State of the Art and Needs in Process Identification

Åström, Karl Johan

1976

Document Version:
Publisher's PDF, also known as Version of record

Link to publication

Citation for published version (APA):
Åström, K. J. (1976). *State of the Art and Needs in Process Identification*. (Technical Reports TFRT-7088). Department of Automatic Control, Lund Institute of Technology (LTH).

Total number of authors:
1

LUND UNIVERSITY

PO Box 117
221 00 Lund
+46 46-222 00 00

TFRT - 7088

STATE OF THE ART AND NEEDS IN PROCESS IDENTIFICATION

K. J. ÅSTRÖM

Report 7601 (C) Januari 1976
Department of Automatic Control
Lund Institute of Technology

STATE OF THE ART AND NEEDS IN PROCESS IDENTIFICATION

K.J. Åström
Department of Automatic Control
Lund Institute of Technology
Lund, Sweden

Contents

1. INTRODUCTION

The word identify is defined as: "to recognize or establish as being a particular person or thing" or "to determine to what group a given specimen belongs". These definitions cover reasonably well the way in which identification is used in the control engineering field. In this context identification usually covers some formalized aspects of modeling of dynamical systems based on experimental data.

Since modeling of dynamical systems appears in many different fields, it is natural that contributions are widely spread in the literature. Apart from engineering systems identification is discussed in physics, biology, medicine and economy. The purpose of this paper is an effort to give the status of the field with particul emphasis on problems related to process control.

System identification played a predominant role in classical control theory. The fact that the transfer function of a system can be determined by frequency or transient response analysis was an important factor which substantially contributed to the success of classical control theory. With the advent of the so-called modern control theory it quickly became apparent that efficient methods to determine the appropriate models were lacking. The search for such methods has been a strong motivation for much of the recent work in system identification.

There is a substantial literature on system identification. IFAC has sponsored a sequence of symposia devoted to the problem. Good source of references are the preprints from the first three which were held in Prague 1967 and 1970 and in the Hague 1973. In 1974 a special issue devoted to system identification was published by IEEE. There are also several survey papers e.g. Åström and Eykhoff (1970), Bekey (1970) and Nieman (1971). It is thus of little use to attempt a survey of the field. It is instead attempted to make a personal evaluation of the field with respect to the needs and uses of process control.

The paper is organized as follows. The formulation of identification problems is discussed in Section 2. Some notation is also introduced in that section. A brief review of some aspects of the theoretical developments is given in Section 3. The emphasis is on recent developments and on results that are of interest to applications. A reader who wants a more complete review of identification theory is recommended also to consult Åström-Eykhoff (1971). The use of system identification techniques when modeling dynamical systems is discussed in Section 4, and the application of system identification to on-line control is covered in Section 5. Particular emphasis has been given to on-line identification methods and their use in self-tuning regulators. The conclusions are given in Section 6 where the importance of interactive computing techniques for modeling is emphasized.

2. FORMULATION OF IDENTIFICATION PROBLEMS

System identification includes the following steps

1. Experimental planning
2. Selection of Model Structure
3. Parameter Estimation
4. Validation

Experimental planning includes selection of input signals and sampling rates but also many practical problems that are concerned with performing experiments in an industrial environment. The experiment results in records of input - output data from the process.

The model structures usually considered involves the usual models used in automatic control.

State models of the form

$$\frac{dx(t)}{dt} = f(x(t), u(t), v(t))$$
$$y(t) = g(x(t), u(t), e(t)) \qquad (2.1)$$

where u is the input, y the output, x the state and e, v disturbances are commonly used. Linear systems where

$$f(x, u, v) = Ax + Bu + v$$
$$g(x, u, e) = Cx + Du + e \qquad (2.2)$$

have been given particular attention.

For linear systems input - output descriptions in terms of impulse responses or the transfer function model

$$y(t) = G(p)\ u(t) + H(p)\ e(t) \qquad (2.3)$$

are also common. In (2.3) u denotes the input, e the white noise, y the output, p = d/dt is a differential operator and G and H are matrices of rational functions in p.

A transfer function matrix is sometimes represented by the differential relation

$$\frac{d^n y}{dt^n} + A_1 \frac{d^{n-1} y}{dt^{n-1}} + \ldots + A_n y = B_1 \frac{du^{n-1}}{dt^{n-1}} + \ldots + B_n u \qquad (2.4)$$

Discrete time versions of the models given above are also commonly used. More general modelstructures, which include transport delays and distributed parameter systems, and Rosenbrock's system matrices are also used.

Notice that a significant trend in the recent development is to attempt to model both the process dynamics and the disturbances. This is of course in close agreement with the needs of the control engineer because without disturbances there is no control problem.

The models are usually obtained from the fundamental physical laws governing the process. They will contain unknown parameters and functions. The class of models may for example be such that it includes descriptions like (2.1) where the differential equations have different order.

The identification problem can be formalized as follows:

> "Given a class of models (*M*), records of input - output data from a process obtained under certain experimental conditions (*E*), and a criterion (*C*). Find a model in the class which fits the experimental data in the sense of the criterion". (2.5)

The criterion is often stated as an optimization criterion, for example to minimize a measure of the deviation of the model output and the measured output. If the disturbances appearing in the model (2.1) are stochastic processes, the parameter estimation problem can also be stated in statistical terms. The maximum likelihood method is a popular method for parameter estimation which again reduces to an optimization problem. The parameter estimation problem thus frequently reduces to an optimization problem.

When choosing the experimental conditions, the model structure and the criterion, several assumptions on the properties of the process have to be made. These assumptions can only rarely be verified. By a careful checking of the results it is, however, possible to see that the measured results at least do not violate the assumptions made. This is the purpose of the validation step. It consists of application of common sense and sometimes also statistics. It is of course never possible to guarantee that the assumptions made are true. Therefore the results must often be crosschecked by repeating the process using new experiments. Serious modelers and identifiers therefore never consider the final model as true, but rather as a reasonable candidate which can be used until it is rejected by further experiments.

3. PROGRESS IN THEORY

The identification problem has received much attention from theoretical researchers over the past decades. The reason has partly been the availability of a set of new problems that are amenable to analysis, Ph.D. theses and appropriate publications. In some cases the problems have been motivated by the desire to obtain models like (2.1), (2.2) for an industrial process, in order to apply modern control theory. The theory developed has undoubtedly given a significant insight and understanding of many problems even if no totally coherent picture is yet available. An attempt has been made here to give an overview of some important results. To avoid duplication of already published material it is recommended that the interested reader also consults the survey paper Åström-Eykhoff (1971).

System Theory

The very active research in system theory has given very important results on the properties of dynamical systems and their different descriptions. A typical example is the decomposition theorem given by Kalman (1963) which says that a linear time invariant system.

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t) \qquad (3.1)$$

can be decomposed into four subsystems and that the transfer function is uniquely given by the subsystem which is completely reachable (controllable) and completely observable.

This result clearly gives a limit to what can be determined by analysing input - output records. Together with the criteria for observability and reachability Kalman's results also provide useful hints as to the selection of suitable sensors and actuators that are needed to obtain relevant information about a system. Kalman's results, however, only apply to linear systems.

Realization Theory

The special case of the identification problem which is obtained when the model is linear, given by (3.1), and the measurements noise free is called the *realization problem*, Ho and Kalman (1965). Even if this problem is highly simplified, its solution provides important insight. A prospective user should however be warned that many specific results, for example the methods to determine the order of the system by determining the rank of the Hankel matrix, are difficult to use in practice because of the very restrictive assumptions made when neglecting disturbances both in the process and in the measurements.

Parametrization of the Models

By defining the criterion (C) in the identification problem (2.5) as an optimization criterion, the identification problem becomes an optimization problem. If the experimental data is gathered digitally, the experiment results in a finite data set. If a non-parametric model is used e.g. an impulse response, then there are roughly speaking an infinite number of parameters to satisfy finitely many constraints and it is not unlikely that a perfect fit can be obtained. The penalty is that the model description obtained is highly irregular. An ad hoc smoothing is then introduced to obtain a smooth result. Typical examples are estimation of spectral densities and determination of transfer functions and impulse responses by correlation methods. In these cases the smoothing appears as truncation of series and selection of spectral or lag windows. By introducing a parametric model, the smoothing is instead done with respect to the structure of the particular model which hopefully is based on sound physical knowledge. The selection of the class of models and the parametrization of a dynamical system are thus important problems.

When the models are derived from physical laws, there are often natural parametrizations. When the parametrization is given, another important problem is to decide if there are several values of the parameters which give the same input - output properties. This is the problem of parameter identifiability. Mathematically this problem reduces to determine if a nonlinear equation has a unique solution. There are several local results, but (naturally) very few global results. In the particular cases where solutions can be found, very valuable information can be extracted from them. For example, it can be decided which parameters can be determined from a particular experiment. The analysis may also suggest changes in the experimental procedure which will result in parameter identifiability. For example introduction of more sensors and more actuators.

Notice, however, that if the aim of the modeling is to design a control law, then parameter identifiability is of less importance because any input - output description will suffice for the control design.

In some cases, for example when strongly simplified models are made for complex phenomena, it may be difficult to have a parametrization with a natural physical interpretation. A model may for example simply be a n:th order linear stochastic system. It may then be asked if there are parameter identifiable representations of such systems and moreover if there are such representations with the smallest number of parameters, so-called canonical representations.

Canonical representations of linear, time invariant stochastic systems are known if the systems have one output or one input only. For multivariable systems, however, no such parametrization can be given unless the observability and reachability indices are known. See e.g. Rosenbrock (1970)

Several methods have been proposed to determine the structural indices (Kronecker invariants). The techniques depend, however, on judicious choice of test quantities, and they do not work well on noisy data. An interesting alternative to estimate the structural indices simultaneously with the parameters has recently been proposed by Ljung and Rissanen (1975).

Another problem which also faces the modeler is the following. A parametric model has been obtained. It is quickly realized that all parameters cannot be determined uniquely. Very poor fit to the experimental data is obtained when attempting to vary a subset of the parameters until the "right" subset is found. The problem is clearly related to sensitivity theory. Physical insight is often a good guide but it would be highly desirable to have systematic tools.

Finally a few comments on discrete time models. Since the input - output data is frequently sampled, it is tempting to fit discrete time models discretly. This usually leads to simpler calculations. Another advantage is that sampling of a linear system consisting of a time delay and a rational transfer function will always yield a rational pulse transfer function. Hence there are no problems of pure time delays. A serious drawback is, however, that the natural physical parametrization is usually expressed in continuous time models. It is therefore useful to have techniques and software available that admits fitting a continuous time model. See Källström et.al. (1975).

Criteria

The first formulation, solution and application of an identification problem was given by Gauss (1809) in his famous determination of the orbit of the planet Ceres. Gauss formulated the identification problem as an optimization problem and introduced the principle of least squares in the following way:

> "Therefore, that will be the most probable system of values of the unknown quantities p, q, r, s, etc., in which the sum of the squares of the differences between the observed and computed values of the functions V, V', V'', etc. is a minimum".

Ever since, the least squares criterion has been used extensively. Nowadays the least squares method (LS) commonly refers to a method where not only the criterion is quadratic but also the model is such that the errors (i.e. the differences between the observed and computed values) are linear in the parameters. The solution of the problem can then be given in closed form. It should, however, always be remembered that least squares is often chosen for mathematical convenience. This was clearly pointed out by Gauss.

> "Denoting the differences between observation and calculation by Δ, Δ', Δ'', etc., the first condition will be satisfied not only if $\Delta\Delta + \Delta'\Delta' + \Delta''\Delta''$ + etc., is a minimum (which is our principle), but also if $\Delta^4 + \Delta'^4 + \Delta''^4$ + etc., or $\Delta^6 + \Delta'^6 + \Delta''^6$ + etc., or in general, if the sum of any of the powers with an even exponent becomes a minimum. But of all these principles ours is the most simply; by the others we should be led into the most complicated calculations".

Because of the simplicity of the least squares problem it is always tempting to use this formulation. There is also a whole collection of methods available which consists of iterative uses of least squares, repeated least squares (2LS, 3LS,... etc.), generalized least squares, instrumental variables. It is, however, useful to remember that many of these methods were introduced before the time when digital computers were easily accessable.

When the disturbances of a process are described as stochastic processes, the identification problem can be formulated as a statistical parameter estimation problem and the whole artillery of statistical estimation methods becomes available. The maximum likelihood method is a popular technique which has many attractive statistical properties. See e.g. Åström and Bohlin (1965), Balakrishnan (1969) and Mehra (1969). This method can also be interpreted as a least squares criterion if the quantity to be minimized is taken as the sum of squares of the prediction errors or more precisely in the case of discrete time observations at times t_o, t_1,...t_N the criterion is given by

$$V(\theta) = N/2 \log \det R + \frac{1}{2} \sum_{1}^{N} \varepsilon^T(t_i) R^{-1} \varepsilon(t_i) + \frac{Np}{2} \log 2\pi \quad (3.2)$$

where $\varepsilon(t_i)$ are the prediction errors

$$\varepsilon(t_i) = y(t_i) - \hat{y}(t_i | t_{i-1}) \quad (3.3)$$

Using such an interpretation it is not necessary to have assumptions on normality of the residuals. Many of the nice properties of the ML technique can also be extended to this case. See Ljung (1975).

Sampling Rates

When the maximum likelihood method is applied to determine the parameters of a dynamical system, the dynamics of the model is thus only judged by its ability to predict the output over intervals corresponding to the spacing of the sampling points. This means that the selection of sampling rates is crucial. It also explains why the models obtained from ML calculation frequently give a bad representation of low frequency dynamics. The discussion also immediately suggests using non-uniform sampling where the spacing between the sampling points cover the time interval of interest. It also emphasizes the desirability to look closer to the criteria used in stating identification problems and if possible relate them to the ultimate use of the model.

Optimization Algorithms

It has already been mentioned that identification problems lead to a nonlinear optimization problem. In the identification problems a function evaluation involves simulation of a dynamical system. Such calculations can easily become excessive. Much effort and ingenuity has therefore gone into the development of suitable computer algorithms. The evaluation of gradients of the loss function can, for example be done either by sensitivity functions or by using the adjoint variables associated with the differential equations which also appear in optimal control problems.

The problems may often be subject to the inherent difficulty of nonlinear optimization, namely existence of multiple minima. These problems are closely related to the problem of identifiability. In special cases when the problem can be formulated in such a way that the criterion is a quadratic function of the parameters, a closed form solution is thus possible. Due to the simplicity of such problems many efforts have been made to invent algorithms which consists of an iterative sequence of least squares problems. Typical examples are the generalized least squares and the iterative least squares methods which originated in econometrics. See e.g. Wold (1964)

Let it suffice to mention here that there are many optimization schemes and many computational tricks available, but that the numerical calculations are far from trivial and rarely investigated. See Åström and Bohlin (1965), Åström (1969) and Gupta and Mehra (1974)

Statistical Analysis

When the identification problem is formulated as a statistical parameter estimation problem, there are many ideas and results from statistics that can be exploited. Such an approach will, however, require that certain assumptions are made on the mechanism which generated the data i.e. the real process. This is most unpleasant because the real process is often nonlinear, time varying, and infinite dimensional and little is known about it. It is also frequently logically inconsistent bacause it leads to "circular proofs". A typical case is that it is assumed that the data was in fact generated by a dynamical system which belongs to the class of models considered.

Great care should therefore be used when the results of statistical analyses are interpreted. It has been found empirically that many methods work very well on simulated data but very poorly on real data. This reflects that certain results are sensitive to variations in the data generation and it indicates tha needs for research into the problem of mismatch between the model structure and the datageneration. Some results in this area have been obtained by Ljung (1975).

Provided that assumptions on the data generation can be made many useful results can be obtained. For example it is sometimes possible to determine the statistical properties of the estimates for. large data sets. Assuming that the mechanism which generated the data is known it is also possible to analyse if the estimates converge with increasing data sets. In particular if the model structure is flexible enough to include the data generating mechanism it is then also possible to obtain conditions such that the estimates will converge to their "true values". Statistical methods can also be used to decide between models having different structures. For example, the choice between the models having a different number of parameters can be formulated as a hypothesis test using the test quantity

$$t = \frac{V_1 - V_2}{V_2} \cdot \frac{N - p_2}{p_1}, \quad p_2 > p_1 \tag{3.4}$$

where V_i is the loss function (e.g. the negative logarithm of the likelihood function) of the model having p_i parameters and N the number of sampling points. The model with more (p_2) parameters is preferred if the value t is sufficiently large.

An interesting approach to this problem has recently been given by Akaike (1973) who suggests using the criterion

$$AIC = -2 \log (ML) + 2p \tag{3.5}$$

where ML is the maximum likelihood and p is the number of parameters. Akaike's criterion, which is based on information theoretic considerations, is equivalent to (3.4) if V_1 is close to V_2. It does, however, dispense with the arbitrary selection of a risk level associated with the hypothesis testing.

Experimental Conditions

It is always difficult and costly to perform experiments on real industrial processes. Many of the recently developed methods for system identification have broadly speaking reduced the constraints on the experiments at the expense of increased computations. For example it is no longer necessary to have input signals with a precisely prescribed form like sinusoids or pulses having special shapes.

There is a substantial literature on planning of statistical experiments. See e.g. Cox (1958) and Federov (1972). These results have been extended to estimation of parameters in models of dynamical systems. See e.g. Goodwin et.al. (1974) and Mehra (1974).

All results on optimal input design are, however, based on the assumption that a model of the process is known. This means that the results can only be used when a reasonably good apriori knowledge of the dynamics of the process and its environment is available. Good applications are known. The results may, however, also be strongly missleading if the process dynamics differs from the apriori assumptions. The results on design of optimal inputs are also restricted because it is frequently assumed that the process is open loop during the experiment. The possibility to base system identification on data obtained under closed loop control of processes have been explored. The presence of the feedback may result in lack of identifiability. If the feedback is sufficiently complex e.g. linear of high order, nonlinear or timevarying, then identifiability may still be retained even if data is gathered during closed loop operation. There are in fact situations where the closed loop experiments will give better results then open loop experiments. A detailed discussion of this is given in Söderström et.al. (1975).

4. THE ROLE OF SYSTEM IDENTIFICATION IN MODELING

Models and Modeling

The major results of control theory are based on the assumption that a model for the dynamics of the process and its environment is available. The lack of such a model is thus a severe obstacle towards a more widespread use of control. Many difficult control problems are created by neglect of dynamics in the process design. The availability of models will also offer the potential of designing an efficient process with a control system as an integral part. Modeling is thus an important task that will gain in importance in all areas of process control.

Before discussing how identification fits into this, I will give a few personal opinions om modeling of dynamical systems. First it is important to realize that there is no such thing as <u>the model</u> of an industrial process. It is much more useful to think in terms of a <u>hierarchy of models</u>, ranging from very detailed and complex simulation models of whole processes to the 'back of an envelop model' which is easily to manipulate analytically. The simple models are used for exploratory purposes to obtain orders of magnitude, the gross features of the system behaviour and to judge if proposed control schemes are reasonable etc. The very complicated simulation models, which may also contain pieces of the real process, are used for a detailed check of the control system to make sure that no details have been neglected. The complicated models take a long time to develop and they are costly to maintain. They do, however, reproduce the properties of the real system with high fidelity and they are a necessity for design of critical processes.

Between the two extremes there may be many different types of models which are used for design of control systems. A characteristic feature of a successful control engineer is that he has a very well developed intuition which allows him to choose the right model for a particular problem. The crucial problem is of course to steer between oversimplification with the danger of disaster and overcomplication which requires too many resources.

Black Boxes, Grey Boxes and White Boxes.

Process models can be obtained from basic physical laws (the White Box approach) or by fitting a linear transfer function or time series model to input-output data (the Black Box approach). There is sometimes a controversy among modelers concerning the appropriate approach.

The Black Box approach can be done fairly quickly. Experience has shown that it usually leads to fairly simple models. A disadvantage is that the approach leads to a linear model for a particular operating condition. The models derived from physical laws are usually valid over a wide operating range. They also provide good insight into the behaviour of the system. A drawback with white box modeling is that the physical knowledge is not always easily available. The models tend to be complex and they take a long time to develop.

Recognizing the advantages and disadvantages of modeling from physical laws and from input-output experiments, it seems highly desirable to try to exploit both methods in order to solve a particular modeling problem (the Grey Box approach). The examples given later in this section illustrate this approach.

Identification as a Modeling Tool

System identification techniques proved useful tools for several aspects of the modeling process. It can be used in exploratory phases when little is known about the process. The order testing procedures can suggest the model complexity needed to explain the measured data. Identification procedures can also be very valuable in those cases when a lot of a priori knowledge is available and the problem is to determine precisely the values of certain coefficients. These aspects are illustrated below by examples from specific applications.

Power Boilers

A detailed presentation of this work is given in Eklund (1971). The goal was to arrive at a reasonably simple model for design of controls for a drum boiler. The basic physics is fairly well understood although the phenomena are complicated. Key questions are related to choice of suitable approximations and lumping of the distributed system. The basis of the work was a set of experiments performed by removing all regulators and perturbing fule flow, steam flow and feedwater. In this modeling exercise, identification was used in the following way. Simple transfer function models were fitted using the maximum likelihood method. The application of statistical methods for order test gave an indication of the model complexity required to explain the measured data. The results indicated clearly that low order models were sufficient. Using these results it was attempted to derive physical models having the appropriate complexity. The major problem was to decide when to describe a conservation law by a static or a dynamic model and to determine a suitable lumping of distributed phenomena. Guided by the results of the identification many possibilities could be eliminated. A few alternative models remained. The parameters of these were estimated. Based on analysis of these model it was finally possible to make the final selection.

Ship Steering Dynamics

A detailed presentation of this work is given in Åström and Källström (1975). The basic physical laws were available. A key problem was to determine if extra state variables had to be included to model disturbances. Another important problem was to determine if certain physical parameters (the so-called hydrodynamic derivatives) which appear in the equations of motion can be determined from an experiment where the rudder is perturbed and the resulting motion observed. An analysis of the conditions for parameter identifiability showed directly that the parameters could not be determined from heading measurements only. I was necessary also to measure a velocity component in order to achieve identifiability. By fitting models of the form (2.3) and testing for the appropriate order it was found that in the particular case a marginal improvement could be obtained by introducing an extra state variable for modeling disturbances. A careful analysis of the model, however, revealed that these dynamics could be attributed to quantization errors in the measurement and not to disturbances generated by wind and waves.

Estimation of Thermal Diffusivity

This work is described in Leden (1974). The process is a copper rod with Peltier effect elements for heating and cooling each end of the rod. The key problem is to determine if the process can be modeled by an equation of the form

$$\frac{\partial u}{\partial t} = a\frac{\partial^2 u}{\partial x^2} + bu, \quad y(t) = u(t,x_o) + e(t) \tag{4.1}$$

to characterize the measurement noise and to determine the parameters accurately. The parameters a and b were determined as maximum likelihood estimates. A careful analysis of the residuals revealed that the available measurements did not contradict the assumption that the process was governed by (4.1). Accurate parameter estimates were also obtained.

Interactive Computing

Interactive computing is an indispensible tool for system identification. It allows a problem solver to combine his intuition and insight with extensive numerical calculation. It also provedes a direct link between the user and numerical calculations without needing programmers as intermediaries. An interactive program package IDPAC, Wieslander (1975), has been in operation for several years at the Department of Automatic Control at Lund Institute of Technology. The program runs on a process computer PDP 15/35.

The program has facilities for input - output, editing and display of data. It includes several estimation procedures like correlation and spectral analysis, least squares and maximum likelihood estimation. It has facilities for simulation and model analysis. The program is command driven, which means that the user initiates the different operations by typing commands on a terminal. The program also has a MACRO facility, which means that a user can combine several commands. In this way it is possible both to have a large flexibility for the experienced user and to allow for a simple use of standardized procedures for an inexperienced user.

An example of the use of the program is given below

1. MOVE DK WORK ← DT DATA (1 3)

2. PLOT WORK

3. TREND ← WORK (2) 1

4. ML PAR1 ← WORK 1

5. ML PAR2 ← WORK 2

6. ML PAR3 ← WORK 3

The first command simply moves the columns 1 and 3 on the data file DATA from magnetic tape to a work area on the disc. The second command plots the data on the graphical display. The third command removes a first order trend from the second column in the file WORK. The commands 4, 5 and 6 perform Maximum Likelihood estimation of the parameters in the discrete time analog of the model (2.4) using the data in the file WORK. The estimated parameters are stored in the files PAR1, PAR2 and PAR3.

To analyse the models we can for example proceed as follows.

7. RESID RES ← PAR2 WRK 20

This means that the residuals of the model with parameters PAR2 are computed and stored in the file RES. In this computation the covariance function of the residuals and the cross covariance function between the input and the residuals are also computed and automatically displayed. The commands

8. DETER DET ← PAR2 WORK (1)

computes the deterministic output of the model with parameters PAR2 when the input is the process input WORK (1) and the disturbances neglected. The command

9. PLOT NL WORK (2) DET

finally plots the process output WORK (2) as separate points and the output of the simulated model.

The experiences with the interactive package IDPAC have been very good. In practically oriented research projects it has been possible to analyse industrial data quickly and at reasonable cost. With the aid of the program it has been easy to teach students and industrial workers to master many techniques of system identification. The computer used gives naturally a limit to the size of problems that can be handled and the complexity of the identification algorithms that can be used.

5. ROLE OF IDENTIFICATION FOR ON-LINE CONTROL

Design of Control Algorithms

In some cases the problem facing a control engineer is simply to design a control algorithm for an existing process using sensors and actuators that are currently available. Many problems of this type are solved simply by installing a three term controller and tuning its parameters. In some cases, for example when the variable to be controlled has a significant effect on product quality, it may be justified to be a little more ambitious and attempt to minimize the standard deviation of the fluctuations. For linear stochastic systems this can be done with a simple stochastic input - output model like (2.3) without having deeper insight into the system dynamics. The problem solver then has to go through the following steps

1. Plan experiments
2. System identification
3. Design of control laws
4. Implementation.

For safety's sake it is sometimes advisable to go through the steps 1 and 2 twice to make sure that the process does not change too much. System identification clearly plays an important role in this procedure. It has been my experience based on several applications spread out over the past 10 years that the procedure can be conveniently done in a week or two provided that suitable software for the steps 2 and 3, as well as an on-line computer with flexible control software are available. A typical case is reported in Åström (1967). The procedure also gives valuable insight in the sense that it tells the best result that can possibly be obtained under the given circumstances. The major obstacle often consists of finding suitable conditions when plant experiments can be performed. The technical problems associated with the system identification are selection of sampling intervals and determination of a suitable model complexity. The particular method used for system identification is not crucial as long as it allows for determination of both process dynamics and the spectral density of the disturbances.

Performance Evaluation of Existing Control Loops

Another problem that occurs in process control is to decide if existing control loops are performing reasonably well or if there is a need to adjust the controller settings. System identification techniques can be very useful for this problem. The idea is very simple. Perform an experiment to determine the dynamics of the process and the disturbances. Carry out the system identification. Evaluate the optimum performance and compare with actual results.

In some cases where the conditions for identifiability under closed loop conditions are satisfied the experiment simply consists of recording the control variable and the system output under normal operating conditions. In other cases it is necessary to introduce perturbations by changing the set point or by changing the regulator settings as was discussed in Section 2.

In the special case of minimum variance control for a minimum phase system it is known that the covariance function will vanish for lags greater than the sum of the transport delay of the system. See Åström (1970). It is then sufficient to record the system output only and compute its covariance function.

Applications of system identification techniques to performance evaluation of control loops both during normal operation and in connection with commissioning of computer control systems in the paper industry have been tried extensively in the Swedish paper industry, see e.g. Häggman (1975).

Self-tuning Regulators

The procedure consisting of on-line experiments and off-line computations can be time consuming and costly, particularly if the off-line computing facilities are not available at the plant. It has also been my experience that the transfer of data between different locations and different computers often involves trivial but unpleasant problems. From a practical point of view it is therefore meaningful to ask if it is not possible to provide the on-line control algorithm with a real-time parameter estimator.

In this way it would be possible both to evaluate the performance of control loops on-line and also to provide on-line tuning. The configuration of the control loop would then be as shown in Fig. 5.1.

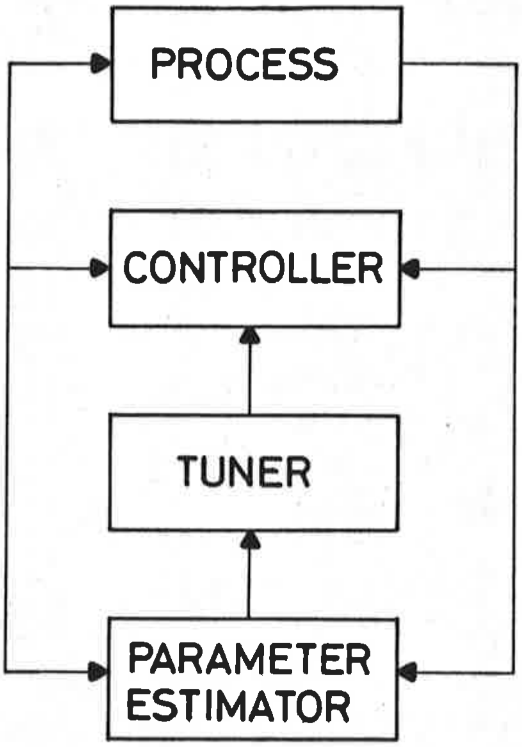

Fig. 5.1. Structure of control loop with on-line tuning.

Control loops of this type have been proposed for a long time. Recently developed analysis has provided valuable insight into the properties of some simple control loops of this type. Simple algorithms of this type, like those based on least squares identification and minimum variance control, have been shown to have some unexpectedly nice properties like ability to stabilize any minimum phase system and convergence toward the minimum variance regulator that could be designed if the process and distrubance dynamics were known.

The self-tuning regulators are also very easy to implement requiring only about 35 lines of FORTRAN programming. Their feasibility in use in the process industry has also been demonstrated. A review of the results are given in Åström et.al. (1975).

6. CONCLUSIONS

There has been substantial progress in the field of system identification over the past 20 years. The research has given valuable insight as well as new algorithms for estimating parameters in models of dynamical systems. Broadly speaking the new methods have made if possible to solve new identification problems. The techniques have also relaxed the requirements on the experimental conditions in return for increased computations.

Many important theoretical issues like convergence of the estimates, design of experiments, etc. have been partly resolved at least for linear stochastic systems. There are, however, important questions still unsolved, like estimation of structural indices of multivariable systems, parametrization of descriptions of dynamical systems, numerical properties of identification algorithms etc. The available results, together with well-known classical methods, provide very effective tools for systems modeling. Many techniques have been tried in special industrial applications. In a few cases they are also being applied in a routine fashion. There is, however, still a long way to go before the methods are part of engineering practice. This is partly a matter of cost. It is a substantial effort to develop the software needed to be able to use the techniques economically. The availability of interactive software for computer aided modeling cannot be overemphasized. Apart from modeling, system identification methods can also be very useful for process diagnostics, trouble shooting and performance evaluation of control systems for industrial processes.

System identification methods are also useful for online control. Particularly the recursive estimation methods can be applied to design self-tuning and adaptive control algorithms.

It is admittedly very difficult to give useful advise on future research needs. Since this is a major purpose of this meeting, I would like to give the following suggestions.

- o Establish groups that can build up and maintain expertise in system identification within the framwork of modelling of industrial processes. Make sure that they have access to real processes.
- o Develop interactive software for system identification.
- o Explore possibilities of using system identification for process diagnostics.
- o Continue work on using recursive identification for self-tuning and adaptive control.
- o Study fundamental theoretical problems.

7. REFERENCES

Akaike, H (1972):
"Use of an information theoretic quantity for statistical model identification". Proc 5th Hawaii Intl Conf on System Science, pp 249-250.

Åström, K J and Bohlin, T (1965):
"Numerical identification of linear dynamic systems from normal operating records". Second IFAC Symposium on the Theory of Self-Adaptive Control Systems, Sept 1965. Also in Hammond, P H (editor) "Theory of Self-Adaptive Control Systems", Plenum Press 1966.

Åström, K J (1967):
"Computer control of a paper machine - an application of linear stochastic control theory". IBM J Res and Development 11, 389-405.

Åström, K J (1969):
"Computational aspects on a class of identification problems". Report Dept EE Univ of Southern California.

Åström, K J (1970):
"Introduction to stochastic control theory". Academic Press, New York.

Åström, K J and Eykhoff, P (1970):
"System identification - a survey". 2nd IFAC Symposium on Identification and Process Parameter Estimation, Prague. Also in Automatica 7, 123-162.

Åström, K J, Borisson, U, Ljung, L and Wittenmark, B (1975):
"Theory and applications of adaptive regulators based on recursive parameter estimation". 6th IFAC Congress, Boston.

Åström, K J and Källström, C G (1975):
"Identification of ship steering dynamics". To appear in Automatica.

Balakrishnan, A V (1969):
"Techniques of system identification". Lecture notes, Institute Electrotecnio, University of Rome.

Bohlin, T (1970):
"On the maximum likelihood method of identification". IBM J of Res and Development 14, 41-51.

Bohlin, T (1971):
"Using statistical identification methods". Technical paper TP 18.206, IBM Nordic Laboratory, July.

Box, G E P and Jenkins, G M (1970):
"Time series analysis, forecasting and control". Holden Day, San Francisco.

Cox, D R (1958):
"Planning of experiments". Wiley, New York.

Eklund, K (1971):
"Linear drum boiler - turbine models". Report 7117, Dept of Automatic Control, Lund Institute of Technology, November.

Eykhoff, P (1974):
"System identification - parameter and state estimation". Wiley, New York.

Federov, V V (1972):
"Theory of optimal experiments". Academic Press, New York.

Gauss, K F (1809):
"Theoria motus corporum coelestium". English translation published by Dover.

Goodwin, C G, Zarrop, M B and Payne, R L (1974):
"Coupled design of test signals sampling interval, and filters for system identification". IEEE Trans AC-19, 748-752.

Graupe, D (1972):
"Identification of systems". Van Nostrand, New York.

Gupta, N K and Mehra, R K (1974):
"Computational aspects of maximum likelihood estimation and reduction in sensitivity function calculations". IEEE Trans AC-19, 774-783.

Gustavsson, I (1975):
"Survey of applications of identification in chemical and physical processes". Automatica 11, 3-24.

Ho, B L and Kalman, R E (1965):
"Effective construction of linear state-variable models from input/output functions". Proc Third Allerton Conf, pp 449-459. Also in Regelungstechnik 14, 545-548.

Häggman, B (1975):
Private communication.

Isermann, R (1971):
"Experimentelle Analyse der Dynamik von Regelsystemen". Hochschultaschenbücher, Bibliographisches Institut, Mannheim.

Kailath, T, editor (1974):
"IEEE Trans on Automatic Control - Special issue on System Identification and Time-Series Analysis". AC-19, Dec 1974.

Kalman, R E (1963):
"Mathematical description of linear dynamical systems". SIAM J on Control 1, 152-192.

Källström, C G, Essebo, T and Åström, K J (1975):
"A computer program for maximum likelihood identification of linear multivariable stochastic systems". To appear 4th IFAC Symposium on Identification and System Parameter Estimation.

Ljung, L (1974):
"On consistency for prediction error identification methods". Report 7405 Dept of Automatic Control, Lund Institute of Technology. To appear in Mehra, R K and Lainiotis, D G "Advances in System Identification", Marcel Dekker.

Ljung, L (1975):
"On consistency and identifiability". Proc Int'l Conf on Stochastic Systems, University of Kentucky, Lexington, Kentucky, June 1975, North-Holland.

Ljung, L and Rissanen, J (1975):
"On canonical forms, parameter identifiability and the concept of complexity". To appear 4th IFAC Symposium on Identification and System Parameter Estimation.

Mehra, R K (1969):
"Identification of stochastic linear systems". Proc IEEE 1969 Symp on Adaptive Processes, Pennsylvania State University.

Mehra, R K (1974):
"Identification in control and econometrics: Similarities and differences". Ann of Economic and Social Measurement 3, 21-47.

Mehra, R K (1974):
"Optimal input signals for parameter estimation in dynamic systems - survey and new results". IEEE Trans AC-19, 753-768.

Mehra, R K, Stepner, D E and Tyler, J S (1974):
"Maximum likelihood identification of aircraft stability and control derivatives". Journal of Aircraft 11, 81-89.

Nieman, R E, Fisher, D G and Seborg, D E (1971):
"A review of process identification and parameter estimation techniques". Int J Control 13, 209-264.

Rissanen, J and Ljung, L (1975):
"Estimation of optimum structures and parameters for linear systems". Symposium - Advanced School on Algebraic System Theory, Udine, Italy, June 1975. Proc by CISM and Springer Verlag.

Rosenbrock, H H (1970):
"State-space and multivariable theory". Nelson, London.

Söderström, T, Gustavsson, I and Ljung, L (1975):
"Identifiability conditions for linear systems operating in closed loop". 6th IFAC Congress, Boston.

Wieslander, J (1975):
"IDPAC users guide, revision 1". Report, Dept of Automatic Control, Lund Institute of Technology.

Wold, H (1964) editor:
"Econometric model building". North-Holland.