the 'tools' used for determination of some properties of the elementary dynamics of the studied processes is given in chapter 4. This phase is in practice also very useful for testing the equipment, especially in an -often rather hostile- industrial surrounding.

-5. Experiment design. Data collection

Besides the already mentioned premeasurements phase experiments have to be performed for process identification and validation of the estimated models. It is possible to increase the information content in the measured process signals with specially constructed input signals. Information is needed on the following experiment parameters:

- The frequency band of the test signal.
 - The sampling rate T_0 .
 - Length (duration) N of the experiment.
 - Type of the test signal.
 - Amplitude A of the test signal, such that the information content of the input and output signals is as great as possible. The design of an optimal¹ experiment however is only possible if the process and its disturbances are known a priori.
- In practical 'explorative' identification projects this is hardly the case.

A minimum requirement for the input test signal is that the dynamics of the identifiable part of the process have to be "persistently excited" during the measurement period long enough to permit the parameter estimation algorithm to converge.

A further description of the practical aspects of experiment design for process identification is given in chapter 4.

-6. Inspection of measured process data, signal analysis

- In this step the measured raw process data has to be inspected carefully for disturbances in the signals and other possible measurement errors.
- With spectral analysis a first investigation of the dynamical behaviour of the process is possible. It may also be used to see if excitation of the process has been sufficient.
- To study the various causal relations and to investigate the possible occurrence of time delays in the different dynamical relations correlation analysis may be applied to the process data.

If the excitation of the process has not been sufficient and thus if the process data is not rich enough in information a re-design of the experiment is necessary.

-7. Data conditioning

Before application of system identification methods the process data has to be corrected for the discovered signal disturbances.

Data from practical processes is generally heavily contaminated with all kinds of disturbances like outliers, slow signal drifts "trends" and measurement noise.

They have large influence on the results of process identification. A description of the different aspects of data conditioning in process identification is given in chapter 5.

-8. Process Identification

The modelling procedure itself is quite complex.

- Select a certain set of candidate models.
- A criterion for estimation must be determined.
- Estimate the parameters, to determine the 'best' parameters of the model.

These choices must be controlled by the intended use of the model. Also aspects like recursive or iterative, on-line or off-line application must be considered.

¹ : In terms of minimization of certain model errors with respect to noise, input and output signal constraints and measurement time.

By selecting one of parameter estimation applications in PRIMAL all aspects named are chosen. The only choice left concerns with the structural invariants (order; time delay) of the model.

Each estimator has its own special properties concerning with :

- (asymptotical) (un)biasedness,
- convergence and,
- efficiency, i.e. the variance of the result compared with other methods and CPU time used by a method. Especially the latter is important in interactive use of a method by the experimenter.

In selection of the listed aspects in identification I have followed a certain path. A description of this path together with some interesting aspects is given now.

- 1. Impulse response estimation (MARKOV) of the process. Although this estimation generally takes a large amount of time and sometimes numerical problems¹ occur in the parameter estimates, the estimate is rather robust for the other important aspects in the procedure like experiment design (see chapter 4). Due to the large model set much freedom exists in fitting the process in the set model set. The resulting model is easy to understand. Special process properties like a time delay or an inverse response are easily determined from the resulting impulse responses. The model however is generally of unnecessarily high order.
- 2. Structural test. With the information from a structural test (ORDERTES) a sensible choice of the structural parameters in a lower order model.
- 3. A more compact model might be constructed in two different ways:
 - 1) One way to construct a model with a small number of parameters is to apply a realization method (HANKEL) to the estimated impulse responses.
 - 2) Another way is successive application of the estimators GUIDORZI or IVM. GUIDORZI however is found to be sensitive to outliers in the process data. The algorithm may not converge within the length of the available dataset. The estimated model is biased if the process output signals are corrupted with 'coloured' noise. Therefore IVM has been used which offers more facilities to handle additive output noise.

¹ : sometimes a complex pole, with the nyquist frequency ($= f_s/2$ with f_s the sampling frequency) as eigen frequency, is estimated. This results in an oscillation on the parameter estimates (some examples of this effect can be found in chapter 4 and 5).

Generally a number of parametric estimates have to be performed with varying structural parameters for the system or noise model to be estimated before an appropriate¹ result is obtained.

Which way to follow depends on the intended use of the model. If the purpose is simulation the impulse response method MARKOV, using an output error criterion in estimation, should be chosen. If one step ahead prediction is performed GUIDORZI or IVM-LS could be chosen. The latter uses an equation error criterion in the parameter estimation. For the other estimators available in the application IVM, due to the different criteria available for selection of the 'best' model in the various steps, this choice is much more complicated. See Berben /12/.

-9. Model verification

In this step the model obtained so far is confronted with the real process behaviour, taken into account the intended use of the model.

The a priori assumptions used in the identification as well as the input-output behaviour of the model compared with the real process are checked, preferably on a different set of data (so-called cross-validation).

As with process identification, validation is not a straight-forward procedure.

PRIMAL offers several facilities for verification of an estimated model. Aspects of interest are :

-1. Is the model estimation unbiased?

In case of an estimator with an equation error criterion: is the equation noise a 'white' noise signal :

$$\hat{\varphi}(\tau)_{VV} = 0 \text{ for } |\tau| \neq 0.$$

-2. How does the model behave compared with real process behaviour?

By comparing the measured output $y(t)$ and the estimated (predicted or simulated) output $\hat{y}(t)$ the output residuals $w(t) = y(t) - \hat{y}(t)$ can be studied.

The application MODELTEST in PRIMAL reviews a model by looking at the simulation behaviour of the model. The criterion used is a simulation error output i ($i=1\dots q$) :

$$\frac{\sum_{t=n_1}^{n_2} E (w_i(t)-w_i)^2}{\sum_{t=n_1}^{n_2} E (y_i(t)-y_i)^2}$$

with $[n_1;n_2]$ an interval in the data sequence.

¹ : this will be determined by the validation principle used controlled by the intended use of the model.

The simulation performance of different models may be compared.

In practice this appears to be a rather fast and powerful way to study the differences between the estimated models.

-3. Does the process fit in the chosen set of candidate models?

Are the output residuals $w(t)$ uncorrelated with the input signals $u(t)$:

$$\hat{\varphi}(\tau)_{uw} = 0 \text{ for all } \tau?$$

-4. Are the premises valid?

Is the equation error uncorrelated with the input signal(s) $u(t)$:

$$\hat{\varphi}(\tau)_{uv} = 0 \text{ for all } \tau?$$

And finally for some modelling purposes the accuracy of the estimated parameters is of importance.

-10. Model use, consistency check.

The final, most important, validation step concerns the use of the derived model. Also the consistency of the model has to be verified by comparing the estimated model with a model estimated on another data set and comparing the model with models estimated with other methods.

If the goals of intended use are not satisfied the identification procedure from experiment design up to validation may be repeated using the knowledge obtained sofar.

As will be clear from the protocol presented, identification of real processes requires an extensive pre-analysis phase. Although this phase takes substantial amount of time of the total project, little literature is available treating aspects like experiment design in the pre-measurement phase and data conditioning for identification.

§ 2.3 Parameter Estimation in PRIMAL

In PRIMAL several different estimation methods are available. The number of model parameters needed may be determined by performing an order- or structure test first.

An overview of the available identification methods in PRIMAL is given in table 2.1.

Application	Model structure ¹	Description
EMM	ARMAX, SISO	Extended Matrix Method
RPE	ARMAX, SISO	Recursive Prediction Error Method
ORDERTEST	MIMO	Prediction Error Ordertest
GUIDORZI	State Space, MIMO	Method of Guidorzi
IVM	MFD, MIMO	(Approximately) Optimal Instrumental Variable Method
TRANSFER	Transfer Function, MIMO ²	Direct Estimation of the Transfer function
MARKOV	Impulse Response, MIMO	Estimation of Markov parameters
HANKEL	State Space, MIMO	Hankel Realization method

Table 2.1 Process identification methods in PRIMAL

¹ : ARMAX : Auto Regressive Moving Average, with exogeneous input

MFD : Matrix Fraction Description

² : Not truly a MIMO estimation method. All the SISO sub-transfer functions are estimated independently from one another.

Not all the identification methods available in PRIMAL have been intensively used by me. The processes studied where both multivariable in input and output. So the SISO methods have hardly been used. The MIMO method TRANSFER has not been used because of its sensitivity to the choice of the parameters concerning with the specification of the "frames" to be used. A frame is a part of the time sequence of input and output samples measured (see van Dijk /21/).

A characterisation of the methods used will follow now. Only some interesting features are listed.

ORDERTEST : Range order test of Guidorzi.
The one step ahead prediction error of a linear MIMO model as a function of its structural invariants is estimated.

$$\begin{aligned} \text{model : } \quad x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \quad \text{with} \end{aligned}$$

$u(t)$: input vector at time t (dimension p)
 $y(t)$: output vector at time t (dimension q)
 $x(t)$: state vector at time t (dimension n)
 A : system matrix (dimension $n \times n$)
 B : input matrix (dimension $n \times p$)
 C : output matrix (dimension $q \times n$)
 D : input-output matrix (dimension $q \times p$)

method : The model is transformed to an observable canonical form in which the system matrix has a special block structure determined completely by the structural invariants.
The application estimates directly from the input output data the one step ahead prediction error of a model as a function of its structural invariants.

GUIDORZI : MIMO State Space Model Estimation

model : State Space model (A,B,C,D) in output companion form with given structural invariants.

method : Uses a recursive least squares (equation error criterion) estimator to estimate the parameters of an input output model equivalent to the state space model (see Renes /22/).

MARKOV : Direct Impulse Response Estimation for MIMO systems. A matrix results containing a MA model of the process.

$$\begin{aligned} \text{model : } y(t) &= M(0)u(t) + M(1)u(t-1) + \dots + M(n)u(t-n) \\ &= B(q^{-1})u(t) \quad \text{with} \end{aligned}$$

M : Markov parameters
 B : a matrix polynomial in the backward shift operator of degree nb .

method : minimization of the one step ahead prediction error $e = y(t) - \hat{y}(t)$ with a recursive least squares method.
 $\hat{y}(t)$ is the predicted output at time instant "t" using the estimated $B(q^{-1})$ and input signals $u(t), u(t-1), \dots$ (output error criterion).

IVM : Instrumental Variable Method for estimation of parameters of a linear MIMO system.
(See Berben /12/.)

model : $A(q^{-1})y(t) = B(q^{-1})u(t) + v(t)$

$v(t) = \{D(q^{-1})^{-1}/C(-1)\}e(t)$.

with

$v(t)$: equation noise

$e(t)$: vector with estimation residuals, it will be approximately a white noise signal.

A,B,C,D are polynomials in the backward shift operator q^{-1} .

method : The MultiStep-algorithm of Söderström & Stoica:

Step 1: A Least Squares Method minimises a least-squares error criterion on the equation error $v(t)$ (LS-IVM) followed by a Bootstrap Instrumental Variable Method (IVM-BT). An iterative IVM that gives unbiased results. This method does not involve noise model estimation.

Step 2: Pseudo Linear Regression (PLR) Method for the noise model.

Step 3: OPTimal Instrumental Variable Method (OPT-IVM). An iterative IVM that gives unbiased results with an optimal accuracy. This method requires data filtering with the inverse noise model.(Step 2).

Step 4: Execute steps 2 and 3 repeatedly.

HANKEL : Hankel Realization method, derives a low dimensional state space model from the estimated impulse response - markov parameters $\{M_k\}$ of a process. (A measured impulse response might also be used.)

model : State Space model (A,B,C,D).

method: First a Hankel matrix is composed of the estimated markov parameters. Then a singular value decomposition of the Hankel matrix is computed. For a k dimensional realization the approximate Hankel matrix H_k is determined by the k-dimensional least squares approximation of the Hankel matrix.

Several different realization methods are supported by the application.

The state space matrices A,B,C and D can be computed directly from this approximate Hankel matrix.

§ 2.5 Remarks

For successful application of system identification to practical industrial processes much attention has to be given to the pre-analysis phase in an identification procedure. Especially the design of experiments, in the premeasurement phase, and the conditioning of data before application of process identification methods are of importance. The influence of disturbances in data of practical processes on the performance and behaviour of the different system identification methods is found to be large. Proper data conditioning therefore is absolutely necessary (see chapter 5).

The development of an application for PRIMAL for conditioning of raw measured process signals however has been given most attention. Also some research has been done on the proper choices to be made for the different operations in data conditioning and the effects of data conditioning on the behaviour and performance of a number of system identification methods.

Some research has been done in this work on the different aspects of experiment design for process identification. The behaviour and performance of a number of system identification methods has been studied with respect to one of the parameters in the design of experiments: the frequency range to enhance by an input test signal. This parameter determines, together with the other parameters in experiment design, the information content of the measured process signals.

Chapter 3. THE PROCESSES

§ 3.1 Introduction

During my work at the System & Control Group I have studied two practical processes.

I started with a thermal-hydraulic laboratory process to study the different aspects in process identification including configuration and installation of equipment, gauging of the instruments, pre-analysis, estimation and validation. The study included the evaluation of PRIMAL as a tool for identification of a practical process.

This process had been used to study dynamic modelling and controller design in the past years.

It is build using standard industrial equipment to imitate practical conditions as much as possible. No special measures have been taken to cope with aspects like process non-linearities, natural disturbances and interaction between variables.

The process is multivariable and the various sub-processes have different (dominant) time constants.

Experiments have been performed to study the effect of several aspects of experiment design -for system identification- on the performance and behaviour of a number of identification methods available in PRIMAL.

In may 1987 I participated in the study of an industrial pilot process, concerning a glass-feeder, with the PICOS group at PHILIPS in Eindhoven with PRIMAL as a tool for on-line experimenting and process identification. Installation and configuration of equipment has been done by PICOS.

Theoretical modelling of the feeder is difficult due to the complicated nature of the process. Several partial differential equations in time and place are necessary to describe the process. The results of the modelling are not reliable and certainly not useful for simulation purposes.

The purpose of this project therefore is to develop an empirical model of the dynamic behaviour of the glass feeder around a certain operating point. The main goal of modelling the dynamic process behaviour is the design of a control system.

A description of the interesting aspects of both processes together with the equipment used for identification is given below.

§ 3.2 A Thermal-Hydraulic Process

Process Description

The process may be divided in a hydraulical part, with water as running medium, and a thermal part. A cold water flow is first heated in a counter current heat exchanger made. The heated water flows through a rubber tube (with a variable length up to 60 m) into a vessel. From this vessel the water flows freely into a second -well mixed- buffer vessel where a valve controls the water flow leaving the system. It shall be clear that an interaction exist between the hydraulical and thermal part of the process. The input variables of the process are the cold water flow entering the system and the warm water flow running through the heat exchanger heating the cold water. The water levels in the vessels and various water temperatures in the process are the output variables.

A nearly identical secondary circuit composed of a heat exchanger and a transport tube is used to generate 'coloured' noise on the various output variables. The water flow from this circuit enters the primary circuit in the first vessel.

Special precautions are taken to stabilize normal process operating conditions.

The cold water used as input for the system is normally tap-water stabilized in pressure (about 2 bar) by a special vessel. The pressure within this vessel is held constant.

The cold water temperature remained nearly constant at about 13 °C during experimentation.

The warm water feeding the heat exchangers runs through a closed warm water circuit (stabilized at 90 °C). In this circuit the water pressure is stabilized.

A number of dynamic elements may be distinguished in the process:

- 1. the heat exchanger,
- 2. the transport tube (not isolated for energy losses),
- 3. a first vessel where both heated water flows debounces in and
- 4. a second vessel (well mixed) beneath the first vessel.

A schematic view of the process together with the process variables of interest is given in figure 3.1.

A list of the variables together with their approximate values in the operating point is given in table 3.1.

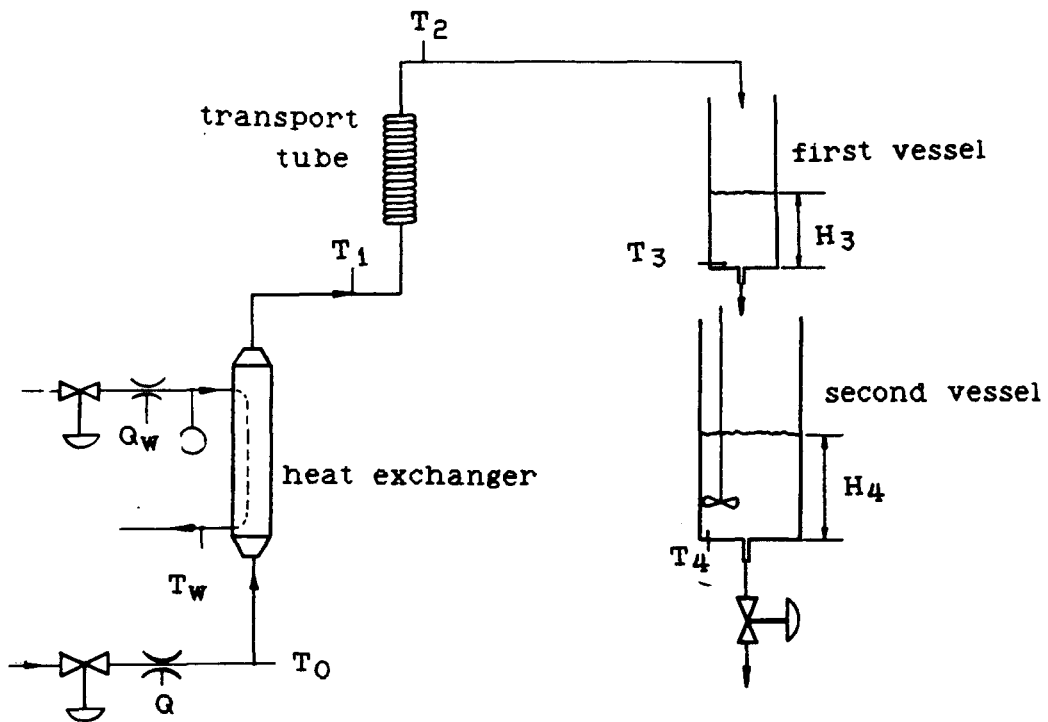


Figure 3.1 Schematic view of the process.

Name Process Variable	Description	Value Operating Point
Input variables		
Q	cold water flow primary circuit	100 l/hr
Q_s	cold water flow secondary circuit	90 l/hr
Q_w	warm water flow primary circuit	200 l/hr
Q_{ws}	warm water flow secondary circuit	200 l/hr
Output variables		
T_0	cold water inlet temperature	13 °C
T_1	water temp. after heat exchanger	77 °C
T_2	water temp. after transport tube	74 °C
T_{2s}	as T_2 secondary circuit	74 °C
H_3	water level first vessel	40 cm
T_3	water temp. at the bottom of the first vessel	70 °C
H_4	water level second vessel	40 cm
T_4	water temp. at the bottom of the second vessel	67 °C
and		
T_w	warm water circuit temp. after the heat exchanger	53 °C
T_{air}	free air temperature	22 °C

Table 3.1 Variables in the process

Instrumentation

The hardware used for measuring and processing of the signals is the so-called PVS-system (Process Signal Processing System). It is built around a LSI-11/23⁺ micro computer.

The LSI computer is connected with a PDP11/23 mini computer on which runs PRIMAL.

Experiment definition is performed with PRIMAL. The measured data is transferred directly to the PDP11/23 computer where further analysis takes place on-line with PRIMAL.

The actuators (valves) controlling the water flows and sensors for measuring the water flows and levels are pneumatic. The sensors used for measurement of the various process temperatures are temperature sensitive resistors (P_{t-100}) made of platinum (range 0-100 °C) with a relative accuracy of about 0.1-0.2 °C.

The sensor measuring the water flow measures the pressure difference over a flange. It can easily be understood that the relation between water flow and pressure difference is quadratic. Also the actuators themselves -the valves- have a non-linear relationship between input signal and resulting flow through the valve. As a result from the gaugelements the other instruments used are found to be nearly linear. Non-linear correction of the process signals may be performed with the results of the gaugelements.

No special difficulties occurred during the measurements. The temperature in the second vessel T_4 however suffered from a bad S/N ratio due to the small temperature variations and a quantisation error of 0.1 °C.

A non-linearity in the dynamic relations between the input variables Q and Q_s the output variables exists due to the dependency of the dynamic properties of the outputs on these inputs.

Experiments for pre-analysis purposes and identification have been performed. During the identification experiments, test signals are superimposed on the process inputs Q and Q_s . Q_w and Q_{ws} have been held constant.

MIMO estimates (with Q and Q_s as inputs) as well as SIMO estimates (with Q as input) with additive noise originating from the secondary circuit are possible.

Identification results

To illustrate the dynamics of a number of output variables some results from identification are given. The results from the pre-analysis phase in identification and the operations performed for proper conditioning of the data are described in chapter 4 and 5.

The results from modelling the dynamic relations between the process inputs Q and Q_s and the output variables T_2 , T_3 , T_4 , H_3 and H_4 are listed in figure 3.2. All the necessary operations for conditioning of the data have been performed.

For each dynamic relation the impulse response of the model is presented together with the simulation output residual computed with the application MODELSTST.

The following dynamic relations are presented:

Input(s)	Output(s)
a. Q	T ₂
b. Q Q _s	T ₃ H ₃
c. Q Q _s	T ₄ H ₄

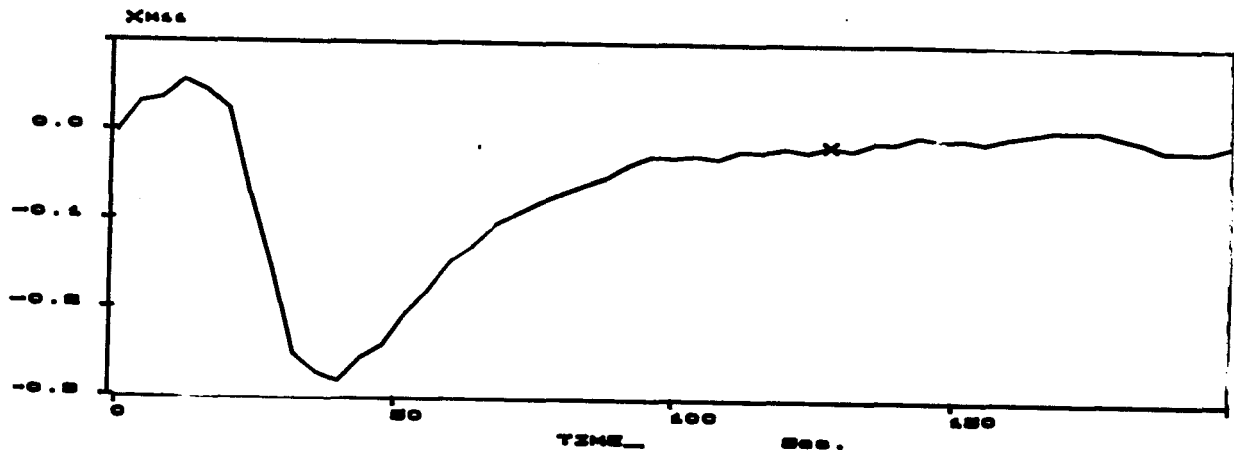
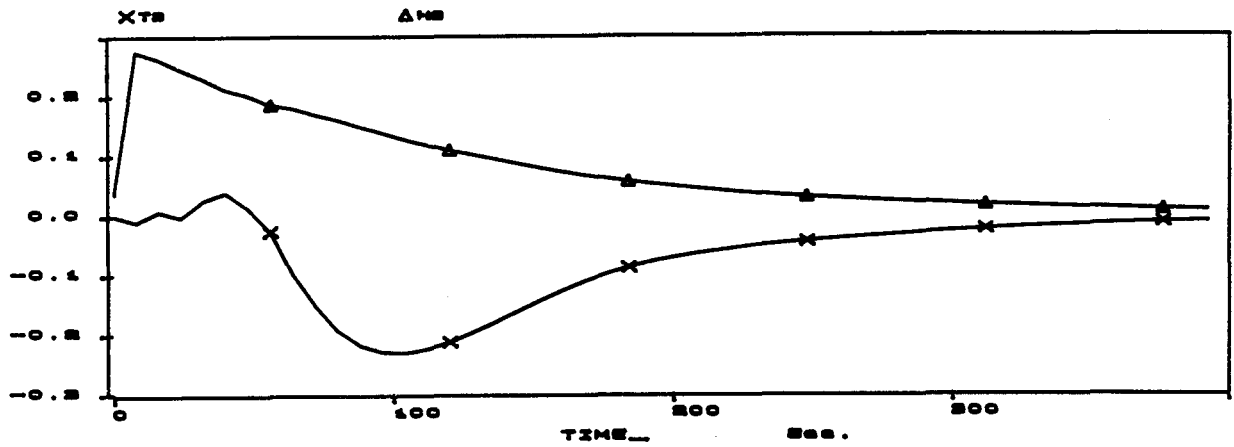
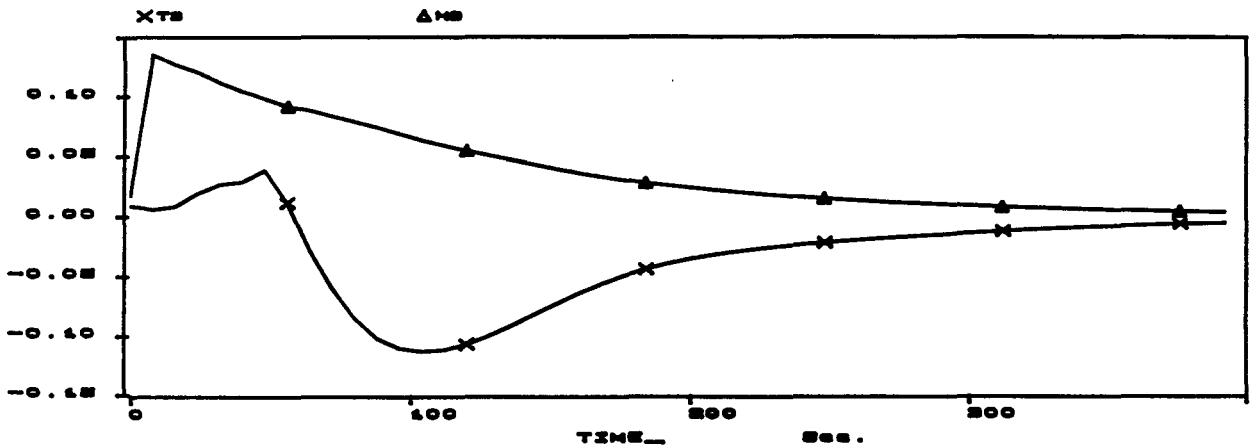


Figure 3.2.a Result from modelling the dynamic relation :
 Q→T₂ estimated with MARKOV, 1783 samples used
 50 parameters estimated, sample time = 4 s.
 Simulation output residual = 6.4 %

In the impulse response of T₂ an inverse response exists. This inverse response occurs due to the fact that the tubes from the heat exchanger to the first vessel are not isolated. The heated water loses energy during transport. The residence time depends on the flow Q (or Q_s). An increasing Q instantaneously leads to a decreasing residence time. As a result the water loses lesser energy and the temperature increases a little. Only after the content of the tubes is passed, the temperature decreases due to the greater Q. In short, an inverse response may be observed.



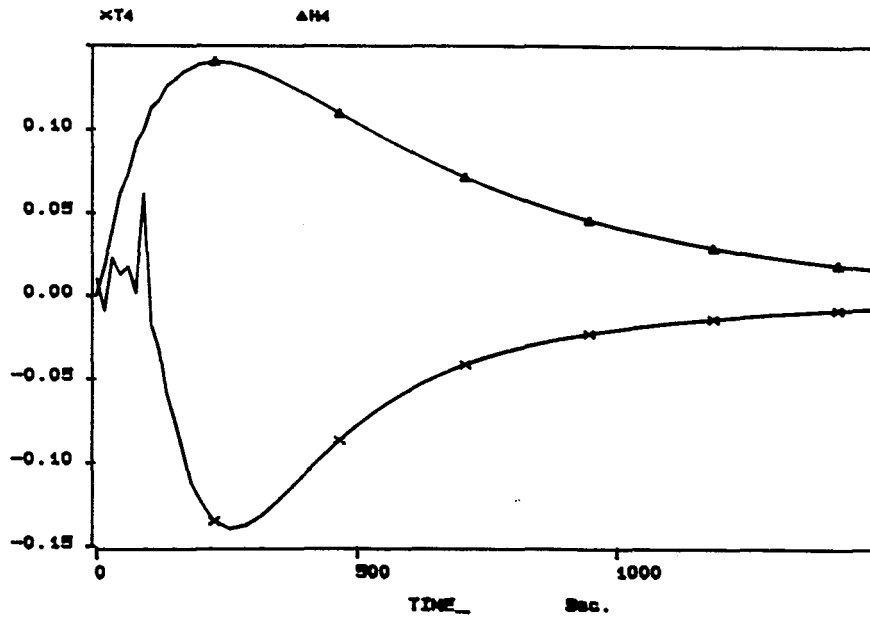
1: Q -> T₃, H₃



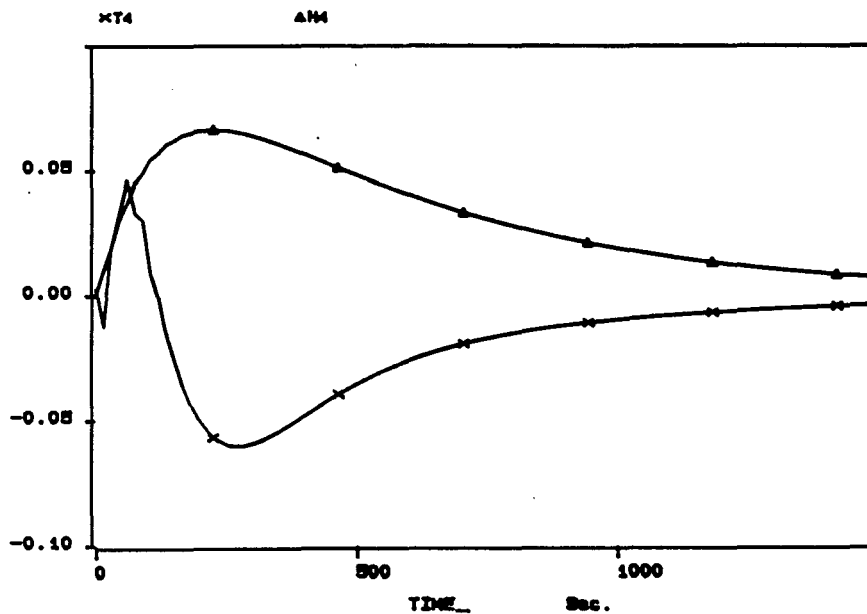
2: Q_s -> T₃, H₃

Figure 3.2.b. Results from modelling the dynamic relation :
 Q (1) and Q_s(2) -> T₃;H₃ estimated with IVM-LS. 891 samples used, model structure nA=8 and nB=6, sampling time = 8 s. Simulation output residuals : T₃ 5.68 % and H₃ 0.45 %.

As can be seen from the impulse responses it is possible to describe the dynamical behaviour between Q;Q_s and T₃ by a second order process with a time delay. Physically this is expected if we study the different elements in the path from Q;Q_s to T₃. An inverse response is found instead of a time delay due to the process property mentioned above. The response to the water level H₃ in the first vessel is nearly a first order process.



1: Q -> T₄, H₄



2: Q_s -> T₄, H₄

Figure 3.2.c Results from modelling the dynamic relation :
 Q (1) and Q_s (2) -> T₄; H₄ estimated with
 IVM-BT, 1492 samples used, model structure nA=6 and
 nB=6, sampling time = 15 s. Simulation output resi-
 duals : T₄ 26.23 % and H₄ 0.77 %.

The dynamic relation between the inputs and H₄ can be described by a second order process and the relation to T₄ by a third order process with a time delay. Due to the quantisation error in the measured signal T₄ a large simulation output residual results.

§ 3.3 A Glass-Feeder Process

Introduction

The production of modern glass products, for instance square television tubes, make high demands on the quality of the glass to be used, with respect to:

- a pure chemical composition,
- no visual disturbances in the glass,
- a constant absolute temperature and
- a homogeneous temperature profile, in place.

The purpose of the identification project is to design a control system for the feeder to meet the last two demands mentioned.

Process Description

The process may be divided in two parts:

- 1. the furnace where the glass is made and
- 2. the feeder where relaxation and temperature conditioning of the glass takes place.

In the furnace glass is made out of sand and some additives. Sand is constantly brought into the furnace by means of two special screws, one at each side of the furnace. The turbulent behaviour of the liquid glass in the furnace assures a proper mixture of all the components.

Through a throat, at bottom level of the furnace, glass pours from the furnace into the feeder. The feeder is a rectangular canal. Two major compartments exist where the temperature of the glass can be affected. The feeder is several decimeters deep and wide and several meters long. The height of the glass bed in the feeder is several decimeters. During experimentation a thorn was mounted in the opening of the spout by which a tube was made of the glass pouring out of the spout. Different possibilities however exist for different production purposes.

An analog instrumentation and signal conditioning system is used to measure 43 process signals. On 27 different spots in the oven and feeder temperatures are measured with thermo-couples. A schematic view of the furnace and the feeder is given in figure 3.3. A list of the variables of interest is given in table 3.2.

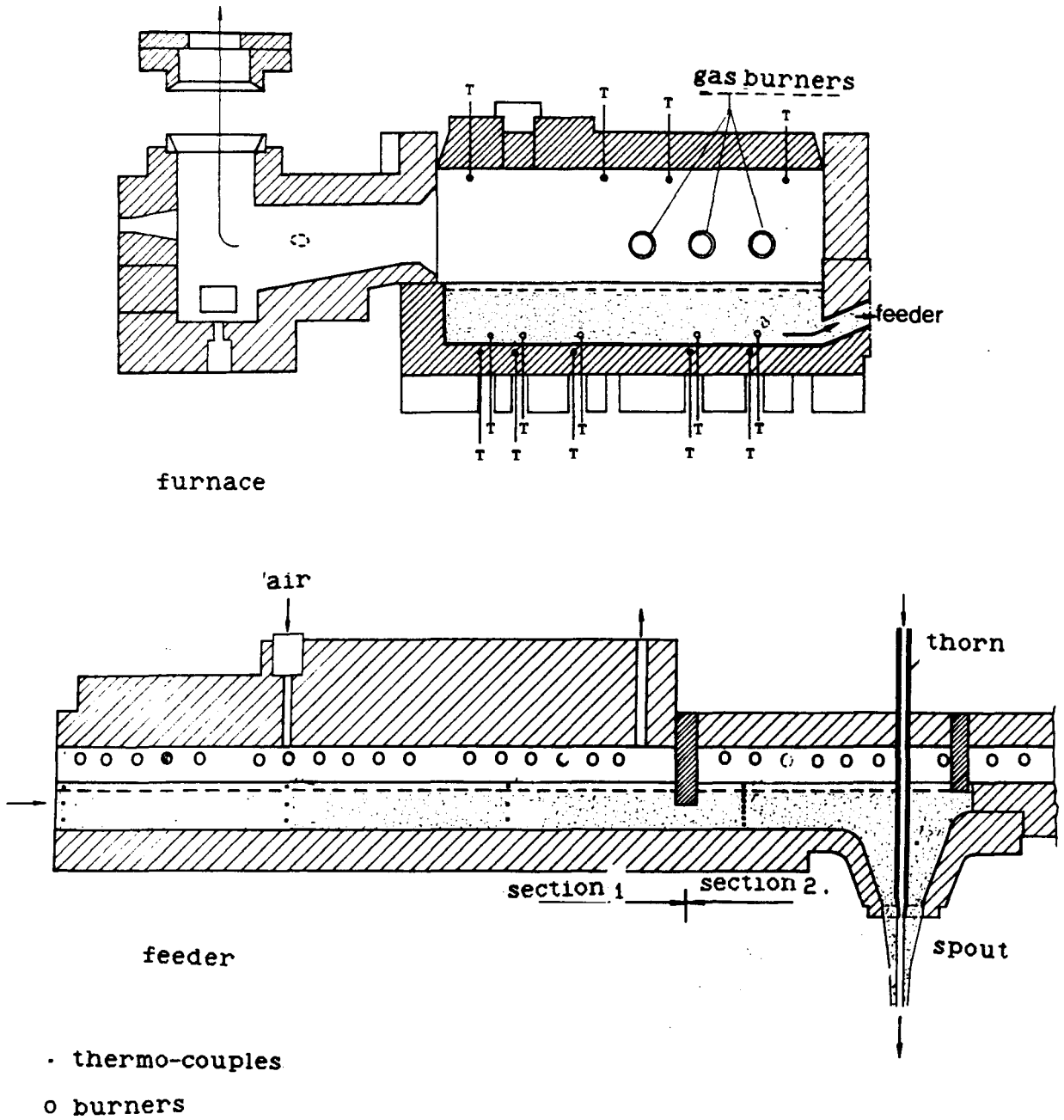


Figure 3.3 Schematic view of the glass-feeder and the position of the thermo-couples in the feeder

position

<u>Process Signal name</u> <u>PICOS/PRIMAL</u>	<u>Description</u>
<u>Oven:</u>	
INPUT	Input of raw material (sand)
GASTOT_T	Gas input, furnace
AIRTOTAL	Airflow, furnace
FURNPRES	Air pressure, furnace
SMEL_HOT	Air temperature, centrum furnace
SMEL_B11	Glas temp. oven, throat to the feeder
<hr/>	
<u>Feeder section 1:</u>	
<u>Input Variables</u>	
F1_GAS	Gas flow burners
F1_AIR	Air flow burners
COOL_AIR	Flow of cooling air
<u>Output Variables</u>	
FDFR_FA1	Air temp., pos. 1, feeder front
FDFR_F11	Glas temp., pos. 1, depth 1
FDFR_F12	Glas temp., pos. 1, depth 2
FDMI_FA2	Air temp., pos. 2, feeder middle
FDMI_F12	Glas temp., pos. 2, depth 1
FDMI_F22	Glas temp., pos. 2, depth 2
FDBA_FA3	Air temp., pos. 3, feeder back
FDBA_F13	Glas temp., pos. 3, depth 1
FDBA_F23	Glas temp., pos. 3, depth 2
FDSP_FA4	Air temp., side section 1
<hr/>	
<u>Feeder section 2</u>	
<u>Spout:</u>	
<u>Input Variables</u>	
F2_GAS	Gas flow burners
F2_AIR	Air flow burners
<u>Output Variables</u>	
FDSP_FLA	Air temp., left
FDSP_FL1	Glas temp., depth 1, left
FDSP_FL2	Glas temp., depth 2, left
FDSP_FM5	Glas temp., pos. 5, center
FDSP_FM4	Glas temp., pos. 4, center
FDSP_FM3	Glas temp., pos. 3, center
FDSP_FM2	Glas temp., pos. 2, center
FDSP_FM1	Glas temp., pos. 1, center
FDSP_FMA	Air temp., center
FDSP_FR2	Glas temp., depth 1, right
FDSP_FR1	Glas temp., depth 2, right
FDSP_FRA	Air temp., right
FDSP_FA6	Air temp., side spout left
FDSP_FA7	Air temp., side spout right
FDSP_F51	Glas temp., center of the spout
<hr/>	
<u>Process Output:</u>	
VELOCITY	Velocity glass tube
DIAMETER	Diameter glass tube
THICKNES	Thickness glass tube

Table 3.2 Variables measured at the glass-furnace/feeder

In the feeder glass cools down to a temperature of about 1000 °C in the spout. When cooling down the viscosity of the glass increases.

The wall of the feeder is made of a ceramic material with a large heat capacity. The average residence time of glass in the feeder is about 1-2 hr. The glass floating in the middle of the glassbed (of a higher temperature) however has a smaller residence time.

In the feeder temperature gradients with differences up to several tens °C exist.

The control possibilities, heating and cooling of glass in the first section and heating in the second section, can be used to reach the control system purposes:

- stabilizing the temperature of the glass in the spout of the feeder to assure a constant glass flow through the spout of the feeder and
- to create an -in place- homogeneous temperature profile to decrease tensions in the glass.

The process has three interesting control variables:

- 1. the gas/air flow to the burners in section 1.
- 2. The cool air flow in section 1 to cool down the surface of the glass in the middle of the glassbed, with the air blowing along the glass stream.
- 3. The gas/air flow to the burners in section 2.

Instrumentation

The hardware used for measurement and pre-processing of the signals is developed by PICOS. This hardware is composed of:

- analog signal conditioning cards for
 - anti-aliasing filtering,
 - off-set value correction,
 - amplification and,
 - scaling of the process signals.

- ADC/DAC transformers (MIOS-system).
- MicroVax, operating system ELN, used as measurement computer (front-end).
- MicroVax, operating system VMS on which PRIMAL is running.
- Ethernet connection between the two computers.
- VT-100 terminals.
- A Tek-4125 graphics terminal

All the equipment (with the exception of the terminals) has been build in a closed car. The software for the front-end is developed by PICOS and operates stand alone. PRIMAL runs on the VMS-MicroVax. For proper communication with the front-end a special purpose application (data handler) has been written for PRIMAL.

During experimentation measurement problems due to all kinds of disturbances in process and equipment occurred.

For instance micro-wave furnaces were radiating not far from the equipment car. A glass-bed depth sensor taking samples in the spout of the feeder disturbed the signals from the thermo-couples in the middle of the second feeder section.

Because of grave disturbances some signals measured are not useful for application in the process identification.

The premeasurements performed with PRIMAL delivered little results due to the measurement problems.

A data-logger coupled to the existing process equipment sampling at a rate of 3 samples per hour delivered some information on the elementary process dynamics which could be used for the design of experiments for identification.

Identification results

The various aspects and results from the pre-analysis phase in identification of the feeder are described in chapter 4 and 5.

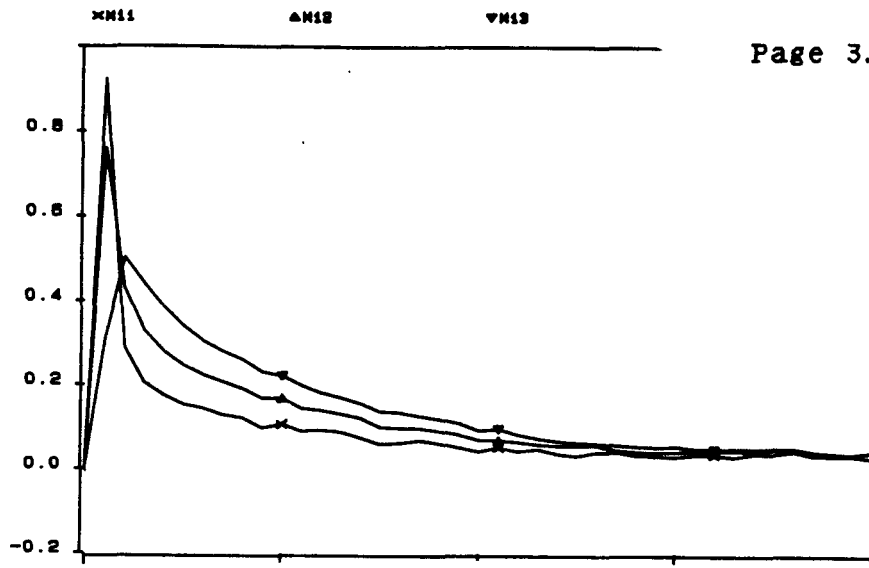
Some interesting results from modelling the dynamic behaviour between the three process inputs mentioned and a number of temperatures measured at various places in the feeder are presented in figure 3.4. Estimation has been performed on fully conditioned process data.

Presented are the transient impulse responses, simulated with the estimated models, and the simulation output residuals, comparing the model behaviour with the real process behaviour measured.

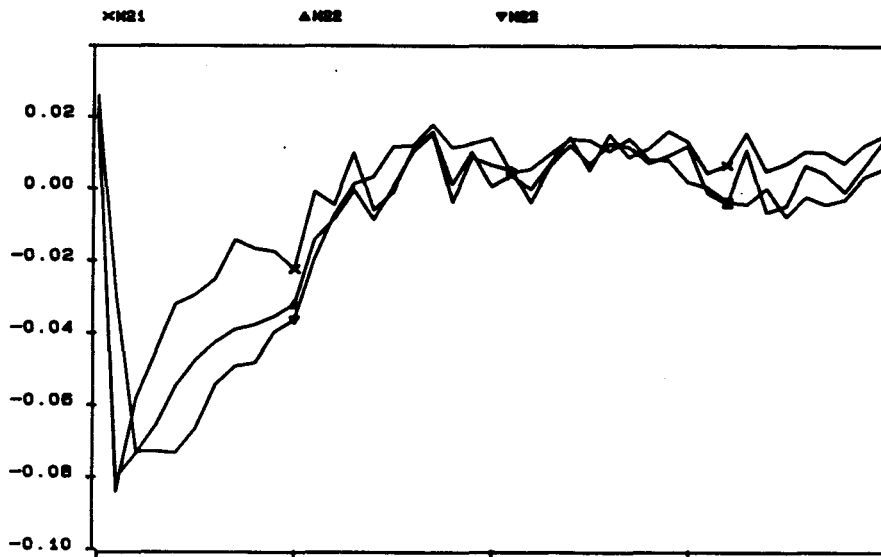
The latter has been performed on the data used for estimation ('best fit').

Results from three dynamic relations are presented, namely:

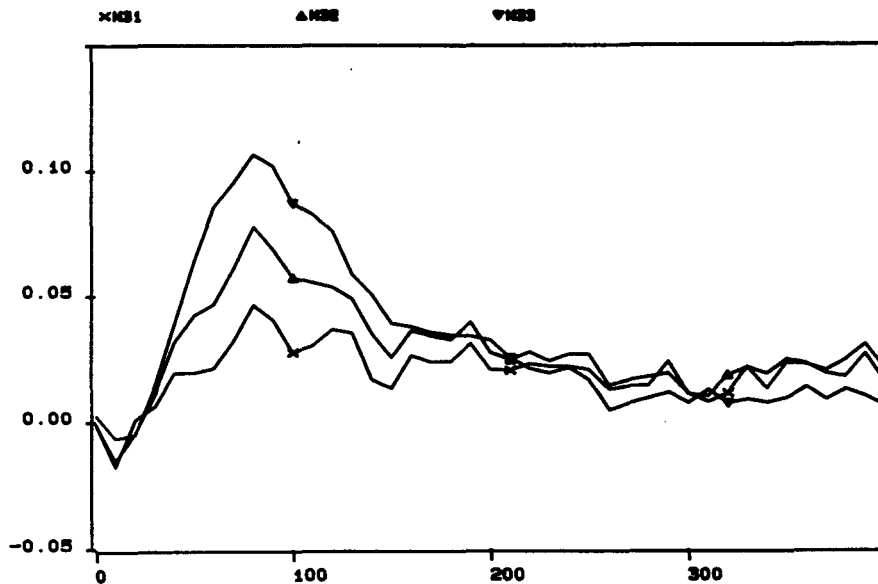
Inputs	Outputs
a. F1_GAS COOL_AIR F2_GAS	FDMI_FA2 FDMI_F21 FDMI_F22
----- b. F1_GAS COOL_AIR F2_GAS	FDSP_FM1 FDSP_FL1
----- c. F1_GAS COOL_AIR F2_GAS	FDSP_F51



1: F1_GAS -> FDMI_FA2 (M11), FDMI_F21 (M12), FDMI_F22 (M13)

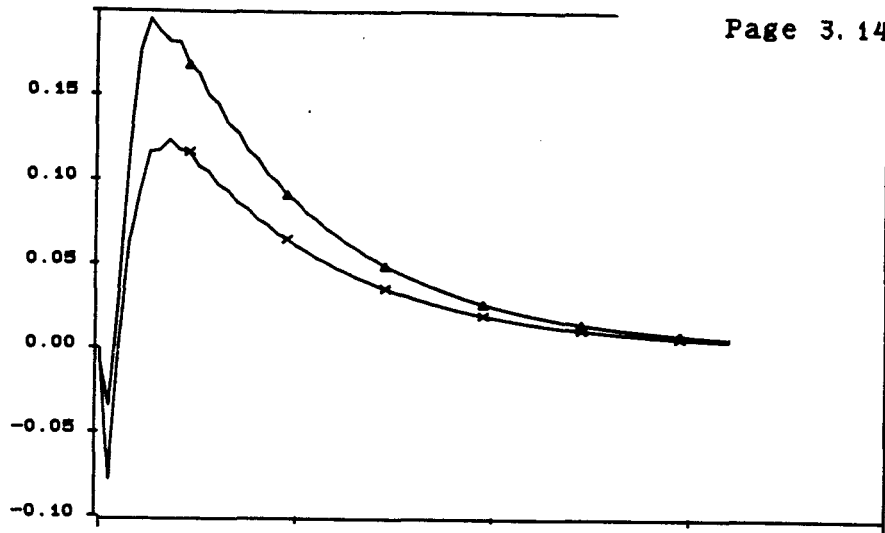


2: COOL_AIR -> FDMI_FA2 (M21), FDMI_F21 (M22), FDMI_F22 (M23)

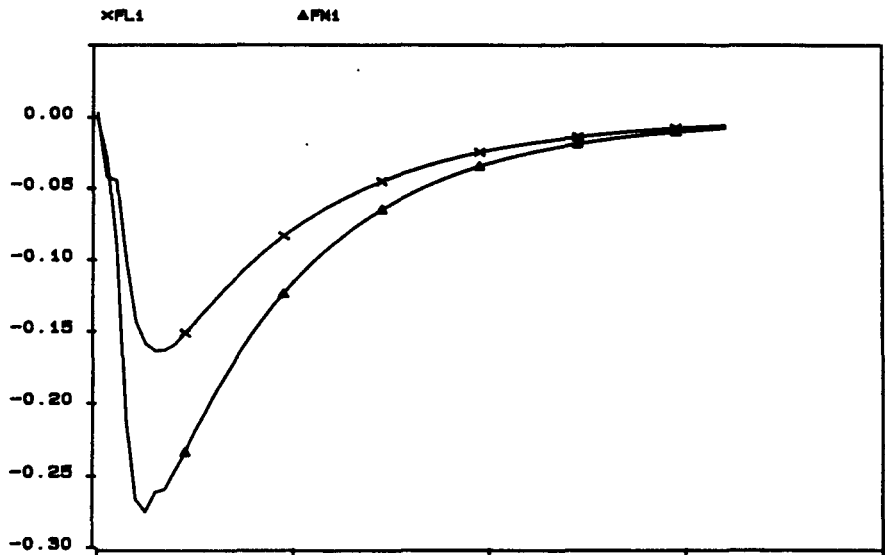


3: F2_GAS -> FDMI_FA2 (M31), FDMI_F21 (M32), FDMI_F22 (M33)

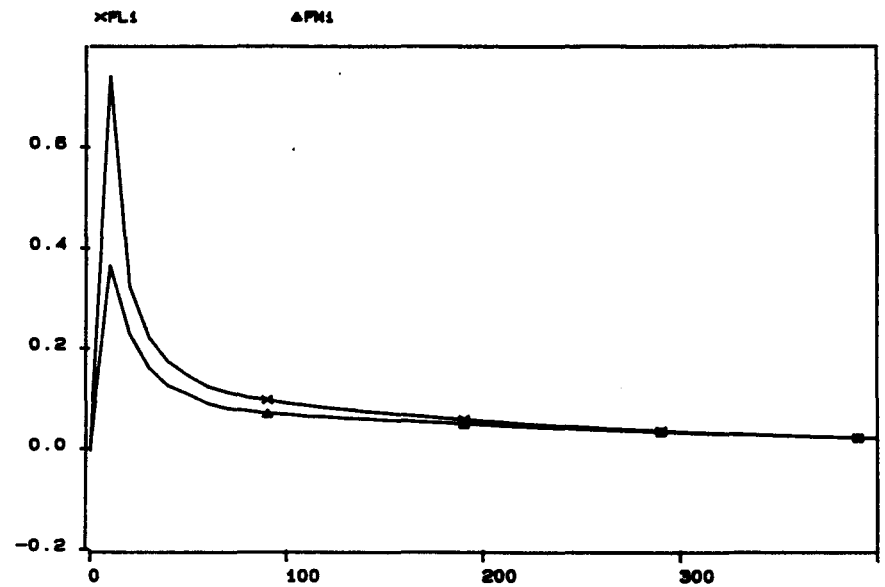
Figure 3.4.a Results from modelling the dynamic relation:
 Inputs -> FDMI_FA2; FDMI_F21 and FDMI_F22 estimated with MARKOV, 912 samples used, response length=65. Simulation output residuals : FDMI_FA2 : 2.98 %, FDMI_F21 : 3.64 % and FDMI_F22 : 6.47 %



1: F1_GAS -> FDSP_FL1 (FL1), FDSP_FM1 (FM1)

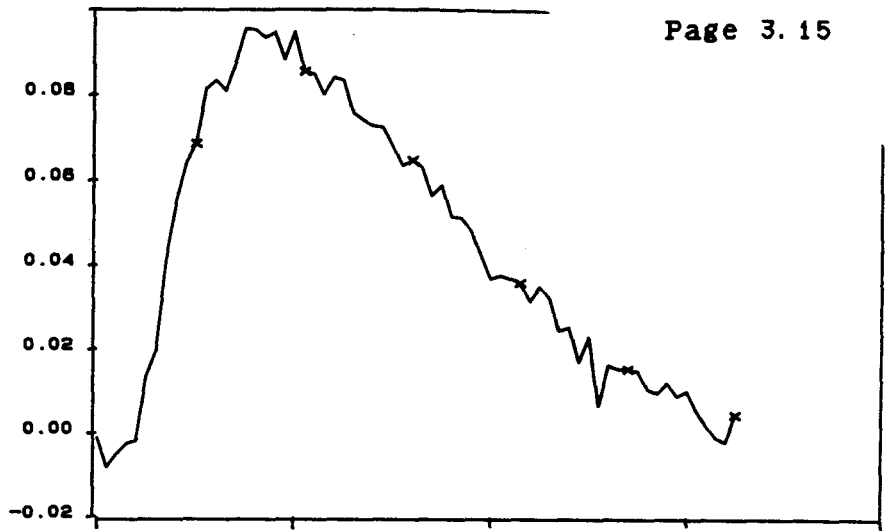


2: COOL_AIR -> FDSP_FL1 (FL1), FDSP_FM1 (FM1)



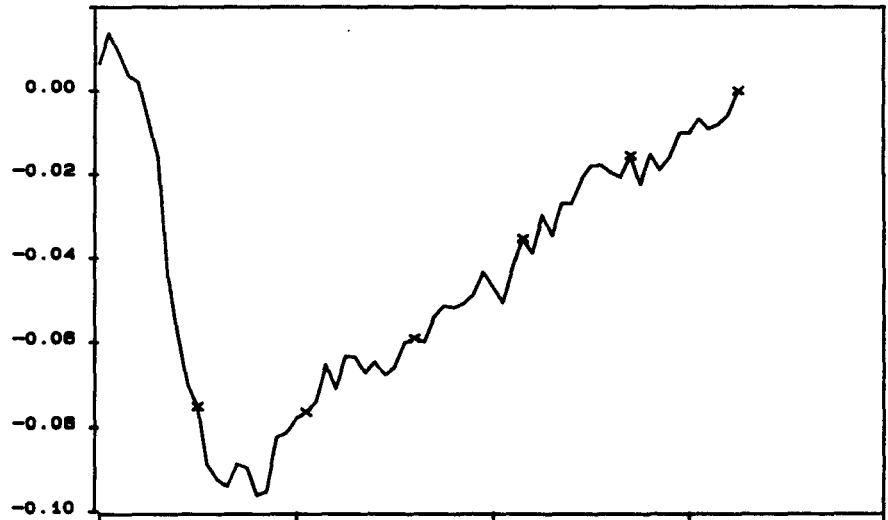
3: F2_GAS -> FDSP_FL1 (FL1), FDSP_FM1 (FM1)

Figure 3.4.b Results from modelling the dynamic relation:
 Inputs -> FDSP_FL1 and FDSP_FM1 estimated with IVM-MS, 912 samples used, model structure $n_A=5$, $n_B=5$, $n_C=3$ and $n_D=2$.
 Simulation output residuals : FDSP_FL1 : 2.25 %, and FDSP_FM1 : 8.96 %



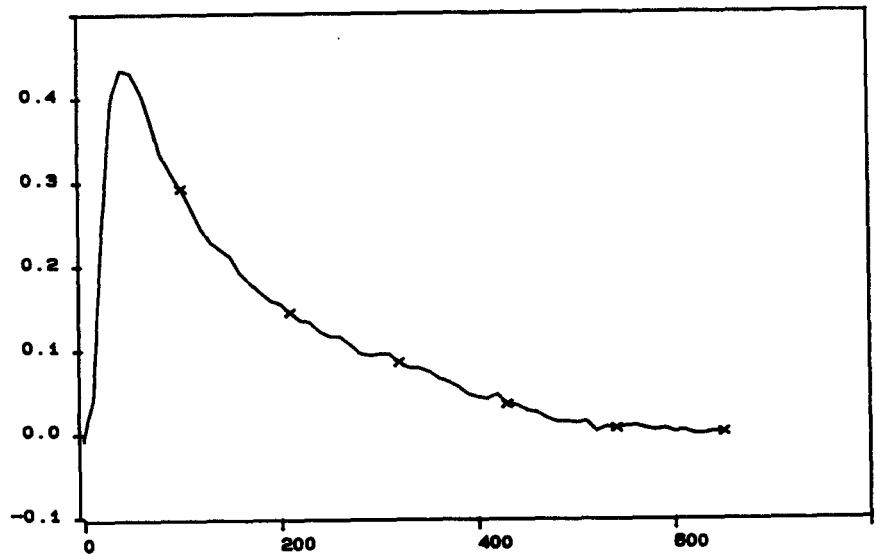
1: F1_GAS -> FDSP_F51 (M11)

xM21



2: COOL_AIR -> FDSP_F51 (M21)

xM21



3: F2_GAS -> FDMI_F51 (M31)

Figure 3.4.c Results from modelling the dynamic relation:
Inputs -> FDSP_F51 estimated with MARKOV, 912
samples used, response length=65.
Simulation output residual : 1.43 %

As mentioned is the main purpose of this identification project the development of a model of the dynamic behaviour of the process for control system design purposes. Identification however often also increases process understanding.

From the estimated models the following, prudently, conclusions can be drawn:

- If we study the impulse responses of the temperatures in section 1 of the feeder we can observe two interesting process properties:
 - 1. The impulse responses of the various temperatures in the feeder are almost instantaneous for all depths, as well for the gas flow (F1_GAS) as for the coolair input (COOL_AIR).
A possible reason for this is that the main mechanism for heat transport is radiation. The largest radiating object in the feeder is the surface of the feeder roof. Burning gas as well as coolair have immediate influence on the temperature of this surface.
 - 2. After the fast response a slow tail occurs which originates from the heating or cooling of the feeder wall due to the impulses in the inputs.
- The latter can be observed in the impulse responses of the temperatures in the middle of section 2.
The responses of the temperatures at the wall of the feeder have a much more pronounced tail than the temperatures in the middle of the glass bed. This effect is caused by the differences in residence time of the glass at the side and the middle of the feeder.
- The response in the spout of the feeder is almost totally affected by the gas flow in section 2. The control variables in section 1 have hardly any effect on the temperature FDSP_F51.

Chapter 4. EXPERIMENT DESIGN IN PROCESS IDENTIFICATION

§ 4.1 Introduction

Generally two types of environments for identification projects can be distinguished:

1) No test signals on the process allowed.

In an industrial surrounding often normal operating conditions may not be disturbed by application of input test signals. Only natural process data is available from logged inputs and outputs. Often the process signals do not contain enough information to model the dynamic behaviour of the process. Correlations between noise and input signals may exist due to control loops operating during measurement. Application of the different identification methods may not be successful due to a bad S/N ratio or the number of observations too small.

Generally the identification methods in PRIMAL do not function properly if little data with a low information content is available. No applications to tackle these kinds of identification problems adequately are available (yet).

2) Test signals allowed but restricted.

If experiments are allowed but normal process operation conditions may not be hindered too much with respect to the amplitude of the input test signals or the length of the experiments, design of experiments and especially optimal experiment design becomes very important. No attention has been given to optimal experiment design in the PRIMAL project yet.

Experiment design is one of the major steps in an identification project. It determines the information content of the measured process data, which sets a limit on the achievable performance in the modelling effort.

When sufficient experimental freedom is allowed concerning the test signals, there seems to be no real problem in gathering appropriate data for parameter estimation. With some simple rules proper design of experiments for identification is possible.

Two types of experiments in identification can be distinguished:

- 1. preliminary experiments for pre-analysis of the dynamic process properties
- 2. experiments for identification.

Prior to, with some simple rules, identification experiments can be designed, a thorough analysis of the elementary dynamical process properties has to be performed. If not enough knowledge about the latter is available preliminary experiments have to be carried out.

These experiments may also be used for obtaining a better understanding of the process dynamics which might be useful with conditioning of the measured data, parameter estimation and validation.

Some aspects of the pre-measurements phase together with the results from the studied processes are discussed in paragraph 4.2.

Some aspects of experiment design for identification are discussed in paragraph 4.3.

§ 4.2 Preliminary Experiments

In the pre-measurements phase a number of preliminary experiments are performed to determine the elementary dynamical properties of the process. This information is needed for the appropriate design of experiments for identification.

The goal of this phase is to determine the following experiment parameters:

- 1. the process inputs and outputs
- 2. the appropriate sampling rate T_0 ,
- 3. input test signals (type, amplitude, spectra)
- 4. the duration of the experiment $N \cdot T_0$ (identification time).

To determine these parameters information is needed on the following process properties:

- 1. Steady state gains K_{10} of all the input-output relations of interest, (sensitivity analysis),
- 2. dominant time constants τ_1 (first order process approximation),
- 3. time delays τ_d ,
- 4. linearity / non-linearity in the operating point:
(in PRIMAL only applications for estimation of linear models are available)
 - static (e.g. instrument) non-linearities: $y=f(u)$
with f a nonlinear function in u or
 - dynamic non-linearities
 - Or other non-linearities like:
 - hysteresis or
 - saturation
- 5. spectrum (bandwidth) of the process signals and if possible of the noise, disturbances occurring in the process signals during normal process operation,
- 6. dynamic ranges of the process signals,
- 7. stationarity of the process,
- 8. technical constraints, e.g. limits on the measurement time $N \cdot T_0$, the amplitude A of the input test signals or the shape and frequency pattern of the input test signals.

The sampling rate is an experiment parameter that has to be determined in the pre-measurements phase. Often this is not a critical choice. Relatively fast sampling with respect to the dynamics of the process will generally be adequate, 10 or more samples within the dominant (first order approximation) time constant will be sufficient.

Also the amplitude of the test signals to be used in the preliminary experiments has to be chosen.

During the experiments these parameters values may be adapted according to the knowledge gained.

In the preliminary experiments a-periodic test signals like step and crenel functions have been used to gather knowledge about the dynamic properties 1 to 4 mentioned in the list above.

They are easily applied to the process. In literature (see Rake /14/ and Ströbel /18/) many methods are presented for estimation of parameters of 2-nd and higher order models with time delays from step responses. Here only the parameters of the process in first order approximation are estimated. Information about the dynamic properties in first order approximation is sufficient for the design of identification experiments (see paragraph 4.3).

Process properties like steady state gain K , time constant τ and time delay τ_d can be determined from the output signals responses on a step input test signal.

Investigation of the linearity of a process in its operating point with crenel functions applied to the process is possible by observing these dynamic properties as function of the amplitude of the test signal: $\{K, \tau, \tau_d\} = f(A)$.

Another method is performing experiments for identification with different amplitudes of the input test signal(s) and comparing the modelling results later.

With both processes studied linearity of the dynamic relations is investigated with use of crenel functions. From the transient response of each step in the crenel function K is determined as function of A . Other process non-linearity like hysteresis is easy to study with crenel-function input signals.

The pre-measurements phase in identification is not efficient. The step responses are easily disrupted by signal disturbances like trends, which makes it hard to determine the process parameters accurately.

The feeder process step responses suffered heavily from low frequency drifts. Determination of the dynamic properties was difficult due to these signal drifts. In figure 4.1 some step responses from glas temperatures in the feeder are given. The amplitude of the input test signals used is 10% of the normal operating condition values.

For MIMO processes an analysis using step responses is very time consuming and gives little information. Generally only the most important sub-processes are studied. The information from these sub-processes is used for experiment design for identification of the whole process.

At the step response analysis of the feeder the input signals applied to the three feeder inputs have been offered in the pattern listed below:

with 1 = +10 % and 0 = -10 % of the operating point values of the inputs (= 0 %), 8 steps have been performed, only one step each time.

Input									
F1_GAS	0	0	0	1	1	0	0	1	1
COOL_AIR	0	1	1	1	0	0	0	0	1
F2_GAS	0	0	1	1	1	1	0	0	0

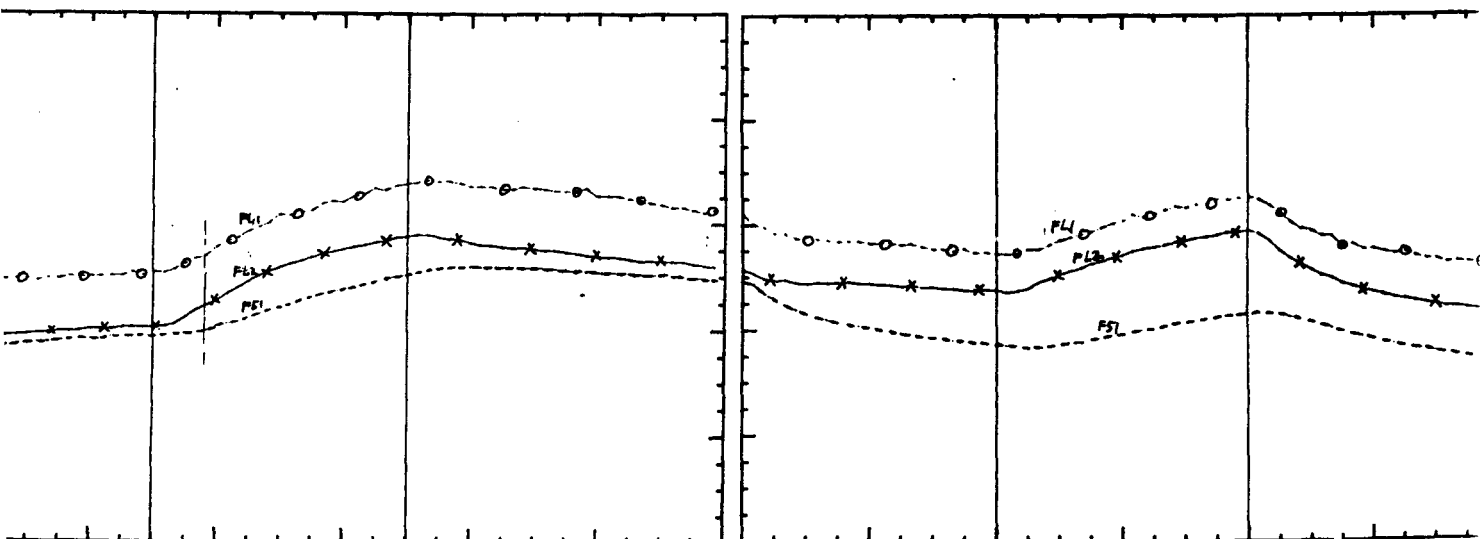
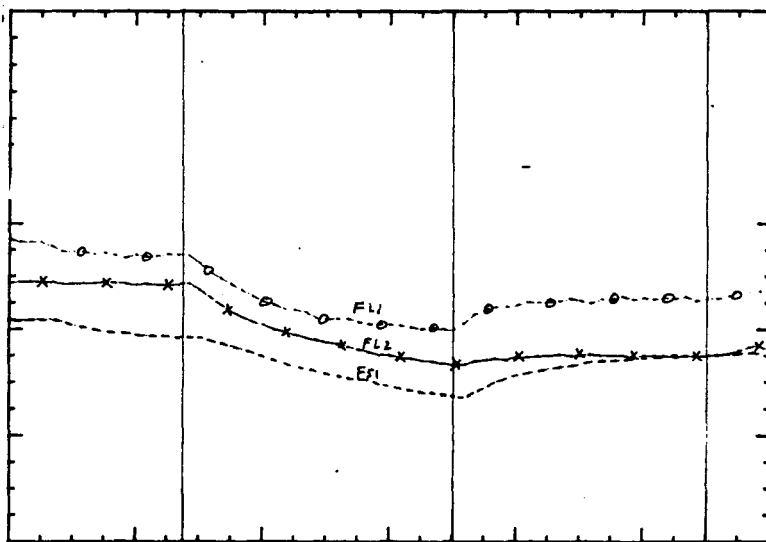


Figure 4.1 Step responses in the feeder spout temperatures:
 FDSP_FL1, FDSP_FL2 and FDSP_F51.
 A = 10 % of value normal operating conditions

As can be seen in figure 4.1 the transient time of the step responses, for the feeder temperatures in the spout, is about greater than the time period (≈ 1 [-]) between two steps. The real transient time is hard to determine due to slow drifts.

The time constants τ of the feeder temperatures for all three inputs is about 0.25. The time delay in the response of FDSP_F51 is about 0.05 for the inputs F1_GAS and COOL_AIR.

From the crenel function experiments in the feeder project little useful information resulted concerning the linearity of the process in the operating point due to shortage of time and measurement problems.

The selection of the amplitude of the input test signals used in the experiment for identification is based on the results from the sensivity analysis.

Some results from the step response experiments on the thermal-hydraulic process concerning the process properties τ and τ_d are given in table 4.1. Also the T_{95}^1 values are determined for the different output variables from the step responses. The amplitude A of the input test signal used is about 20 l/hours. The step is applied to Q.

Process Output	τ [s]	τ_d [s]	T_{95} [s]
T ₁	20	2	50
T ₂	30	10	60
vessel 1			
T ₃	70	30	100
H ₃	80	0	230
vessel 2			
T ₄	250	100	1200
H ₄	1000	0	1700

Table 4.1 Results from the step response experiments of the thermal-hydraulic process

From the transient response of each step in the crenel function K as function A has been determined for a number of process outputs i. Non-linearities like hysteresis have not been found.

¹: The value T_{95} of a step response is the time at which 95% of the steady state value is reached.

Static non-linearities of the form $y = f(u)$ can be found from the results of the gaugements. For the thermal-hydraulic process two non-linear relations were found. The valve controlling the cold water flow Q is non-linear and the flow measurement sensors produce an output signal (a pressure) non-linear with the flow. Another way to study a (possibly) non-linear relation is frequency-analysis of the output signal in application of a sine input signal (Meerman /25/). Harmonics in the spectrum occur if the input-output relation is non-linear. This can be seen easily by fourier transformation of the taylor sequence of the function $y = f(u)$.

From the results of the sensitivity analysis, using step functions, an estimation of the dynamic ranges of the process signals is possible. Together with the results from the linearity analysis an adequate amplitude of the input test signals for identification is determined.

Stationarity of the process can be observed by examining the process signals under normal operating conditions. This may also be used for analysis of the disturbances in the process signals. Spectral analysis of these disturbances might be of help in later steps of the process analysis e.g. determination of the proper trend filter.

In the analysis of the thermal-hydraulic process some experiments have been performed using gaussian white noise test signals. Spectral analysis is useful for determination of the frequency band of the process. Especially for MIMO processes with dynamic relations with different time constants (see table 4.1 vessel 1 and vessel 2) this experiment parameter is important. The dynamic relations of interest in the spout of the feeder all have time constants of the same magnitude as can be seen from the responses of the step input signals. Some simple rules based on the estimated time constant, can be used for design of an identification experiment. A description of these rules is given in paragraph 4.3.

§ 4.3 Experiment Design for Process Identification

To design input signals for process identification a number of experiment parameters have to be determined. An acceptable estimation of the process parameters within the length of the experiment must be possible. The experiment parameters of interest are:

- 1. signal type;
Kind of test signal to apply to the process inputs,
- 2. bandwidth B ;
frequency band in which the test signal excites the process,
- 3. sampling rate T_0 ,
- 4. amplitude A
- 5. experiment length N ;
number of records to be taken.

A number of simple rules have been proposed by different authors to determine the experiment parameters.

The first choice that has to be made concerns the type of the input signal. It is determined by the concept of identifiability of a process which is a joint property of an identification experiment and a model estimation. It establishes that the model parameters can be estimated consistently from the data obtained from the process.

This means that the parameter estimates \hat{a} converge to their "true" values a^* for the number of observations N tending to infinity:

$$(4.3.1) \quad \lim_{N \rightarrow \infty} (\hat{a} - a^*) = 0$$

Identifiability of the process depends on a number of factors: (Norton /23/)

- 1. scope and quality of the observations which is related to the conditioning of the measured process data (see chapter 5),
- 2. nature and location of the inputs related to the design of experiments for identification,
- 3. parametrisation, model structure selection and
- 4. properties of the estimation algorithm.

The requirements on input signals in an identification experiment to ensure adequate excitation of the process long enough to permit the estimation to converge are called "persistency of excitation conditions". These conditions specify how many independent components have to be present in the input signal.

A detailed description of the conditions of an input signal $\{u\}$ to be persistently exciting can be found in Norton /23/.

Persistent excitation implies that the power spectral density $\phi_{uu}(\omega)$ of the input signal does not vanish inside the frequency range that has to be identified :

$\omega_{\min} \leq \omega \leq \omega_{\max}$
Practically the input signal bandwidth must at least be comparable to the process bandwidth.

Non-zero power at a minimum number of frequencies may ensure asymptotic convergence but does not guarantee satisfactory finite sample performance. Also the energy in the input signal is of importance.

A convenient deterministic signal which satisfies these properties is the so-called pseudo random binary noise signal (PRBNS). A detailed description of this signal can be found in Eykhoff /13/ and van den Boom et. al. /6/.

The PRBNS has an approximate white spectrum up to a certain boundary frequency determined by the sampling time T_0 and the minimum pulse duration T ($=\lambda \cdot T_0$) of the signal chosen. The amplitude A of the two signal levels is constant. By changing the minimum pulse duration the frequency range can be modified.

Determination of these three signal parameters can be performed with a trial and error approach: from selection of the experiment parameters followed by a model estimation and successive validation back to experiment parameters selection until an appropriate model is achieved. This in fact is the fourth loop in the methodology in process identification mentioned in chapter 2.2.

Another way is to use the simple rules as mentioned by various authors, Isermann /17/ and Eykhoff /13/. A rule described below used in identification of the feeder process to determine the frequency range to enhance proved to be very useful. For processes like the thermal-hydraulic process with dynamic relations with different time constants different experiments might be needed.

The first important parameter of the PRBNS to be determined concerns with the bandwidth of the input test signal. The boundary frequency f_0 of the PRBNS is the frequency up to which the signal has an approximate "white" spectrum. This value is determined by the minimum pulse duration time T . $f_0 = 1/T$ with $T = T_0 * \lambda$.

The power spectral density of a PRBNS is given by:

(4. 3. 2)

$$\phi(f) = A^2 \cdot T \left[\frac{\sin(\pi f T)}{\pi f T} \right]^2 \cdot \sum_{k=-\infty}^{\infty} \delta(2\pi f - k \cdot \frac{2\pi}{T_r})$$

with T_r the cycle time of the signal (see van den Boom /6/).

Determination of T can be performed with the following rule:

generally: the fastest variation in the input signal must lead to a visible change in the output variables. This fastest variation must be sampled at least 5-10 times.

- Determine the bandwidth B of the process. In first order process approximation $B = 1/\tau$. In a MIMO process the smallest time constant has to be taken.
- Take the frequency B_{20} at which the power spectral density $\phi(B_{20})$ of the process has decreased about 20 dB with respect to $\phi(B)$.
For a first order process the frequency B_{20} is about $5*B$.
- The boundary frequency of the PRBNS is chosen:
 $f_0 = B_{20} = 5*B = 5/\tau$ (Hz),
and thus the minimum pulse duration time: $T = \tau/5$ s.

The sampling time T_0 is chosen $1/5-1/10$ of the minimum pulse duration time T ($\lambda = 5 - 10$) to prohibit aliasing in the spectra of the process signals. Also easy repair of the disturbances in the process signals is possible if enough samples are available. The frequency range enhanced, although the input power density spectrum is not "white" anymore, by the input signal in fact runs to $1/T_0$. Process modes may be studied up to the Nyquist frequency $f = 1/2.T_0$ Hz. The data redundancy is used to repair disturbances in the measured process signals.

For low-pass processes Isermann /17/ gives the following rules for determination of the sampling rate T_0 :

1) using the Shannon's theorem:

$$T_0 = \pi/\omega_{\max} \quad \text{with } \omega_{\max} \text{ such that}$$

$$|H(\omega_{\max})| = 0.02 \dots 0.1$$

of the value at the pass band .

2) with the estimated time constants:

$$T_0/T_E = 0.18 \dots 0.36 \quad \text{with}$$

$$T_E = (\Sigma T_a)_{\text{numerator}} - (\Sigma T_b)_{\text{denominator}} + (T_t)_{\text{time delay}}$$

and

3) using the transient time T_{95} :

$$T_0/T_{95} = 0.09 \dots 0.18$$

Rules 2 and 3 have been used for the thermal-hydraulic process. Due to the different time constants of the dynamic relations the choices have been made dependent on the relations of interest. For identification, within one experiment, of T_2 , T_3 and H_3 $T = 16$ s has been chosen. For identification of T_3 , H_3 , T_4 and H_4 $T = 30$ s. has been chosen. As will be clear from these rules the selection of T and T_0 is not really critical. As long as the process modes of interest are sufficiently excited no real problems will occur.

In the first rule the sampling time is immediately related to T ($T_0 = T/\lambda$). The selection of the sampling time however is also influenced by:

- possible aliasing which might occur in the spectra of the process signals if T_0 is chosen too large and no hardware anti-aliasing filters are present.
- easy repair of signal disturbances if enough samples are available,
- the sampling time in application of the derived model,

- accuracy requirements of the model; the influence of T_0 on the accuracy of the estimated steady state gain K has been studied by Isermann /17/. With a small sampling time the estimation becomes inaccurate. Also the numerical conditioning of the estimation methods is influenced by the choice of the sampling time. A small sampling time might lead to singularities in the estimation methods. If the sampling time is chosen too large the dynamic behaviour is not described precisely. The model order reduces. Fast dynamics can not be modelled.

The decimation factor which can be chosen in analysis of the measured process signals is limited to the range $[1, \lambda]$ for a PRBNS. For later analysis it is therefore not convenient to choose a prime number for λ .

The amplitude of the test signal is determined by the results from the sensitivity analysis. The amplitude has to be chosen such that all the process modes of interest are sufficiently excited by the input signal. Technical limits and the results from the linearity analysis however restrict the allowable amplitude of the input signal.

At both processes studied non-linearities were found not to play a significant role in the identification.

The length of the identification experiment N is determined by the number of samples required for adequate estimation of the parameters of the system. Desired model accuracy, the time available for the experiments and the S/N ratio play a role here. For the feeder about 12000 samples have been taken in the identification experiment. With a sampling time of 1 s. With $\lambda=10$ 1200 samples remained after decimation of the measured data. For the thermal-hydraulic process N depends on the studied dynamic relation. For identification of the output variables of the second vessel experiments of about 7 hours have been performed.

To study the effects of the experiment parameter concerning the bandwidth of the input signal a number of experiments have been performed with varying boundary frequencies of the PRBNS. The sampling time used in the experiments is 2 s. A total of 3600 samples have been taken. The amplitude applied to Q is about 20 l/hours.

A total number of five experiments have been performed with λ 2, 4, 8, 16 and 32 s for the primary circuit and 1, 2, 4, 8 and 16 for the secondary circuit.

The dynamic relations studied are the SISO process with input Q and output T_2 and the MIMO process with inputs Q and Q_s and outputs T_3 and H_3 .

Decimation of the measured samples of the data sequences is performed with the maximum factor allowed (determined by the secondary circuit: 1 (exp.1), 2 (2), 4 (3), 8 (4) and 16 (5)). As well as the frequency range enhanced as the sampling time after reduction varies.

Two identification methods have been used:

- non-parametric identification with MARKOV; the ratio between the number of samples available and the number of markov-parameters estimated is constant,
- and a parametric identification with IVM.

The results of the estimations are presented in figure 4.1. The impulse responses are presented together with the validation result in an output error simulation on the data used for estimation.

Interesting aspects:

1. The equation error estimation IVM-LS of the SISO process fails in data sequence 1 (with $T = 2$ s.) due to the inverse response of the process.
This effect may possibly be explained by the fact that an equation error parameter estimation method uses the measured output signals in the estimation criterion. The prediction (high frequency) behaviour of the equation error model will generally be good. It can be proved (van den Boom /6/) that the first impulse response samples are estimated very good by an equation error method.
2. The equation error estimation IVM of the MIMO process leads to unstable models for the data sequences 4 (with $T = 16$ s.) and 5 (with $T=32$ s.) for model orders $\{n_A;n_B\}$ higher than $\{2;2\}$. Model order reduction occurs due to the large sampling time after decimation. This can be seen clearly in the estimates of the SISO and the MIMO process for high sampling time values T after decimation. In estimation of too high order models, if the measured data is not rich enough, pole-zero cancellations of poles outside the unit circle might fail. In study of the pole-zero plots of the estimated unstable models this is seen.
3. The output error estimation MARKOV of the SISO and the MIMO process is at all data sequences successful. Although sometimes oscillations occur in the parameter estimation is the non-parametric estimator markov robust with respect to the experiment parameter concerning with the band width of the input signal and the sampling time after decimation. In any case a model is estimated with a good output simulation behaviour (see figure 4.2).
4. The estimation of the nearly first order process from Q to H_3 is at all experiments succesful.

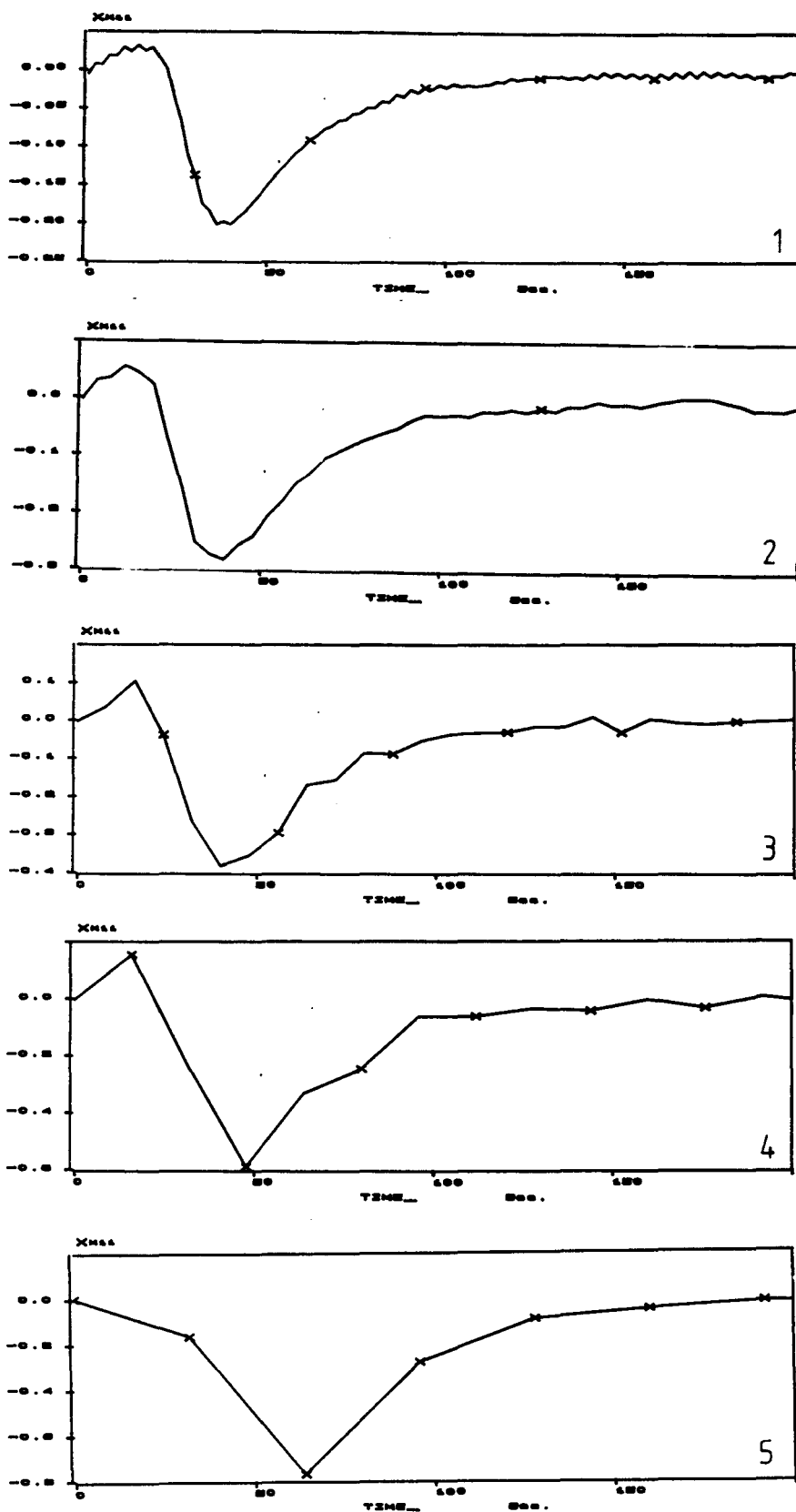


Figure 4.2.a Estimation results (MARKOV) on the dynamic relation $Q \rightarrow T_2$, $N=3600$, $T_0 = 2$ s. Decimation factor = 1, 2, 4, 8 and 16. Simulation output residuals :
 1. 3.74 % 2. 6.42 % 3. 8.54 % 4. 5.38 % 5. 2.81 %

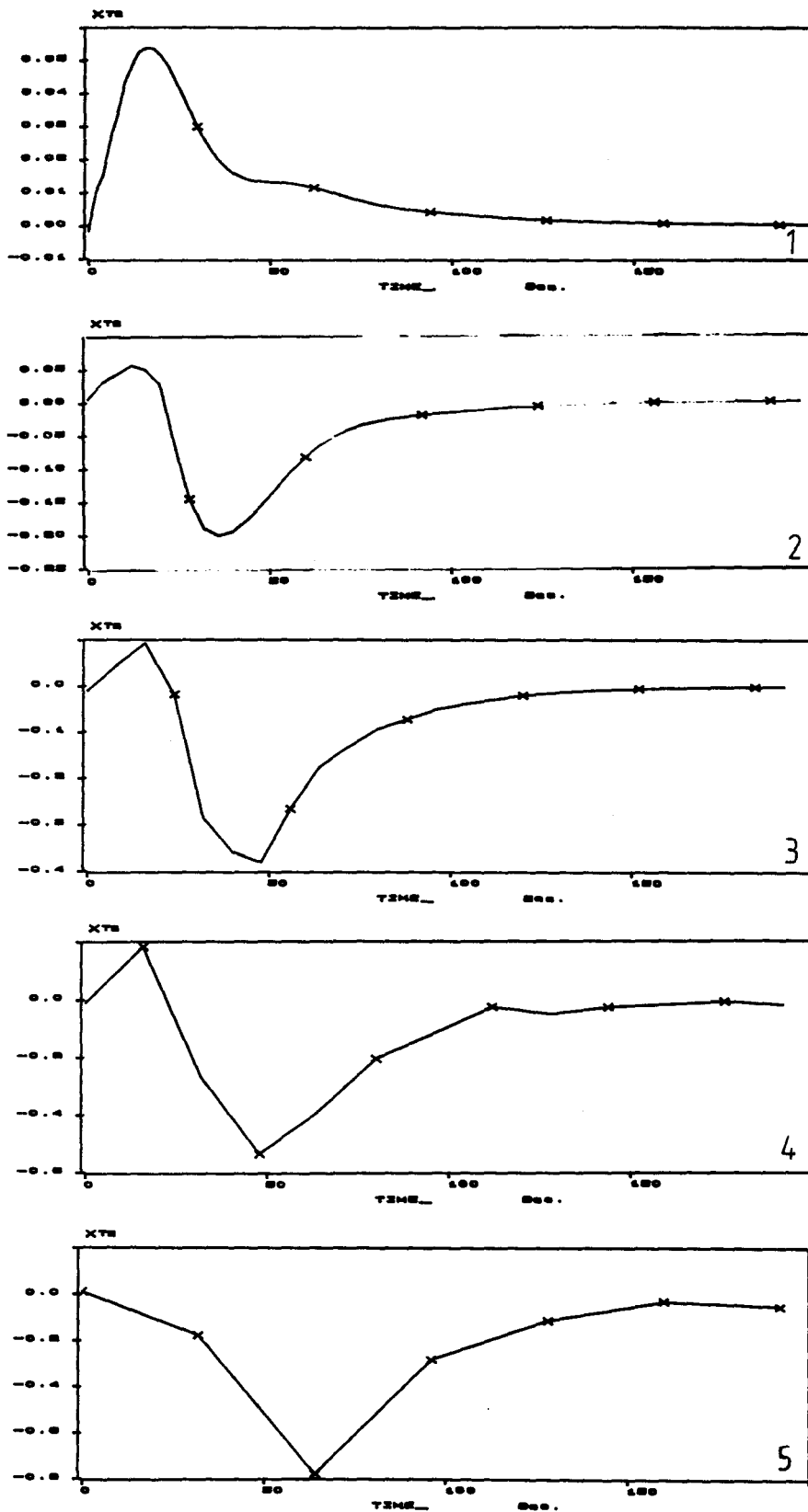


Figure 4.2.b Estimation results (IVM) on the dynamic relation $Q \rightarrow T_2$, $N=3600$, $T_0 = 2$ s., Decimation factor = 1, 2, 4, 8 and 16. Simulation output residuals: 1.120.30 % 2. 16.78 % 3. 8.66 % 4. 5.39 % 5. 2.70 %

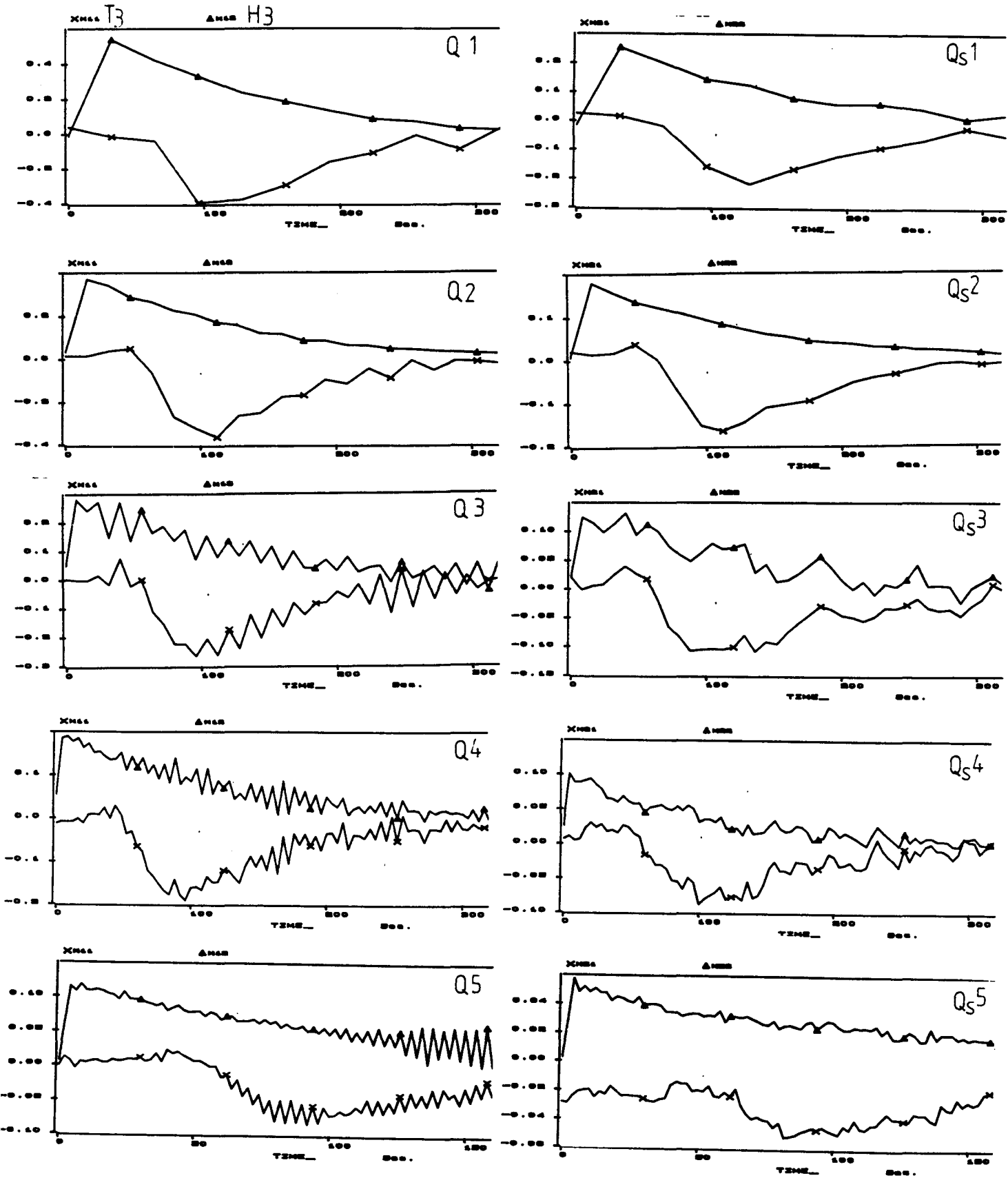


Figure 4.2.c Estimation results (MARKOV) on the dynamic relation $Q; Q_S \rightarrow T_3; H_3$, $N = 3600$, $T_0 = 2$ s.

Decimation factor = 1, 2, 4, 8 and 16. Simulation output residuals :

T3:	1.	55.33 %	2.	7.26 %	3.	5.04 %	4.	5.88 %	5.	28.93 %
H3:	1.	3.51 %	2.	1.59 %	3.	2.28 %	4.	0.30 %	5.	0.47 %

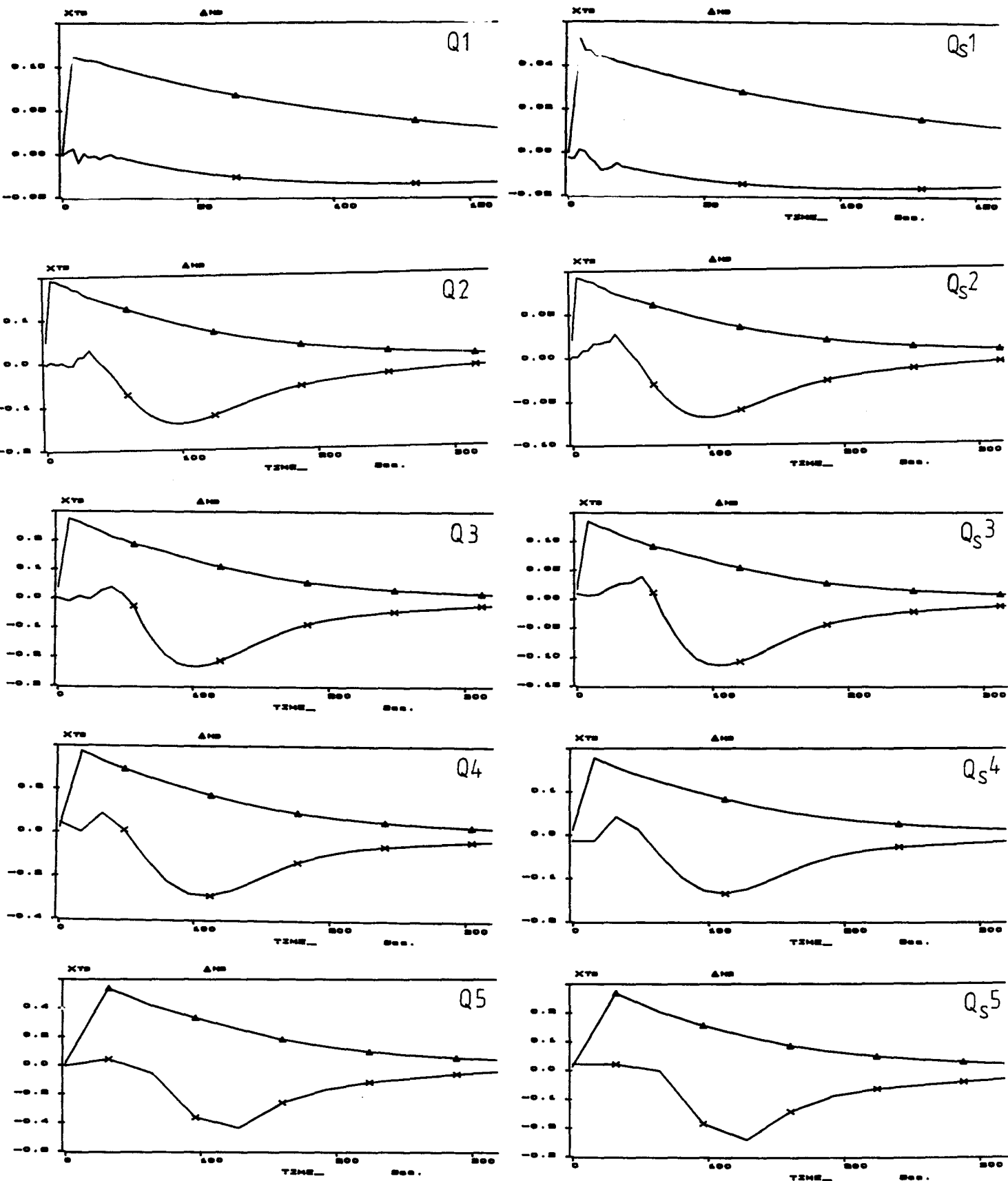


Figure 4.2.d Estimation results (IVM) on the dynamic relation $Q; Q_S \rightarrow T_3; H_3$, $N = 3600$, $T_0 = 2$ s.
 Decimation factor = 1, 2, 4, 8 and 16. Simulation output residuals:

T3:	1.	56.31 %	2.	9.36 %	3.	3.68 %	4.	9.73 %	5.	28.18 %
H3:	1.	1.69 %	2.	0.81 %	3.	0.45 %	4.	0.22 %	5.	0.27 %

§ 4.4 Conclusions

The simple tools used during the pre-measurement phase like step responses for determination of sensitivities, time constants and time delays and crenel functions for investigation of linearity of the process in its operating point are found to be easily disturbed. Little information is gathered in relatively long experiments.

Many empirical rules exist for the design of experiments for identification based on the information about the dynamic process properties. A global investigation of the linearity of the process in its operating point with respect to the determination of the amplitude to be used in the identification experiment is sufficient. Also is it possible to determine an adequate band width and sampling time of the input signal based on an estimation of the smallest time constant of the process.

If excitation of the process is adequate (visible) and enough data can be gathered no real problems exist. The measured data from practical processes however generally contains all kinds of disturbances. The next important step in an identification procedure therefore is the conditioning of measured process data for identification. This is discussed in detail in chapter 5.

The performance and behaviour of the identification method MARKOV using an output error criterion for parameter estimation is found to be rather insensitive with respect to the experiment parameters. The first step in the estimation method IVM (IVM-LS) using an equation error sometimes fails. If the sampling time (after decimation) is small with respect to the dynamics of the process problems with inverse responses can occur. If the sampling time is large and the information content of the measurement data is low problems in estimation of high-order models can occur.

Chapter 5. Data Conditioning in Process Identification

§ 5.1 Introduction

The set of raw input-output measurement data collected during experiments on practical (industrial) processes is seldomly suited for direct use in analysis and identification. All types of disturbances appear in the data which have to be removed before identification can be performed.

Before the data is filtered, first a thorough analysis of the data has to be performed. Spectral analysis is used to check if the frequency range enhanced by the input signal is adequate (see paragraph 4.3). With spectral analysis also a first impression of the possible disturbances, low or high frequent may be obtained.

Visual inspection of the measured data for outliers and other disturbances is the next step to be performed. Not all outliers in the data can be filtered with an automatic routine. Some of the outliers have to be repaired manually.

In paragraph 5.2 the application FILTER for conditioning of measurement data is discussed. Paragraph 5.3 treats a protocol for solving an important question in data conditioning: how do we determine the proper filter for removing the trends from the measurement data?

§ 5.2 Data Conditioning in PRIMAL: the Application FILTER

In PRIMAL only an (on-line) application named PREFILTER was available for filtering of the measurement data. This application supports reduction of measured data by means of averaging a contiguous set of samples with given length and trend filtering with a moving average or an exponential filter. For application of PRIMAL in identification of industrial processes this proved to be insufficient. An off-line application named FILTER was developed for pre-processing data.

A number of operations are provided which may be applied independently from one another. The supported operations are:

- 1. Signal Selection,
- 2. Delay Correction,
- 3. Signal Repair,
- 4. Filtering of Outliers,
- 5. Static Non-Linear Correction,
- 6. Trend Correction & Noise Reduction,
- 7. Data Reduction,
- 8. Offset Correction and Scaling.

The different operations are discussed now separately. Attention will be spent to the methods applied in the different steps and some important aspects.

Step 1: SIGNAL SELECTION

In the first step a group of signals and the range of samples from these signals is selected from the process data.

Step 2: DELAY CORRECTION

After estimation of the time delays in the process signals with correlation analysis or impulse response estimation, correction may be performed.

In this step a delay correction may be specified for each selected signal. A positive delay d means the signal is shifted for d samples to the future (with respect to the original time index). Because of this shifting d samples preceding the selected startsample are shifted into the range. When such samples are not available the first sample is repeatedly shifted in (and has therefore extra weight). Analogously a negative delay shifts in samples at the end of the range.

Typically delay correction is useful in the following cases:

- when the dynamic response of an output signal to an input signal is delayed for a large, fixed time interval (transportation time, delays in sensors, ..). often the delay is known and not interesting. However, when it is not taken into account explicitly, it leads to unnecessarily high order models.
- restoration the natural interrelation of the signals. When measured process signals are used as inputs for the model the input signal should be corrected for the delays introduced by the measurement itself. Otherwise apparent non-causal behaviour of the output on the input might result.

Step 3: SIGNAL REPAIR

During data-aquisition in practice all kinds of signal disruptions are possible that do not represent dynamical behaviour of the process, but which are the result of sensor failure or other equipment malfunctioning. Repair is necessary when the disturbances have a high energy content.

It is often very difficult to automatically recognize and repair these disruptions. The human eye however proves to be most successful in recognizing disturbance patterns. FILTER therefore provides facilities for the user to manually repair the signals. The user selects so-called 'repair intervals'. A repair interval consists of a signal name, a begin sample nb , an end sample ne and a repair method. The range of samples $nb \dots ne$ of the selected signal will be repaired, using one of the following methods:

- MEAN** : The signal values are replaced by the signal mean, calculated over the sample range specified in step 1 minus the selected repair intervals.
- INTERPOL**: The signal values are replaced by values resulting from a linear interpolation between the signal value at sample nb-1 and the value at sample ne+1.
- CONSTANT**: A specified constant value is added to the actual signal values in the specified range.
- REPLACE**: A specified constant value replaces the actual signal values in the specified range.

Step 4: FILTERING of OUTLIERS

In (statistical) literature a number of outlier detecting algorithms are proposed. After application of a regression, between the independent and dependent variables, outliers in the dependent variables can be detected by observing the residuals of the dependent variables. In data from practical processes however outliers may be found as well in the outputs as the inputs. FILTER offers several routines which treat the signals independently. In application of the outlier filter one has to remember that outliers generally have a high energy content with great influence on the variance of the unfiltered signal. In selection of the parameter controlling the performance of the detection, the "Shaving Strength", therefore small values proved to be proper (1.5-2). The implemented techniques for outlier detection use an amplitude criterion. Signal values that exceed the expected range of values are presumed to be outliers. One of the supported techniques combines an amplitude with a frequency criterion, assuming that outliers are essentially high-frequent. Dependent on the chosen method also parameters like a cut-off frequency or the size of a data subset have influence on the performance of the detection. The detection methods note the position of outliers and transfer this information to the correction methods. For each desired signal a range of samples must be specified. The computations will take place only on these data ranges.

The following detection methods are provided:

- LEVEL**: This method is recommended for process signals with no significant trends. It uses a straightforward amplitude criterion. When the signal shows a significant trend it might not function properly. The mean \bar{x} and the standard deviation $\sigma(x)$ of the signal $x(t)$ are computed over the selected data range. Outliers satisfy the following test:

$$(5.2.1) \quad | x(t) - \bar{x} | > S \cdot \sigma(x)$$

with S the shaving strength.

TREND: This method might be used for signals contaminated with slow drifts. The signal $x(t)$ is first filtered with a high-pass filter to eliminate the slow drifts from the signal. Subsequently the standard deviation of this filtered signal is computed to define, together with the shaving strength, an upper bound on the accepted signal amplitudes. For the detection of outliers the following test is performed on the filtered signal:

$$(5.2.2) \quad |x_{hp}(t)| > S \cdot \sigma_{hp}(x)$$

with index 'hp': high-pass filtered.

MEDIAN : This method starts the same as TREND. After trend correction the standard deviation is computed to define an upper bound for the amplitude criterion. The original, unfiltered, signal is now divided into contiguous subsets of samples. From each subset the median is computed. Outliers satisfy the following test:

$$(5.2.3) \quad |x(t) - \text{median}(x)| > S \cdot \sigma_{hp}(x).$$

Unlike the average signal value of a data subset the median value is rather insensitive to the occurrence of outliers in the set. This method may also conveniently be used for deterministic signals like PRBNS.

BACKX : This method uses a combined amplitude and frequency criterion. The method is developed by T. Backx (see Backx /28/). First the mean and variance of the high pass filtered signals are computed (as with TREND). The detection starts with low-pass filtering of the unfiltered original data. Assuming that spikes are essentially high frequent these can be detected by comparing the original signal with the low-pass filtered signal:

$$(5.2.4) \quad |x_{lp}(t) - x(t)| > S \cdot \sigma_{hp}(x)$$

with index 'lp': low-pass filtered.

The high and low-pass filters used in the detection steps are 2nd order symmetric digital IIR (Infinite Impulse Response) Chebyshev filters, introducing no phase shift. These filters are designed according to the desired cut-off frequencies. The design is based on the analog 'normalized' low pass Chebyshev filter (see Jong /9/).

The bilinear mapping method is used for transformation to a digital high or low-pass filter. For proper filtering of the first samples startup with past data samples is possible. If no data samples are preserved the first available sample is repeatedly used. In application of these filters in the different detection methods the transition bandwidth has to be considered.

The following correction methods are provided:

- MEAN : Replaces the outliers with the signal mean, computed over the selected datarange, corrected for the signal values of the outliers.
- INTERPOL : Replaces the outliers with the interpolated signal.
- MEDIAN : Replaces the outliers with the subset median value. Only applicable when the detection method is also MEDIAN.

Step 5: STATIC NON-LINEAR CORRECTION

From the gaugements non-linear relations of for instance instruments may be discovered. If a linear model of the process has to be formed it is necessary to correct for the known nonlinearities.

In this step a number of static non-linear filters may be defined. Besides correction of a non-linearity also signal repair may be performed by specifying a data range for the filter. The filters have the following format:

$$(5.2.5) \quad y(t) = a_0 + a_1 \cdot x(t) + a_2 \cdot x^2(t) + a_3 \cdot x^4(t)$$

with: $x(t)$ the input signal
 $y(t)$ the corrected signal.

The user supplies the coefficients a_1 and a data-range for application and specifies which filter to use for each selected signal.

Step 6: TREND FILTERING & NOISE REDUCTION

Slow drifts (trends) are found to be a severe problem in measured data from practical (industrial) processes. Several authors (Isermann /17/ and Baur /25/) have done some research on proper trend filtering of the data. All the methods proposed have the disadvantage that parameters of a preproposed trend model have to be estimated in parallel to the process parameters. High pass filtering of the data is a much simpler method for detrending data. If the spectral band of the trends is close to the spectral band of the process a difficulty exist in establishing of the proper trend filter to use. We do not want the filter to eliminate process information from the data, but we also do not want to leave trends in the data.

A protocol, making use of the behaviour of a Least Squares parameter estimator on data with trends, is developed for determination of the proper trend filter. A description of this protocol is given in chapter 5.3.

This steps offers several filters for trend correction and correction of high frequencies representing noise.

Using a high-pass filter (with cut-off frequency ω_{c1}) removes the signal trends caused by the drift. By using a low-pass filter (with cut-off frequency $\omega_{c2} > \omega_{c1}$) the noise level may be reduced. A band-pass filter can be used to perform these actions simultaneously.

A band-stop filter may be used to extract a specific frequency-range from the process signals.

Digital FIR (Finite Impulse Response) filters (see literature /9/,/10/ and /11/) are used to approximate the desired frequency characteristic $H(\omega)$:

$$(5.2.6) \quad H(\omega) = \begin{cases} 0 & \text{for } \omega < \omega_{c1} \\ 1 & \text{for } \omega_{c1} \leq \omega \leq \omega_{c2} \\ 0 & \text{for } \omega_{c2} < \omega \leq \omega_s/2 \end{cases}$$

with ω_{c1}, ω_{c2} : cut-off frequencies
 ω_s : the sample frequency

For the approximation of this filter the frequency scale is divided into three sections : the pass band ($H \approx 1$), the transition band and the stop band ($H \approx 0$).

The desired frequency response $H(\omega)$ is expanded into a fourier series. A finite order unit sample response sequence $h(k)'$, representing a digital filter of the FIR type, is obtained by truncating the infinite fourier series and performing an inverse z-transform. The oscillations occurring in the frequency response due to the truncation can be reduced by application of a window function $w(k)$. The filter coefficients sequence as well as the window function is symmetric around $k=0$.

The resulting response sequence $h(k)$ is found by multiplying $h(k)'$ with $w(k)$:

$$(5.2.7) \quad h(k) = h(k)' * w(k) \text{ for } k = -M:M$$

with M the filter order.

Besides the cut-off frequencies also the width of the transition band and the type of window to be used (SQUARE, HANNING, HAMMING or BLACKMAN) may be specified.

The type of window influences the the maximum pass band and stop band ripple and the width of the transition band.

Table 5.1. presents the window functions and some characteristic values of the FIR-filters designed with these windows.

	Maximum Stop Band Ripple	Transition Bandwidth (ω_s/M)
SQUARE	-21 dB	0.9
HANNING	-44 dB	3.1
HAMMING	-53 dB	3.3
BLACKMAN	-74 dB	5.5

Table 5.1 Characteristical features of the FIR-filters designed with the different window functions. For a given filter order M a smaller stopband ripple is exchanged for a larger transition bandwidth.

The data is filtered by convoluting the unfiltered data with the symmetric impulse reponse of the filter. No phase-shift is introduced due to the symmetry of the impulse response of the filter. A number of filters may be defined and for each signal a filter may be selected. The original data is divided into a filtered signal and a signal that has been filtered out, which is stored in a separate dataset. For proper filtering at the boundaries of the selected data range the buffer may be extended at the beginning and the end with samples from the raw dataset and to use them for starting the filter properly. The number of extra samples used depends on the order of the filter. The corrective steps 2,4 and 5 are also applied to the additional data. When insufficient data is available the start and stop sample of the input dataset are repeatedly used.

Step 7: DATA REDUCTION

Using a high sampling frequency for the experiments leads to a large amount of data that may be conveniently used for the previously discussed correction steps. Also aliasing may be prohibited if a high sampling frequency is used. To prevent unnecessary high order models and numerical problems the excess of data must be removed in the data reduction step. The data reduction factor *redfac* is supplied by the user. Two methods for data reduction are available:

DECIMATION : the data is divided into contiguous groups of *redfac* samples. Of each group the first sample is selected.

AVERAGE : The data is divided into contiguous groups of *redfac* samples. The samples in each group are averaged and result in one new sample. Consider the filtering effect of this operation.

Using PRBNS input test signals the reduction factor is limited to the range $[1, \lambda]$ with λ the minimum pulse length. If a PRBNS is used as input signal the maximum reduction factor λ is used. In identification of a process with more different time constants it may be convenient to use reduction factors other than λ .

Step 8: SCALING & OFFSET CORRECTION

Offset values in the signals may cause biased results in the estimates. To increase accuracy in parameter estimation scaling may be performed on the process signals.

After calculation of the signal means and variances of the conditioned data, the data may be transformed to:

$$E=0 \quad \text{offset correction: } y(t)=Y(t)-\bar{Y} \text{ and}$$

$$\sigma=1 \quad \text{scaling: } y(t)=(Y(t)-\bar{Y})/\sigma_{Y+\bar{Y}}.$$

Not all disturbances in the data can be tackled with FILTER. For instance dynamic (and unknown static) non-linearities in the process or measurement errors like quantisation noise. To solve these problems experiment parameters have to be adapted or installation of improved equipment should be considered.

§ 5.3 A Protocol for Trend Filter Determination

The disturbances signal $w(t)$ may be written as:

$$(5.3.1) \quad w(t) = w_1(t) + w_2(t) + w_3(t) + w_4(t)$$

with

$w_1(t)$: stationary stochastic noise with zero mean,

$w_2(t)$: low frequency noise; slow signal drifts (trends),

$w_3(t)$: outliers; spikes; signal distortions, missing data pieces,

$w_4(t)$: other disturbances like process non-linearities that do not fit in the linear process output $x(t)$.

The bias in the Least Squares estimation of the process parameters $\{A;B\}$ due to the trends $w_2(t)$ (see appendix 1), can be used to establish the proper specification of a trend filter. With a protocol described below the cut-off frequency F_c for a high-pass trend filter with a given transition bandwidth, can be determined.

The protocol is based on the behaviour of process models estimated with an ordinary Least Squares method on the filtered process data.

First the measured process data is filtered with a number (n) of high-pass filters with cut-off frequencies $F_i = i \cdot \Delta f$ for $i = [0, n]$ such that with F_n the data is certainly detrended.

Then a model $i: \{\hat{A}; \hat{B}\}_i^1$ is estimated for each filtered data sequence $\{u; y\}_{F_i}$.

With these models simulation is performed on a fully detrended data sequence e.g. $\{u; y\}_n$, filtered with cut-off frequency F_n .

By studying the simulated output residuals $\Delta \hat{y}(t)$ as function of the cut-off frequencies F_i of the high-pass filters used the proper trend filter can be determined:

with the linear process output $x(t)$ and the simulated output $\hat{y}(t)$ the output residuals $\partial y(t)$ are computed as follows, using the process description as mentioned in chapter 2:

$$(5.3.2) \quad S: y(t) = x(t) + w(t) \quad \text{with}$$

$$(5.3.3) \quad x(t) = (A^{-1}.B)^* . u(t) \quad \text{and}$$

$$(5.3.4) \quad \hat{y}(t) = \hat{A}^{-1} . \hat{B} . u(t)$$

the simulated output residuals are:

$$(5.3.5) \quad \Delta \hat{y}(t) = y(t) - \hat{y}(t) =$$

$$\left[(A^{-1}.B)^* - \hat{A}^{-1} . \hat{B} \right] . u(t) + w(t)$$

As can be seen from equation 5.3.5 two terms attribute to the output error residual $\Delta \hat{y}(t)$, namely:

- 1. a term resulting from the bias in the estimation of the process parameters $\{A; B\}$ and
- 2. the residuals term $w(t)$ of the process description S .

The first term can be studied separately by simulation with (biased) models on a fully detrended data sequence.

In these simulations the input vector $u(t)$, the residuals vector $w(t)$ and the "true" process model¹ estimation $\{A^*; B^*\}$ (on the data without trends) do not change.

The output error residuals $\Delta \hat{y}^1(t)$ from model $i: \{\hat{A}; \hat{B}\}_i^1$ simulated on a fully detrended data sequence $\{u; y\}_{F_n}$ (filtered with cut-off frequency F_n) are:

$$(5.3.6) \quad \Delta \hat{y}^1(t) = y_{F_n}(t) - \hat{y}^1_{F_n}(t) =$$

$$\left[A^{-1} . B^*_{F_n} - \hat{A}^{-1} . \hat{B}^1_{F_1} \right] . u_{F_n}(t) + w_{F_n}(t)$$

¹: If the high-pass filter frequencies are taken too high the "true" parameters $\{A^*; B^*\}$ may change.

Using this method the second term $w_{nF}(t)$ in the simulations is constant. Only differences in the estimated model parameters cause a variation in the output error residuals term $\Delta \hat{y}^1(t)$.

The estimated parameters will be unbiased with respect to the trends in the process outputs if these trends are eliminated from the signals. As a result the simulated output residuals will remain constant. From a plot of the simulated output residuals of model $\{A;B\}^1$ as function of F_1 on the data sequence $\{u;y\}_{F_1}$ the frequency of the proper trend filter to be used F_c (Hz) can be determined.

A protocol with all the aspects of importance for application of the scheme described above is given in figure 5.2.

The protocol starts with decimation of the process data and selection of an input-output relation. Essential in the protocol is the success of the LS parameter estimation, meaning that a LS estimation $\{A;B\}^0$ must have a relative simulation output error on the unfiltered sequence $\{u;y\}^{F_0}$ of at least less than 100 %. Before filtering and successive parameter estimation can be performed adaption of the model order, time delay correction, decimation factor or input-output selection may be necessary.

Generally the model order $\{nA;nB\}$ to use has to be chosen high enough to prohibit side effects from this choice. The procedure is found to be not working properly if the latter is not taken high enough!

A simple rule is : take the order of the A and B polynomials $\{nA;nB\}$ equal to the order as follows from an equation-error test (with the application ORDERTEST) and add a few orders.

The protocol has been applied to the measured data of the feeder and the hydraulic-thermic process.

The process signals of the feeder, figure 5.1, are heavily corrupted by trends.

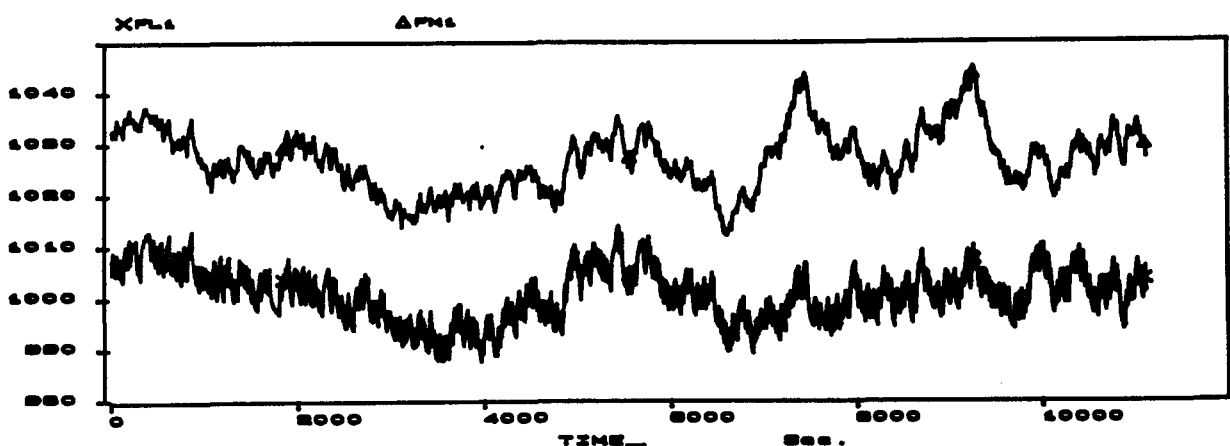


Figure 5.1 Measured output signals in the second section of the feeder, FDSP_FM1 and FDSP_FL1

2: The application MODELST is used to calculate the simulation output residuals : $\text{var}\{\delta y(t)\}/\text{var}\{y(t)\}$.

We start with raw measured process data sampled with sample time T_0 : $\{U;Y\};T_0$.

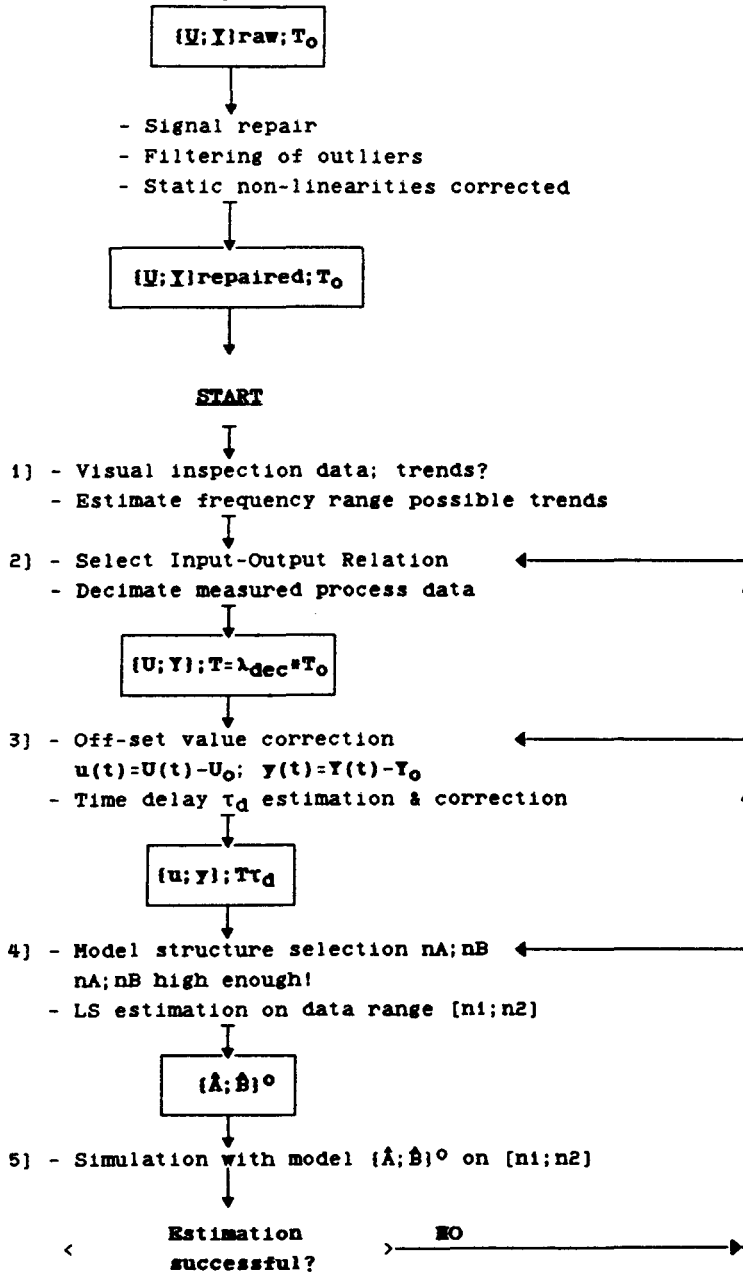


Figure 5.2.a A protocol for the determination of the proper trend filter, phase 1: input-output selection, decimation and model order determination for LS estimator.

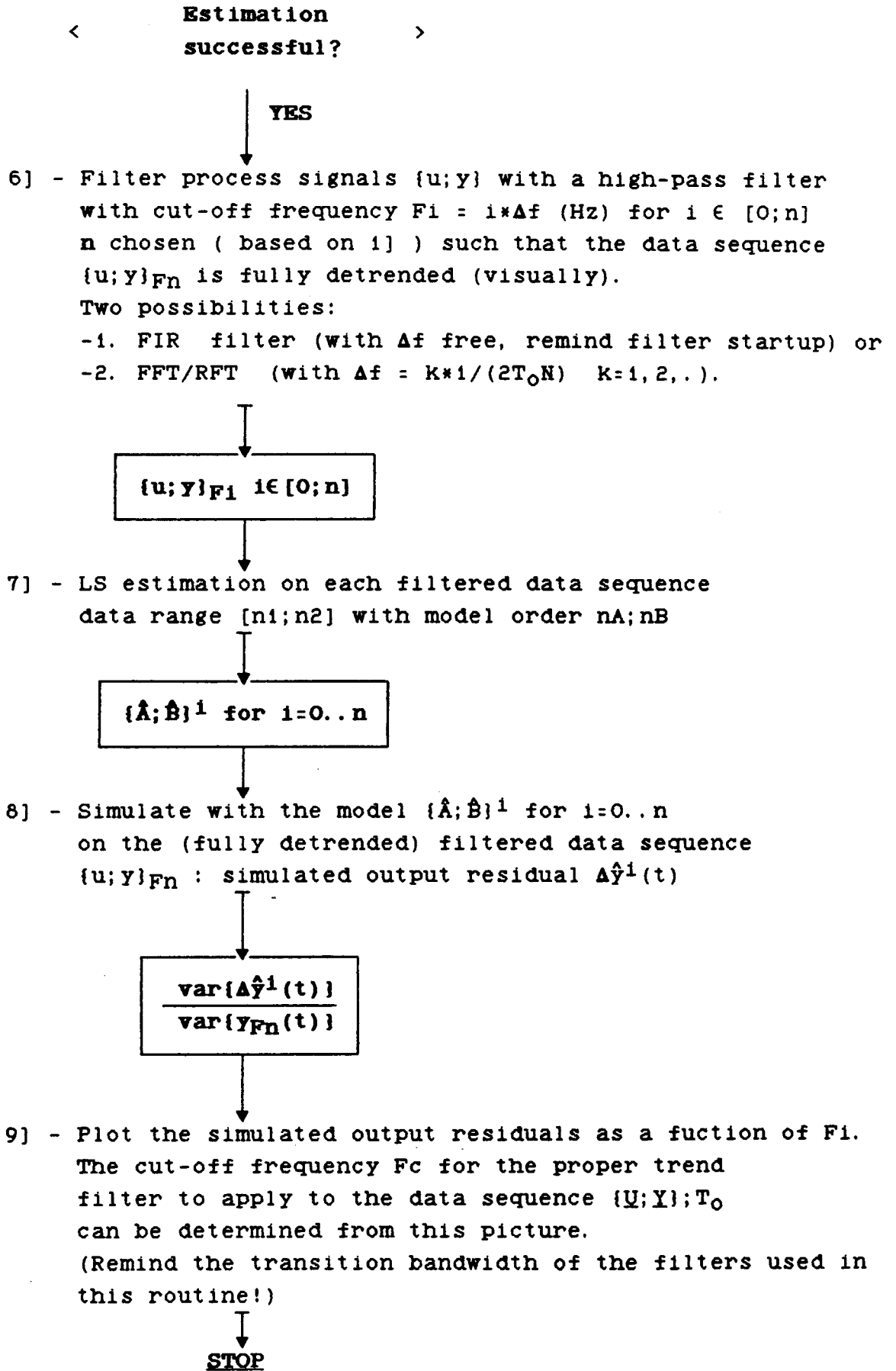


Figure 5.2.b A protocol for the determination of the proper trend filter, phase 2: filtering, model estimation and simulation.

After decimation of the feeder data with a factor 10 the protocol is applied to the temperatures FDSP_FM1 and FDSP_FL1 (MIMO estimation).

The model order used is $n_A=6; n_B=6$. All available samples (1100) are used. High pass filtering is performed with FIR filters using a HAMMING window function with minimum transition bandwidth $8.3E-4$ Hz). For proper startup of the FIR filters 100 samples at the beginning and at the end are taken. 8 filters are used with cut-off frequencies : $F_i = i \cdot \Delta f$ with $\Delta f = 2.0E-4$ Hz and $i = [0, 7]$.

The biasedness of the LS estimator due to the trends in the measured data can be observed if we look at the estimated models. In figure 5.3 the simulated impulse responses of the estimated models are given. The tail of the impulse responses varies with the trend filter used up to a certain frequency.

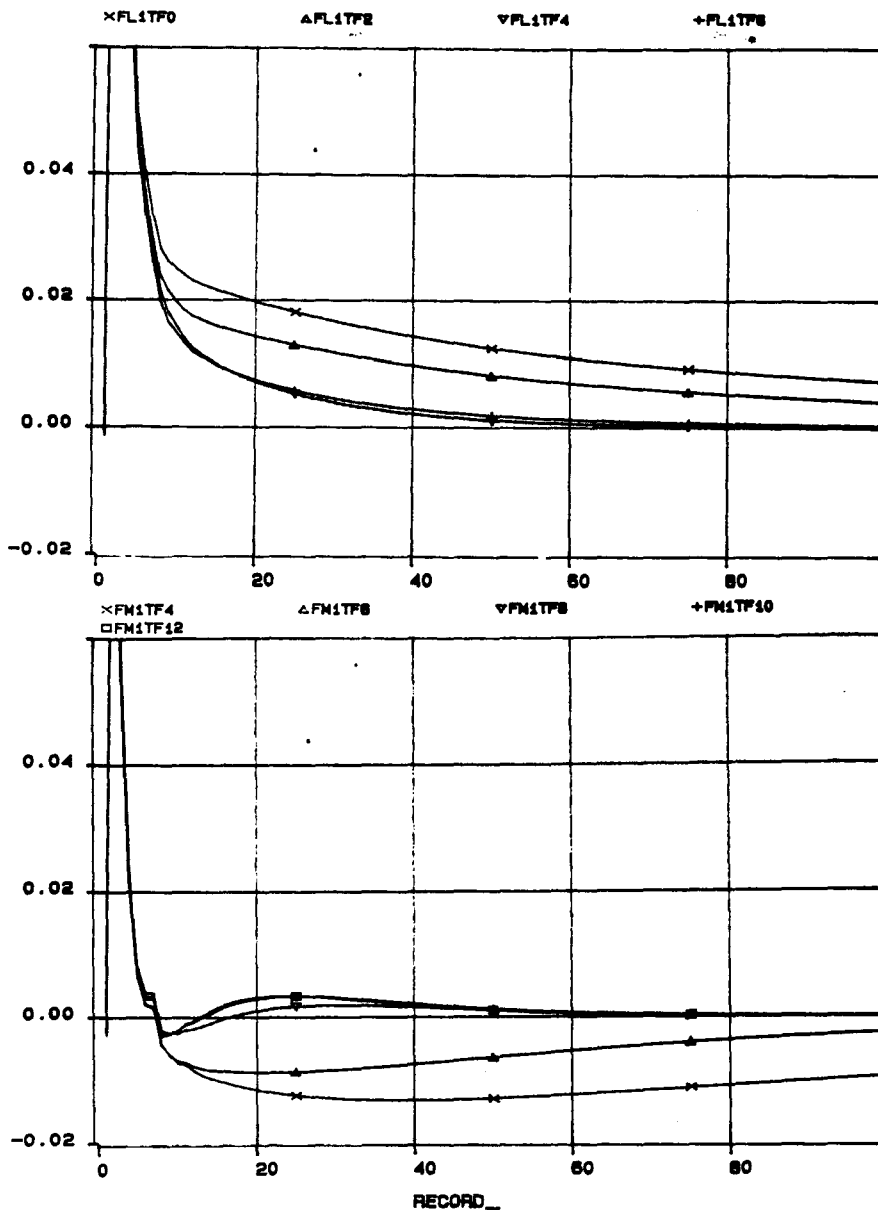


Figure 5.3 Simulated impulse reponses for the feeder temperatures FDSP_FL1 and FDSP_FM1 with the estimated models {A;B}¹

The result from the protocol is given in figure 5.4. The cut-off frequency of a proper trend filter for the temperature FDSP_FL1 is found to be $4.0E-4$ Hz for the FIR filter used. For the temperature FDSP_FM1 a cut-off frequency of $8.0E-4$ Hz is found. Dependent on the variables used in an estimation the highest cut-off frequency has to be selected. In successive trend filtering of the raw measured data using the result of the protocol the finite transition bandwidth of a filter has to be remembered.

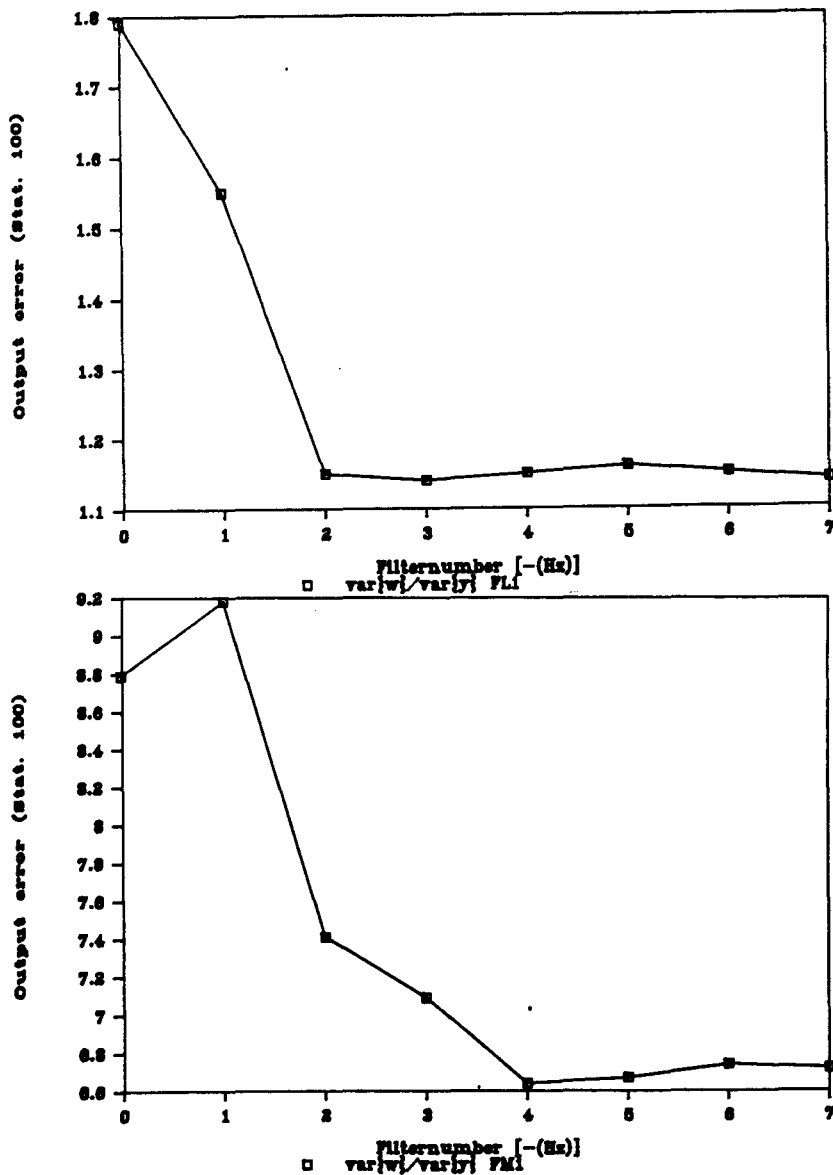


Figure 5.4 Result from the trend filter determination protocol for the feeder temperatures FDSP_FL1 and FDSP_FM1. $\Delta f = 2.0E-4$ Hz. Transition bandwidth FIR (HAMMING) filters = $8.3E-4$ Hz.

If we study the trend filtered from the feeder signals, figure 5.5 we observe two terms: a very low-frequency term originating possibly from the furnace and a second term with a period of about 24 hours. In the feeder temperature FDSP_FM1 this day-night rhythm can be seen.

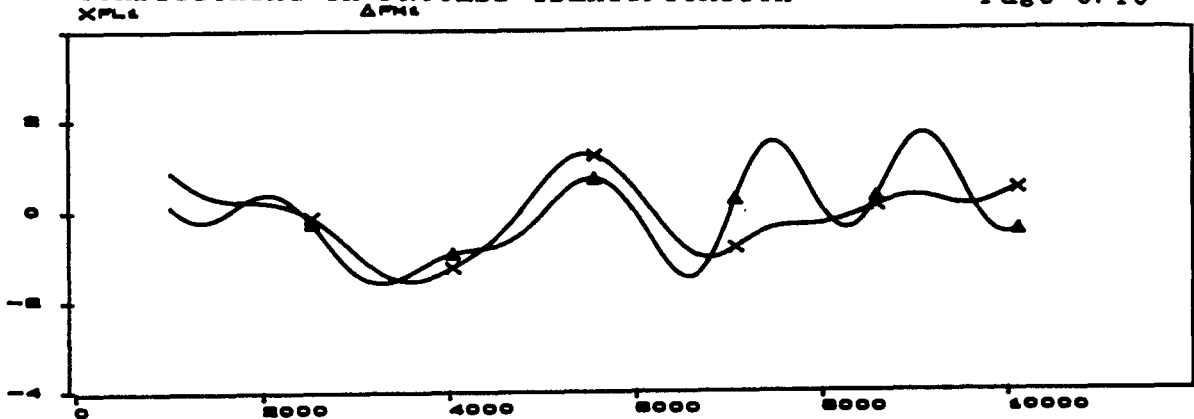


Figure 5.5 Trends filtered from the feeder temperatures FDSP_FL1 and FDSP_FM1 with a FIR filter with minimum transition bandwidth $8.3E-4$ Hz and cut-off frequency $8.0E-4$ Hz

The protocol has also successfully been applied to other feeder temperatures. In application to simulation data, disturbed on purpose with trends, the exact cut-off frequency (remember the finite transition bandwidth of the FIR filter) for filtering of the trends resulted.

If we study the output signals, figure 5.6, from the second vessel T_4 and H_4 , in the thermal-hydraulical process we can see a "dip" in the middle of the signals. This might be a trend signal. In application of the protocol however no trends are discovered. The simulated output residuals on a fully "detrended" data sequence stay almost constant as function of the filter cut-off frequency. Model estimations on the "trend" filtered process data in fact generally had a worse simulation behaviour. If we study the "trend" filtered inputs, Q and Q_s , the same "dip" can be seen in signal Q . This means that the "dip" in the output signals can be explained from a low frequency component in the input signals.

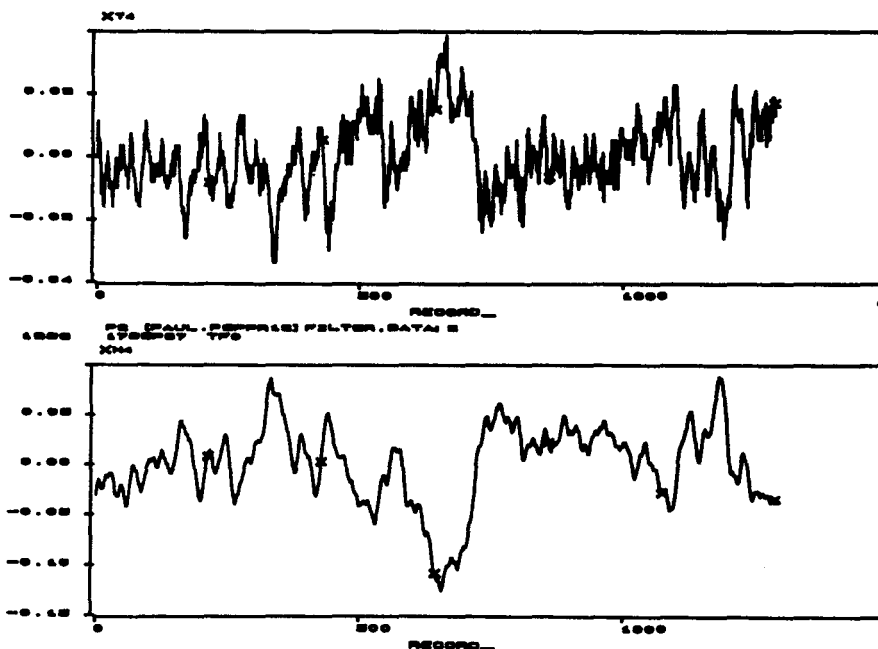


Figure 5.6.a Measured output signals at the second vessel of the thermal-hydraulical process

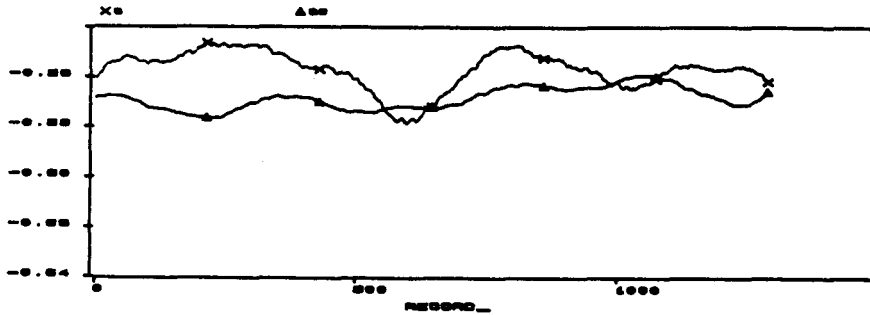


Figure 5.6.b "Trends" filtered from the inputs Q and Q_s of the hydraulic-thermic process

§ 5.4 Influence of Data Conditioning on Process Identification

In this paragraph some aspects of data conditioning on the raw measurement data from the feeder process are discussed. In analysis of the feeder data first a thorough visual inspection is performed. Several disturbances in the inputs COOL_AIR and F2_GAS exist. If we look at the different signals from the feeder trends are apparent. These trends mainly originate from the oven where large disturbances in the energy input are visible, see figure 5.7.

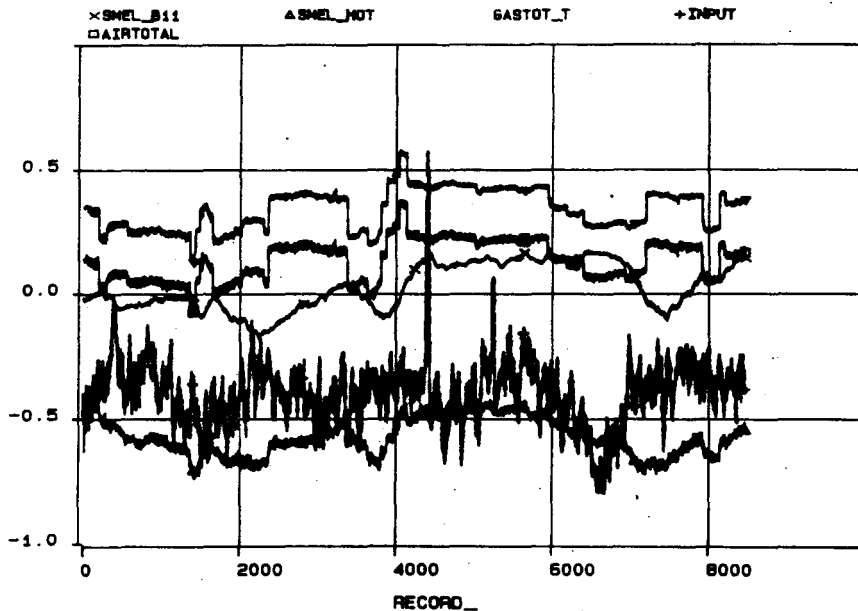


Figure 5.7 Signals from the glass-oven causing trends in the feeder temperatures

Apart from the the improved simulation result of a model on conditioned data the estimated model of the process dynamics is better. Due to the high energy content of the disturbances in the raw data a parameter estimator tries to incorporate these effects into the model. This can be seen clearly if we look at, figure 5.8. Poles with very large time constants occur in the model if the trends in the data are not filtered. In figure 5.8 the impulse responses of the estimation (with MARKOV), presents the spout temperature FDSP_F51. Estimation has been performed on the "raw" data and on the fully filtered data. On the "raw" data offset value correction and sample reduction with a factor 10 is performed. On the fully filtered data sequence the input signal disturbances are repaired and trend filtered with a FIR (Hamming window) filter of maximum size with cut-off frequency $8.0E-4$ Hz and transition bandwidth $8.3E-4$ Hz. The simulation output residuals are calculated with MODELST.

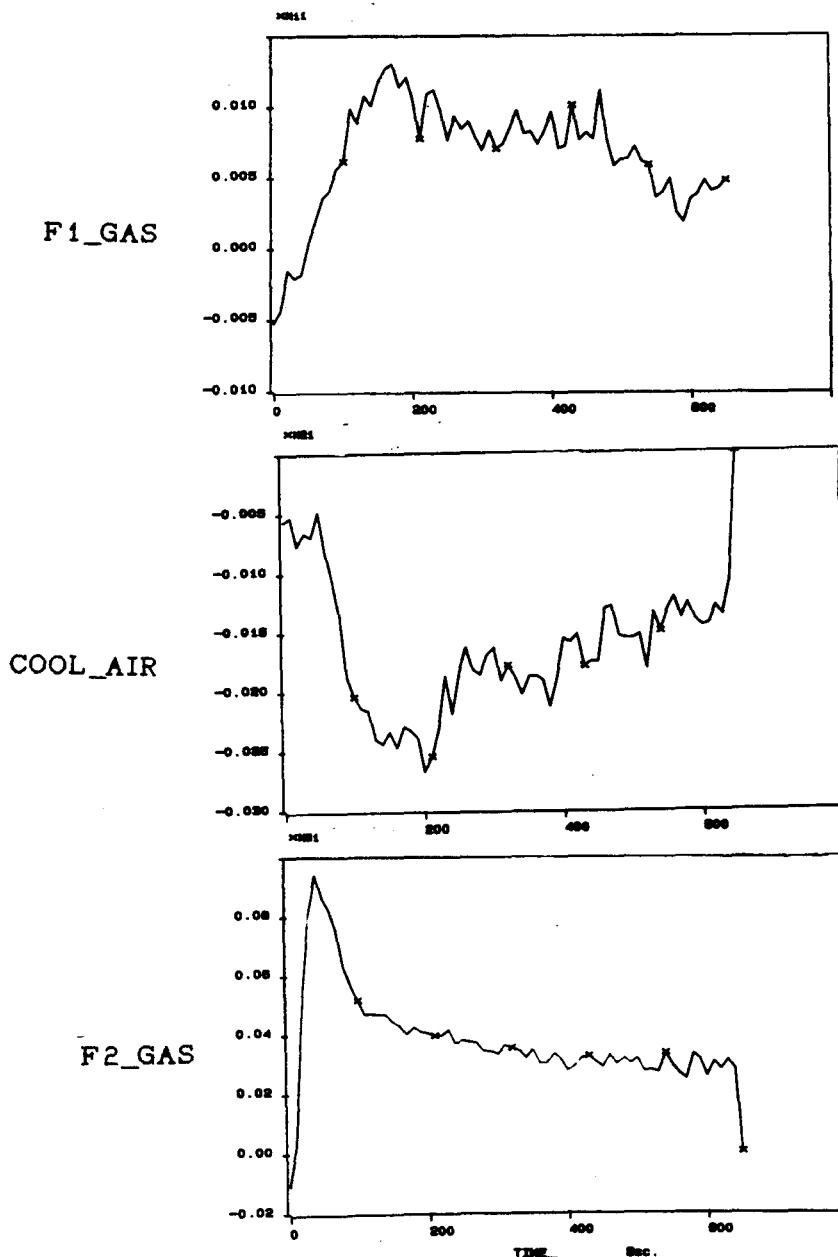


Figure 5.8.a Estimation result of MARKOV (response length=65, 912 samples) of FDSP_F51 on the "raw" data: reduction factor 10, offset values corrected. Sim. error N/S = 39.38%. on the data range [91,912].

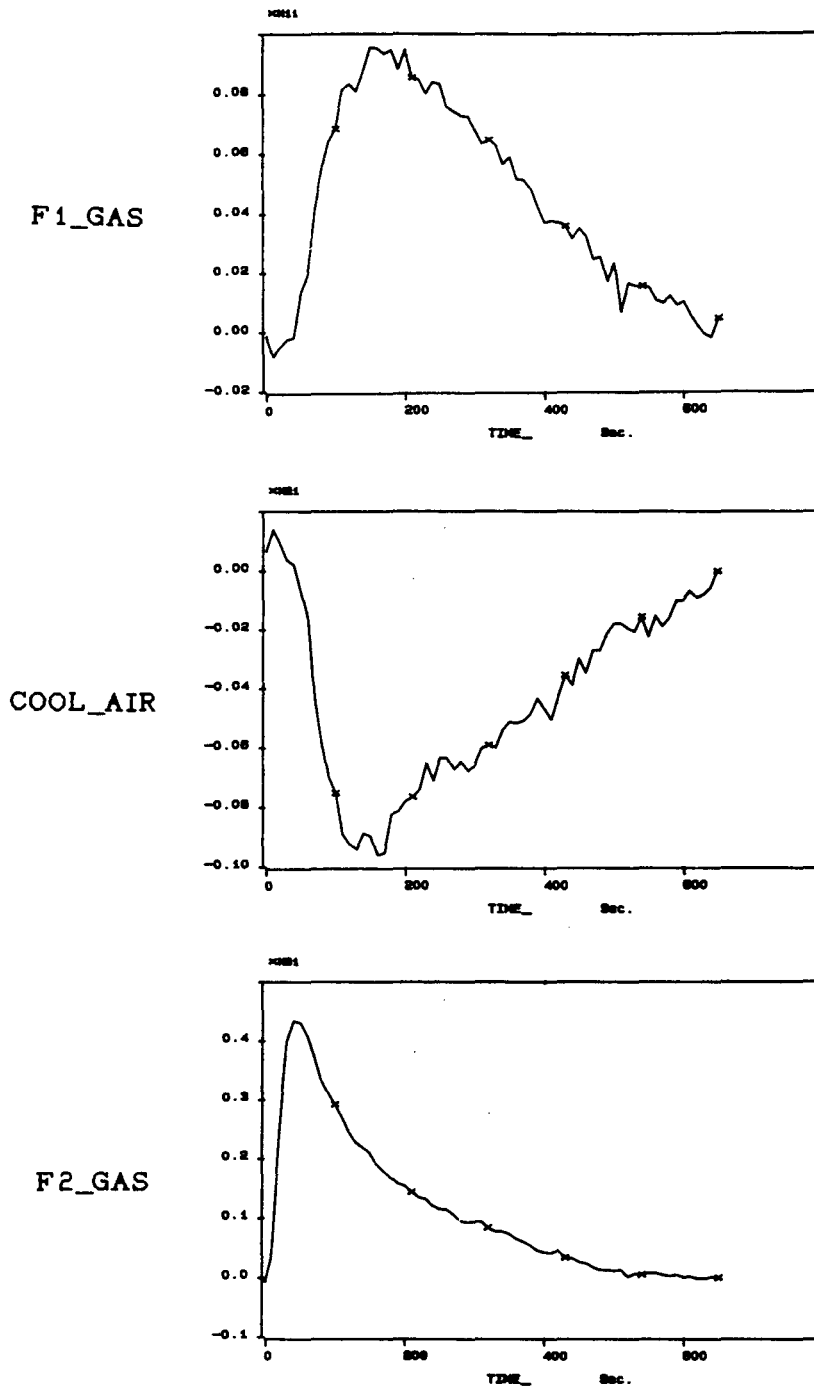


Figure 5.8.b Estimation result of MARKOV (response length=65, 912 samples) of FDSP_F51 on the filtered data: disturbances repaired, trend filtered : FIR filter, Hamming window, $F_c=8.0E-4$ Hz and minimum transition bandwidth, reduction factor 10. Sim. error N/S = 1.43 % on [91,912].

Not only the parameter estimation on the raw data is influenced by the trends but also the accuracy (estimation!) is worse. If we study the estimates of the parameter accuracy of the markov impulse response estimates from the input F2_GAS to the feeder temperature FDSP_F51 on the "raw" and the filtered data, figure 5.9 clearly the parameter estimation accuracy is less for the "raw" data.

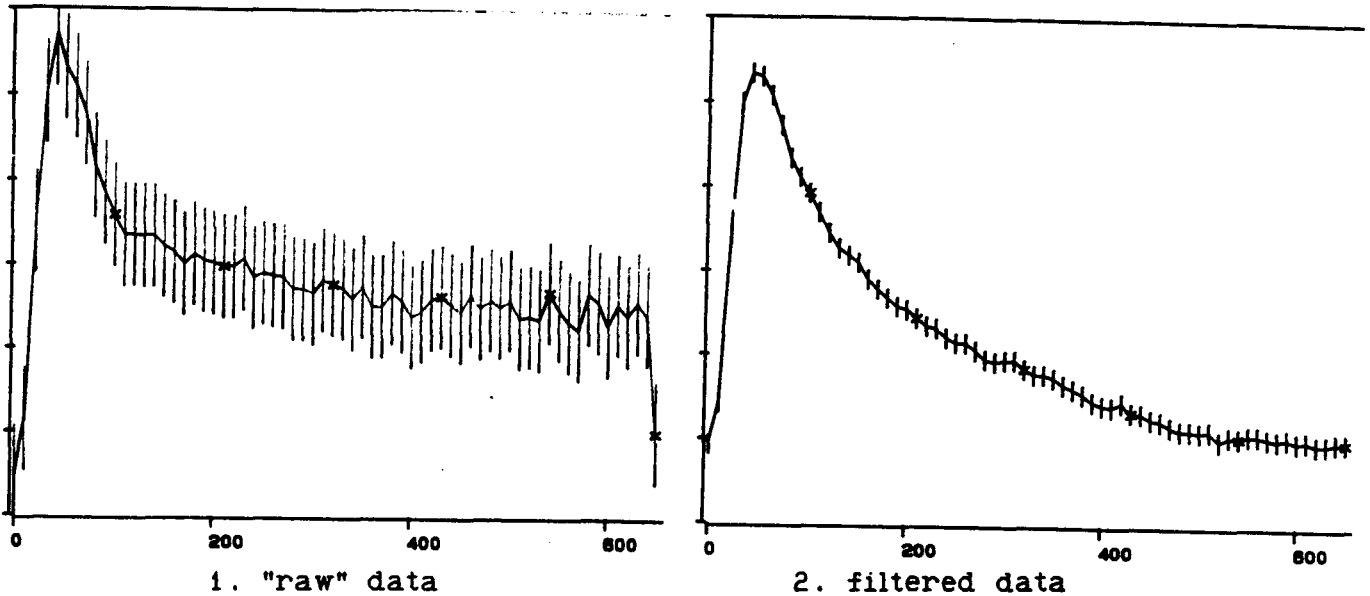


Figure 5.9 Estimation result of MARKOV (response length 65, 912 samples) from input F2_GAS to FDSP_F51 on the "raw" 1. and the filtered 2. data.

Numerical conditioning of the estimation problem and the converge of the estimate of the covariance matrix P influence the accuracy of the parameter estimation.

It is found that the direct impulse response estimates with MARKOV on the filtered data suffer less from oscillations (with $\omega = \omega_s/2$ (nyquist frequency)) in the parameters than the estimates on the "raw" data. Probably the better numerical conditioning of the parameter estimation on the filtered data is responsible for this. The results from the equation error order-test are found to be influenced by disturbances in data. In using the recursive application Guidorzi sometimes unstable models resulted after encountering an outlier in the data.

§ 5.5 Conclusions

Disturbances in measured process data have influence on the performance and result from identification methods. Since the parameter estimator tries to incorporate trends and outliers with high energy content in the model.

Most disturbances in measured process data can be taken care of with the application FILTER. The usage of FILTER for the different operations is straightforward. Only the determination of the trend filter to use is a problem if the spectral band of the trends is close to the process band. A sharp filter has to be used to be certain that all trends are filtered, but as little as possible information of the process is removed from the measurement data.

A protocol is developed to solve this problem. The least squares estimator to use in the protocol has to be successful. On the process data sequences studied the protocol is found to be working properly.

Chapter 6. CONCLUSIONS

This report discusses interactive modelling of the dynamical behaviour of practical processes. Attention is focused on the experiment design and conditioning of the raw measured process data. A protocol has been developed which proves to be working properly for the process studied.

Furthermore, conditioning the raw data proved to be of key importance for the success of the identification methods. For this purpose the PRIMAL package has been extended with a new application (FILTER) which offers the most important operations for data conditioning.

A first study is performed with respect to the different aspects of experiment design in process identification. Especially experiments performed in the pre-measurements phase are found to be inefficient. The amount of time spent in this phase however is large. It is suggested that the design of experiments deserves additional attention in the PRIMAL project.

The application of PRIMAL in identification of a practical process proved to be powerful with respect to the interactive and on-line features of the package. Especially the on-line visual monitoring of process signals & results of the analyses proves to be very useful in all the stages of an identification project. PRIMAL offers many tools for analysis of process data. This allows the user to search for the best possible method for a particular problem. It is therefore possible to generate (a picture of) the obtainable results in a short time. A drawback is that in this approach an often enormous amount of data is generated and the user may lose the overview of his actions.

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APPENDIX 1. Least Squares Parameter Estimation (IVM-LS)

The process S that generates the data may be described by a deterministic (model) part and a disturbances part:

$$(A1.1) \quad S: y(t) = x(t) + w(t) \quad \text{with}$$

$y(t)$ the measured output vector at time instant t ,
 $x(t)$ the linear system output vector and
 $w(t)$ the output disturbances vector.

The deterministic part can be described by a transfer function matrix :

$$(A1.2) \quad x(t) = G(q^{-1}).u(t) \quad \text{with}$$

q^{-1} is the back shift operator: $q^{-1} u(t) = u(t-1)$
 $u(t)$ the measured input vector at time instant t .

The disturbances vector contains all the output signal disturbances which can not be described by the transfer function matrix $G(q^{-1})$. It is assumed that these disturbances are not correlated with the input signals.

In practical process data the disturbances vector $w(t)$ not only contains stationary stochastic noise with zero mean but all kinds of disturbances occur (see chapter 5.3).

The LS estimator used by the application IVM-LS estimates the parameters of the model using a Matrix Fraction Description (MFD) to describe the relation between the inputs and the outputs. (Söderström /15/):

$$(A1.4) \quad M: A(q^{-1}, \Theta).y(t) = B(q^{-1}, \Theta).u(t) + v(t, \Theta) \quad \text{with}$$

Θ : a $n\Theta$ -dimensional vector of unknown parameters compounded of the elements from $A(q^{-1}, \Theta)$ and $B(q^{-1}, \Theta)$.
 $v(t, \Theta)$: the model (equation) error at time instant t .

$$A(q^{-1}, \Theta) = I + q^{-1}A(1)(\Theta) + \dots + q^{-n_A}A(n_A)(\Theta)$$

Autoregressive part of the system model
 n_A : order of the polynomial $A(q^{-1}, \Theta)$ and

$$B(q^{-1}, \Theta) = B(0)(\Theta) + q^{-1}B(1)(\Theta) + \dots + q^{-n_B}B(n_B)(\Theta)$$

Moving average part of the system model
 n_B : order of the polynomial $B(q^{-1}, \Theta)$

With the matrix coefficients $\{A^1(\Theta); B^1(\Theta)\}$ linear functions of Θ the model can also be written as a regression equation:

$$(A1.5) \quad M: y(t) = \phi^T(t) \cdot \Theta + v(t, \Theta) \quad \text{with}$$

$\phi(t)$ a data matrix containing the delayed output and input samples.

Assumption: there exists an unique vector Θ^* such that

$$(A1.6) \quad A(q^{-1}, \Theta^*)^{-1} \cdot B(q^{-1}, \Theta^*) = G(q^{-1}).$$

Thus the process can be rewritten as:

$$(A1.7) \quad M: y(t) = \phi^T(t) \cdot \Theta^* + v(t, \Theta^*) \text{ with}$$

$$(A1.8) \quad v(t) = A(q^{-1}, \Theta^*) w(t)$$

The structure of the parameter vector Θ and the data matrix $\phi(t)$ used in the application is described in Berben /12/.

The model parameters are estimated using a quadratic criterion function on the equation error $v(t, \Theta)$ with respect to the parameter vector Θ :

with N observations for $u(t)$ and $y(t)$ available:

$$(A1.9) \quad V(\Theta) = (1/N) \cdot \sum_{t=1}^N v^T(t, \Theta) v(t, \Theta)$$

With respect to Θ the minimizing element is taken as the estimate $\hat{\Theta}$ which follows from $\partial V(\Theta) / \partial \Theta = 0$. It is given by, using equation A1.6:

$$(A1.10) \quad \hat{\Theta} = \Theta^* + \underbrace{\left[\frac{1}{N} \sum_{t=1}^N \phi(t) \phi^T(t) \right]^{-1} \cdot \left[\frac{1}{N} \sum_{t=1}^N \phi(t) v(t) \right]}_{\text{bias}}$$

Due to these signal disturbances the parameter estimation will be biased if the equation error $v(t)$ (equal to $A^* w(t)$) is correlated to the measured output signal $y(t)$.

APPENDIX 2. The Application Filter:
Text data set example

```
Dataset Title      :      FILTER
Creation Date/Time:      2300187      15:48:36
Dataset Size       :      93 records
```

FILTER Application: ver. 1.0

-----Input Data-----

```
[SYSTEM.DATABAD.DATA.DATA]1      24AUG87      ASTROM      1000 records
Sample Frequency      :      1.000      [Hz]
```

STEP 1---Data Selection-----

```
Signal Selection      : See table.
Number of Samples     :      800      Start Sample      :      101
```

STEP 2---Delay Correction-----

See table.

STEP 3---Signal Repair-----

No Signal Repair

STEP 4---Filtering of Outliers-----

```
---Signal---Start sample---Stop sample
1: U      101      900
2: Y      101      900
```

```
Outliers Detection Method      :MEDIAN
Cutoff freq. highpassfilter (Hz) : 0.1000E-01
Start Filter with past samples : T
Data Subset Dimension          :      80
Shaving Strength               :      1.500
Outliers Correction Method     :INTERPOL
```

STEP 5---Non-Linear Correction-----

No Non-Linear Correction

STEP 6---Trend Correction & Noise Reduction-----

```
Filter Coefficients:
Filter-Filter---Window---Filter---Lower / Upper --->
Number Class      Function Type      Cut-off Frequency(Hz)
1 : FIR      HANNING      HIGHPASS      0.2000E-02      --
```

```
->Filter--Transition---Filter-
Number Bandwidth(Hz) Size
1 : 0.5000E-01      33
```

```
Record Signal part Filtered off? : F
Start-up with additional data : T
```

STEP 7---Data Reduction,Scaling & Offset Correction-----

```
Data Reduction Factor: 1
Scaling : F
Offset correction : F
```

		Delay	Non-Linear	Trend & Noise
Signal-----	Correction---	Correction---	Filtering	
U	:	0	0	1
Y	:	-20	0	1

----- Spike Detection Results -----

Signal : U
 Number of Outliers : 109
 Number of Intervals : 94

Interval		Interval		Interval	
Begin-----	End	Begin-----	End	Begin-----	End
1:	106 106	2:	109 109	3:	120 120
4:	124 124	5:	126 126	6:	133 133
7:	136 136	8:	143 143	9:	151 151
10:	153 153	11:	155 155	12:	163 163
13:	166 166	14:	181 181	15:	185 188

Maximally 15 intervals per signal will be written down.

Signal : Y
 Number of Outliers : 47
 Number of Intervals : 19

Interval		Interval		Interval	
Begin-----	End	Begin-----	End	Begin-----	End
1:	153 154	2:	192 196	3:	200 201
4:	243 244	5:	249 249	6:	285 290
7:	297 297	8:	349 350	9:	499 502
10:	634 635	11:	718 721	12:	731 733
13:	778 778	14:	787 787	15:	801 803

Maximally 15 intervals per signal will be written down.

----- Signal Statistics (before scaling and Offset Correction) -----

-Signal-----	Mean-----	Variance-----
U	:	2.5824
Y	:	15.145
		0.14030E-01
		39.297