ON ADVANCED METHODS OF PROCESS COMPUTER CONTROL FOR INDUSTRIAL PROCESSES

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Abstract. In recent years, the requirements for the performance of multilevel process control, including feedforward and feedback control, monitoring and optimization have increased. Applying process computers and micro computers, the functions of analog equipment and hardwired logic devices cannot only be replaced. Extended or quite new methods can be realized improving the performance of multilevel process control. These advanced methods for process control are characterized by: more sophisticated, better adjusted control algorithms, forecasting of process variables, estimation of not direct measurable variables, computer aided design of algorithms and adaptive or selftuning algorithms. The basis of these advanced methods are mathematical models of the processes and their signals, often gained by the process computer itself during on-line operation.

It will be discussed shortly how process models in open and closed loop can be obtained by on-line identification methods. Then will be regarded, based on these models, the computer aided design of control algorithms, adaptive control algorithms and adaptive steady-state on-line optimization. Monitoring of not direct measurable variables will be mentioned. For some methods, practical results with real and simulated processes are shown. Interactive process computer software packages are used which can easily be transferred to other process computers.

Keywords. Process computer control; mathematical process models; identification; parameter estimation; computer aided design; adaptive control; optimization; monitoring.

1. ADVANCED PROCESS CONTROL SYSTEMS AND THEIR BENEFITS

The various tasks of automatic process control (or guidance) generally are organized in different hierarchically structured levels, e.g.

direct control	(level 1)
monitoring (security control)	(level 2)
optimization	(level 3)
coordination	(level 4)

In all levels of the resulting multi-level control system, the principles of feedback and feedforward are used and knowledge of process statics and dynamics are required for the design.

Why is advanced control needed?

During the past two decades, it could be observed that the requirements for the performance of control systems increased continuously. Sophisticated control systems first have been applied in aircraft and space technology followed for example by power industries, petrochemical and chemical industries and presently special efforts are made in manufacturing technology, metal and basic industries.

Some reasons for the increasing requirements are:
- higher demands on product quality,
- higher production (better usage of capacity, less rejects, less break-down time),
- increasing unit power,
- increasing complexity of processes,
- decreasing process storage capacity,
- increasing demands on reliability and security,
- increasing awareness to take care of the environment,
- higher costs of energy and raw materials,
- higher wages,
- normal competition.

A part of the increasing performance requirements for the lower control levels could be matched by analog and hard-wired logic devices Further improvements, however, in many cases can only be realized by the use of digital and programmable devices as process computers (including microcomputers). In the lower levels, process computers cannot only replace the functions of analog systems but they are able to solve additional tasks thus performing new and more sophisticated functions which may include many calculations. For the higher levels, especially optimization, coordination and more sophisticated process monitoring, including failure detection, analysis and security control, automatic process control only can be performed by process computers. To realize these extended control tasks, *advanced control systems and methods* are required. In comparison to simpler control systems, advanced process control systems are *more sophisticated, more complex, better adapted* to the processes. Their signals can make use of *predicted signal values* and *estimated*, nonmeasurable *process variables*. Advanced control systems may be *computer aided designed* or *self adapting*.

However, the question comes up on the economic justification of the higher expenses for hardware, software and skilled manpower. What can really be gained by better direct control, on-line steady-state optimization or monitoring? This question is difficult to answer because a basis for quantitative and fair comparisons often is missing. Furthermore, not all results are going to be published. In spite of this, the number of papers is increasing in which economic or other benefits by advanced process guidance and control are reported. See for example the preprints of recent IFAC-Symposia.[1,2,3]

What can be gained by advanced control?

Gains by advanced control depend first on the process under consideration. Some obvious facts which are dedicated to the various control levels are listed below. Also, some recent references are given in which economic returns are expressed explicitly.

a) Direct Control

o *Better control performance of flow chart proc.*
Better performance of direct feedback and feedforward control in general result in *smaller variances* of the process outputs and therefore, for example, enable
- more continuous product quality and quantity,
- change of controller setpoints towards more economic optimal values (see also optimization),
- smaller stress of materials (especially heat stresses),
- smaller wear,
- saving of big storages.

o *Better control performance for charge processes*
- final value reached quicker (higher throughput),
- final value distributed equally through the materials (e.g. ingots),
- no rejects by avoiding overshoots (e.g. coating).

o *Control of processes which are difficult to control*
Processes which can only be controlled by advanced control methods often can be characterized as follows:
- strongly nonlinear processes,
- processes with large time-delays,
- unstable processes,
- strongly interacted multivariable processes

(e.g. chemical reactors, pH-value plants, distillation columns, cement kilns, blast furnaces, extruders, paper production plants)

o *Control of not directly measurable variables* by use of measurable variables and process models (e.g. temperatures in steel melts, cement kilns, humidity in pieced goods, heat and mass transfer coefficients)

Stout (1973) gave a summary on published economic improvements by direct digital control with process computers in paper-, petro-, glass- and chemical industries for the period 1966-1972. Benefits of 1-10 % could be gained, especially if the processes are disturbed remarkably, are complex, good instrumented, often in a transient state and if small variations result in significant economic changes (large units). Aström and colleagues (1977) have improved the control of a paper machine and an ore-crusher by self-tuning controllers to obtain a better economy and quality of the production. The ore-crusher throughput was increased by 10 %. Richalet and colleagues (1977) reported on returns of $ 100.000 -150.000 a year by smaller variances of controlled variables obtained through process identification and succeeding computer aided designed control algorithms for a PVC plant, a distillation column and a cracking tower.

b) On-line Optimization

The economic return of steady-state on-line optimization mostly can be directly calculated from the objective function (optimization criterion) if the results with and without on-line optimization are known. Objective functions to be optimized are for example:
- consumption (materials, energy) for given production,
- production for given consumption,
- costs (total).

For flow chart processes two cases have to be distinguished: If process variables for the optimization have *hard constraints* beyond the optimum, absolute optima cannot be reached, but objective functions closer to the optimum are possible by moving the *setpoints of loops as close as possible to the constraint.*

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[1] 5th IFAC/IFIP Int. Conf. on Dig. Comp. Appl. to Process Contr., June 1977, The Hague. Proceedings North Holland, Amsterdam.

[2] 3rd IFAC-Symp. on Instrument. and Automat. in the Paper, Rubber and Plastics Industries, May 1976, Brussels. Proc. Vol.1 and 2 by Spruyt, Van Mantgem and De Does BV, Leiden.

[3] 1st IFAC-Symp. on Automatic Control and Protection of Electric Power Systems. February 1977, Melbourne. Preprints by The Institution of Engineers, Sydney/Australia.

The optimization then requires a calculation of the constraint (if necessary) and a small variance of the variables by best direct control, see a). If however, absolute optima do exist and the process variables to be manipulated by the optimization have *no constraints* around the optimum, an *absolute optimum can be adjusted*. The optimization then may be performed feedforward using a predetermined model, or feedback, using e.g. hill climbing methods, see section 6.

It is typical for on-line optimization of large processes, that small changes can give high economic returns. On-line feedforward optimization of ethylene oxide units including distillation columns have been reported to yield returns of $ 180.000 (Larmon and colleagues, 1977) and $ 1.000.000 (Baxley, 1977) a year. Production maximization in thermomechanical pulping (Tavi, 1977) and blockpower maximization of thermal power plants (Dittmar, 1967) are other examples. If the blockpower of a 1000 MW plant is improved by only 0.25 % through continuously optimal adjusting the speed of the cooling water pump, this can result in a saving of $ 380.000 a year (Bamberger, 1977).

Since *coordination* can be interpreted as the overall-optimization of different process units (e.g. load dispatchers), similar facts as for on-line optimization hold for the coordination level. Coordination often includes optimal scheduling of different plants and use of storages (water, gas, heat).

c) Monitoring and Fault Detection

For process monitoring, traditionally only limit values or trends are checked. Advanced monitoring methods include e.g.

- protocolling the time histories of alarms,
- monitoring of nonmeasurable variables (e.g. heat stresses, leaks, rents, network overloads),
- signal analysis (acoustic signals, stochastic process signals),
- fault detection and localisation.

The goal in any monitoring is to detect and localize faults in a process as early as possible. The early control action sometimes is referred to as *security control* which means manipulation of the process in normal operation to undergo a disturbance without getting into an emergency condition (Dy Liacco, 1977).

The economic justification of advanced monitoring methods depends on the size and importance of the plant, the probability of failures and their effects: for large processes a sophisticated monitoring system can be justified even if only very few break-downs are avoided. The monitoring level in general is the most important level in process guidance and therefore advanced monitoring and security control methods are quickly accepted if they really have advantages.

When will advanced control methods be accepted?

Even if the economic justification of advanced process control methods is positively answered these mostly more complex, mathematically oriented methods have to be accepted by the control engineers, the plant engineers and the plant personnel and by the plant management. So, the advanced methods really have to have significant advantages; they have to show confidence and must not let expect hidden costs.

The decision making procedure for the implementation of advanced control systems has been investigated by Beaverstock and Bernard (1977). They concluded that the control system design has to be early involved in the process design and that aggregated, not incremental, decisions first have to be made. Advanced, hierarchical and distributed control systems increasingly influence the way in which plants are managed.

An interesting summary of questions and answers concerned with the applications of modern control theory to computer control in the process industry has been compiled by Duyfjes, de Jong and Verbruggen (1977). The wellknown gap between control theory and practice was confirmed by most of the 61 participants who answered to a questionnaire. Some reasons have been given: the isolation between the theoretical and practical people; a lack of experienced and qualified people to bring theory into practice; industrial people are more interested in a robust, easy-to-implement, standardized, classical, easy-to-maintain, reliable solution which provides above all an indisputable profit. To narrow the gap, following is recommended: theory has to be more plausible and simplified; comparison between advanced and classical methods is needed; operator's acceptance is different from the engineer's motivation to improve; profits to be gained by improving the last steps towards optimality will usually only be accepted if all other possibilities to improve the technological part of the process have smaller influence or are more expensive.

As a result of these discussions it now may be concluded that advanced control methods will be applied if

a) distributed digital control systems are installed (clearness, reliability),
b) they are just software program packages, easy to transfer and easy to operate,
c) no other methods can solve the problem,
d) considerable manpower is saved,
e) return of additional investment is smaller than about 2 years.

(Some of these items may be sufficient.) There are many industrial processes which fall into this category. At least, the increasing shortage of raw materials and energy will force the implementation of advanced control systems.

In this paper, it will be discussed how some advanced control systems for flow-chart processes can be developed and realized systematically. Since it is not possible to describe even the main approaches and developments of such a broad field in one paper, only a general overall scheme for some advanced control systems is given in the next sections. This scheme is a basis for the methods described shortly afterwards. The discussed methods for computer aided design of control algorithms, self-adaptive control algorithms and on-line steady-state optimization make use of parametric process models with time-discrete signals. To obtain a unified presentation, results of our own work are shown as examples.

2. AN OVERALL SCHEME OF ADVANCED PROCESS CONTROL SYSTEMS

Significant improvement of process guidance/control systems in general is only possible through better knowledge of process' behaviour. Therefore, the advanced process control systems discussed in this paper are characterized by extensive use of *mathematical process* and *signal models*.

Figure 1 shows a general overall scheme which

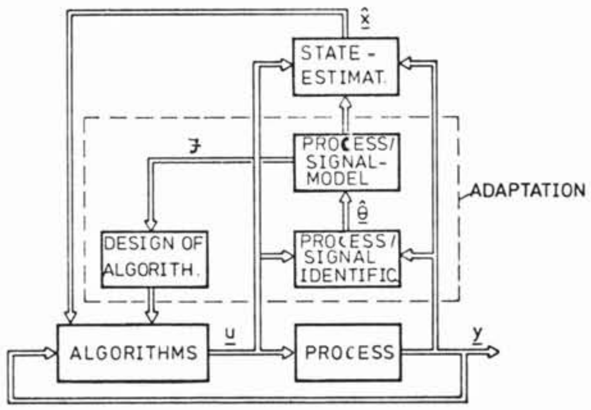

Fig. 1. Overall scheme of advanced methods for direct process control, optimization and monitoring
$\underline{\hat{\theta}}$: process/signal parameter vector estimate
$\underline{\hat{x}}$: process/signal state vector estimate
$\mathfrak{J}$: information used for the design of control, monitoring or optimization algorithm (e.g. process parameter estimates and their variances or predicted signal values)

describes the basic signal flow of many advanced methods for direct control, monitoring and on-line optimization. In general, 3 steps are required:

1. *Process/signal-identification*
2. *Design of algorithms*
3. *Implementation of algorithms*

Steps 1 and 2 can be summarized as *adaptation*. The basic process models for control purposes mostly can be determined easier, cheaper and more precisely by process identification than by theoretical modelling. Then also disturbance signal models can be included. Parametric models are to be preferred for many applications. Therefore, parameter estimation methods are often used. Based on the identified process and signal model, the control, optimization or monitoring algorithm is designed. After it's implementation, the algorithm calculates the process input, using process state estimates, if required.

There are two ways of algorithm adaptation. If the process model is only determined once and an algorithm is designed by a computer (off-line or on-line), this is referred to as *computer aided design of the algorithm*. However, if the process model is identified continuously and the algorithm is designed after each process identification, a *self-adaptive algorithm* results.

As well for parameter estimation as for algorithm design exclusive use of models with *time-discrete signals* is highly preferable, because of smaller computational effort, simple inclusion of time-delays, direct programming for process computers and often simpler theoretical treatment.

3. IDENTIFICATION METHODS FOR PROCESSES IN OPEN AND CLOSED LOOP

For the design of direct control algorithms many processes can be described by linear difference equations

$$y(k) + a_1 y(k-1) + \ldots + a_m y(k-m) = b_1 u(k-d-1) + \ldots + b_m y(k-d-m) \qquad (1)$$

respective the z-transfer function

$$G_p(z) = \frac{y(z)}{u(z)} \quad \frac{B(z^{-1})}{A(z^{-1})} z^{-d} = \frac{b_1 z^{-1} + \ldots + b_m z^{-m}}{1 + a_1 z^{-1} + \ldots + a_m z^{-m}} \qquad (2)$$

where d is a time delay and $z = \exp(T_O s)$ with T_O the sampling time. Hereby, the signal variations are defined by

$$u(k) = U(k) - U_{OO}; \quad y(k) = Y(k) - Y_{OO} \qquad (3)$$

with U_{OO} and Y_{OO} as reference values. Additive stochastic noise on the output may be modelled by an autoregressive moving average process

$$n(k) + c_1 n(k-1) + \ldots + c_m n(k-m) = v(k) + d_1 v(k-1) + \ldots + d_m v(k-m) \qquad (4)$$

so that for the parametric process/signal model

$$y(z) = \frac{B(z^{-1})}{A(z^{-1})} z^{-d} u(z) + \frac{D(z^{-1})}{C(z^{-1})} v(z) \qquad (5)$$

results. Different methods for the estimation of the unknown parameters a_i, b_i, c_i and d_i

have been developed (Eykhoff, 1974; Isermann, 1974). They differ first in the assumption on the noise model. E.g. for the least-squares method (LS) D=1 and C=A must be assumed, which leads to biased estimates in most cases, for the maximum likelihood method (ML) C=A is specialized which, however, is a sufficient approximation for many processes, and for the instrumental variables method (IV) C and D is independent from the process model. The estimation algorithm can be processed one-shot, iterative or recursive and performed off-line or on-line. For computer aided design of control algorithms, all types of algorithms can be used. Adaptive algorithms, however, require on-line identification in real-time which can be realized by recursive parameter estimation algorithms. These recursive parameter estimation algorithms can be represented in a unified form (Söderström and colleagues, 1976; Isermann, 1977),

$$
\begin{aligned}
\underline{\hat{\theta}}(k+1) &= \underline{\hat{\theta}}(k) + \underline{\gamma}(k)\ e(k+1) \\
e(k+1) &= y(k+1) - \underline{\psi}^T(k+1)\ \underline{\hat{\theta}}(k) \\
\underline{\gamma}(k) &= \mu(k+1)\ \underline{P}(k)\ \underline{\varphi}(k+1) \qquad (6) \\
\mu(k) &= [\underline{\psi}^T(k+1)\ \underline{P}(k)\ \underline{\psi}(k+1) + \lambda]^{-1} \\
\underline{P}(k+1) &= [\underline{I} - \underline{\gamma}(k)\ \underline{\psi}^T(k+1)]\ \underline{P}(k)\ \frac{1}{\lambda}
\end{aligned}
$$

for the methods: Recursive least-squares (RLS), extended least-squares (RELS), instrumental variables (RIV), maximum likelihood (RML), stochastic approximation (STA). Hereby, following notations are used

$\underline{\hat{\theta}}$ parameter vector; e equation error;
$\underline{\psi}$ and $\underline{\varphi}$ data vectors;
λ factor for exponential data weighting $0.95 < \lambda < 1$.

$\underline{\hat{\theta}}$, $\underline{\psi}$, $\underline{\varphi}$, μ and $\underline{P}$ depend on the various methods.

These recursive parameter estimation methods have been compared by simulations (Isermann and colleagues, 1974; Saridis, 1974), theoretically (Söderström, 1976) and by real processes (Baur, 1977). Their properties are now well understood for time invariant or slowly time varying single-input single-output processes in *open loop*. Program packages are available which include also test signal generation, data filtering, drift elimination, model order estimation and model verification and which, after an introduction, are relatively easy to apply. Also in the identification of *nonlinear processes* progress has been made (Haber, Keviczky, 1976). Similar or even the same methods as for linear processes can be used if the assumed models are linear in the parameters as for example Hammerstein-models.

If the process identification has to be performed in *closed loop*, most identification methods can be used if an external measurable signal is acting on the loop. If, however, only not measurable signals (noise) are acting, nonparametric identification methods cannot be applied in general but some parameter estimation methods, if the error signal e(k) is not correlated with the elements of the data vector $\underline{\psi}(k)$ and if some identifiability conditions are fulfilled (Kurz, 1975; Söderström, 1976). For the model eq. (5) with $C(z^{-1}) = A(z^{-1})$ these identifiability conditions are:

1. The process model order has to be known a priori.
2. The order of the linear controller, eq. (8), has to satisfy
$$\max[\mu-m,\ \nu+d-m] \geq 0 \qquad (7)$$

Then, the methods LS, ELS and ML can be applied in the same way as for open loop identification.

4. COMPUTER AIDED DESIGN OF CONTROL ALGORITHMS

Up to now, control algorithms for direct digital control are mostly derived by discretizing the differential equations of continuous PI or PID controllers. Their parameters are often tuned by trial and error methods supported by rules of thumb. Especially for processes with large settling times, large time delays, significant parameter variations and multivariable processes this procedure can be quite time consuming and does not result in a best possible control performance. In such cases, better control performance in shorter design time periods and quicker adjustment and implementation of control algorithms can be achieved by computer aided design if mathematical process models are known. These process models can be obtained by process identification with process computers, see section 3, or by theoretically modelling if this leads to models which are accurate enough and if this is not too time consuming.

Based on mathematical process models, the computer aided design of control systems may consist in following steps (Dymschiz and Isermann, 1977):

1) Assumption of a control scheme
   - single loop, cascaded loops, multi loops
   - feedforward paths
2) Transfer of process and noise models to the controller design program
3) Design of different control algorithms
4) Simulation of closed loop behaviour
5) Modification of control algorithms and final selection
6) Control algorithm implementation
7) Setting of operating conditions (restrictions, reference values)
8) Closed loop operation and monitoring of the resulting control performance.

A part of these tasks can be performed on general purpose digital computers. If the computer aided design is, however, carried out with a process computer in on-line operation with the process and use of an interactive dialog is made, following advantages can be observed:

- o Automation of design and start-up of computer control.
- o Simulations of the closed loop behaviour with various control algorithms and control schemes without disturbing the process. Easy modification.
- o Saving of implementation and start-up time, especially for processes with large sett-

ling times or complicated behaviour.

- o Improvement of control performance by better adapted simple algorithms or more sophisticated control algorithms.
- o Determination of the dependence of controller parameters on the operating point can be made exactly and quickly (→ feed forward adapted controller parameters).

These advantages are especially valid for processes which are difficult to control, for slow processes and multi input/multi output processes. The computer aided control algorithm design can be restricted to one or some few important controlled variables. Notice, however, that the process' behaviour may not change significantly during design time.

The z-transfer function of a linear single input/single output controller be

$$G_c(z)=\frac{u(z)}{e(z)}=\frac{Q(z^{-1})}{P(z^{-1})}=\frac{q_0+q_1z^{-1}+\ldots+q_\nu z^{-\nu}}{1+p_1z^{-1}+\ldots+p_\mu z^{-\mu}} \quad (8)$$

$$e(z) = w(z) - y(z) \text{ (w: reference value).} \quad (9)$$

Following control algorithms are preferred:
- Parameteroptimized (PID-type)
- Deadbeat
- Minimal-variance
- State feedback

They are mostly designed by
- numerical parameter optimization (quadratic performance index),
- pole assignment,
- minimal settling time or minimal variance principle,
- matrix Riccati equation.

Comparisons of different control algorithms are given for example by Uronen and Yliniemi (1976), Isermann (1977), Kurz (1977), Unbehauen and colleagues (1976).

Based on the results of simulations and practical experiences some popular control algorithms show following properties for many linearizable single-input single output processes:

Parameteroptimized controllers (PID, PI)
3-parameter-controllers (PID) are better than 2-parameter-controllers (PI) since better control performance with smaller input power (smaller settling time, better damping) and smaller sensitivity for varying process parameters can be obtained. Parameteroptimized low order controllers have smallest computing time between samples. However, relatively large design time is required if numerical parameter optimization methods are used.

Deadbeat controllers
Deadbeat controllers with settling times k = m+d mostly show too large process inputs. A modified version with increased settling time k = m+d+1 is to be preferred. Deadbeat control algorithms can be designed with extremely small design time. They are applicable for asymptotic stable processes.

Minimal variance controllers
Minimal variance algorithms are suited for dominant stochastic disturbances, not for deterministic disturbances. They require a process and a noise model. If the input is not weighted the inputs are often too large and the algorithms are restricted to minimum phase processes. Weighting of inputs leads to better behaviour in many cases and opens application also to nonminimum phase processes. The design time is small.

State controllers with observers
Control behaviour is better damped as with PID-controllers. Relatively large computing time, due to observer updating, is required. However, design time is medium.

The sensitivity to unexact process models or changing process behaviour depends not only on the algorithm itself but also on the chosen free design parameters and acting disturbances. Under comparable conditions less sensitive are state controllers and parameter optimized PID-controllers. Higher sensitivity may be observed for deadbeat, minimal variance and PI-controllers.

Only some few reports on the application of computer aided designed control algorithms for real processes have been given until now. Based on identified process models computer aided design has been recently applied e.g. to chemical plants and steam generators (Richalet and colleagues, 1976), heat exchangers (Dymschiz and Isermann, 1976) and thin film evaporization (Boehm, 1976).

Figure 2 shows an example for the on-line identification of a steam heated heat exchanger with method "recursive correlation and least squares" and the resulting closed loop behaviour for computer aided designed control algorithms. The closed loop behaviour depends on the direction of the set point change due to the nonlinear static characteristic of the valve and the nonlinear dynamic behaviour. The predicted controlled variable y(k) and also the process input u(k) during design phase shows in average a good agreement with the measured behaviour.

5. ADAPTIVE CONTROL ALGORITHMS

In recent years a new development for digital adaptive controllers can be observed. These adaptive algorithms are characterized by combining a recursive parameter estimation algorithm for a time discrete process and signal model and a suited control algorithm. The parameter estimates are calculated after each sampling and used for calculating the parameters of the control algorithm. Peterka (1970), Aström and Wittenmark (1973) combined recursive least squares parameter estimation with a minimal variance controller. Successful application of this "self-tuning regulator" are given by Aström and colleagues (1975). Clarke and Gawthrope (1975) used recursive least squares estimation in combination with an extended minimal variance controller.

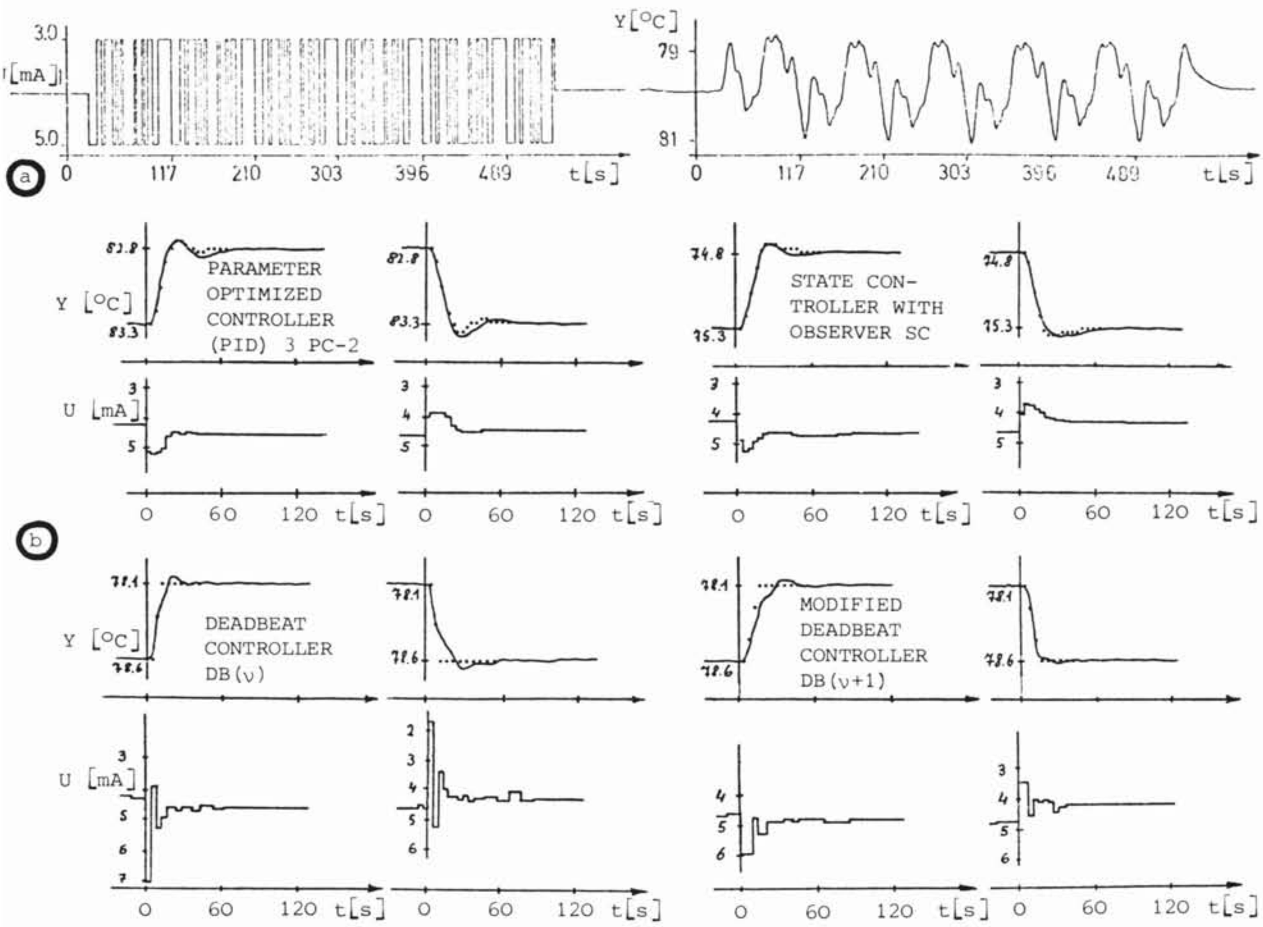

Fig. 2. On-line identification and computer aided design of various control algorithms for a steam heated heat exchanger (Dymschiz, Isermann, 1977)

a) On-line identification with program package OLID; sampling time T_0 = 3 sec.

b) Closed loop behaviour of 4 different with program package CADCA designed control algorithms for set point changes in both directions.
—— measured behaviour; ····· predicted behaviour during design.

Saridis and Lobbia (1972) proposed stochastic approximation with a state feedback controller.

Many other combinations of recursive parameter estimation algorithms and feedback control algorithms are possible (Isermann, 1977; Kurz, Isermann, Schumann, 1978). Parameter estimation and controller design is simplified considerably if $C(z^{-1}) = A(z^{-1})$ is assumed in the general process/signal model, eq. (5). Recursive parameter estimation algorithms must be suited for closed loop identification and may require only small computation time. Therefore,

- recursive least squares (RLS)
- recursive maximum likelihood (RML)

algorithms may be used, compare section 3. The control algorithms also must be designed with small computational expense and should fulfill the closed loop identifiability conditions, eq. (7). Following control algorithms fall into this category:

- Minimal variance controllers (MV)
- Deadbeat controllers (DB)
- PID-controllers for $m \leq d+2$ (3PC)

A comparison of 21 combinations has been performed, using a process computer connected to analog simulated and real processes (Kurz, Isermann, Schumann, 1978). Some of the results are:

- Digital adaptive control algorithms can adapt very quickly.
- The resulting control performance is very good in comparison to the optimally designed algorithms.
- The a priori knowledge on the process is relatively small. Only process order and time delay and a proper sampling time must be known and in some cases a design parameter (process input weighting factor) has to be selected.
- Combinations RLS-MV and RLS-DB show best overall properties, if minimal variance algorithms with weighted process input and deadbeat algorithms with increased settling time are used.

An example of the application of RLS-DB to an air heater of a climate chamber which shows strongly nonlinear dynamic behaviour, is shown in Fig. 3. After closing the loop, the adaptive controller adapts within the first 10 samples. Set point changes show a near optimal deadbeat behaviour after the second step around a definite working point. These adaptive control algorithms can be used for example for

- tuning of digital control algorithms,
- adaptive control of slowly time varying processes,
- adaptive control of nonlinear processes.

Digital adaptive controllers, realized either by process computers or micro computers, may play an important role in the future.

6. ON-LINE STEADY STATE OPTIMIZATION

Increasing shortage and prices of raw materials and energy require more and more an overall optimization of processes with regard to their efficiency. In most cases already during design phase the process and its operating points have been optimized towards maximum efficiency. However, process data change or are not known accurately before operation. Also operating points, processed materials, environmental conditions, prices of raw materials and energy or parts of the process itself change with time. Therefore, in addition to the preoptimization during design, an on-line process optimization during operation nowadays becomes more interesting if absolute optima do exist, which are not too flat. Already small improvements in efficiency of 1 % or less can result in remarkable returns of investment.

As indicated in section 1b) for flow chart processes two cases have to be distinguished: *hard constraints* beyond the optimum of process variables and *no constraints* around the optimum. The first case requires better control performance and change of set points closer to the constraint, see section 1a). The second case is regarded here.

To find absolute optimal working conditions, an objective function $Q = f(\underline{u},\underline{y})$ has to be optimized subject to constraints. The objective function can be e.g. consumption, production or total costs. For steady-state optimization it is a function of measurable process inputs $\underline{u}$ and outputs $\underline{y}$ in steady-state.

There are two basic different approaches of on-line optimization. In the first case a predetermined process model of the static behaviour $Q = f(\underline{u},\underline{y})$ is used in parallel to the process, Fig. 4a, and for measured inputs and outputs an optimal operating point is calculated via $\partial Q/\partial \underline{u} = \underline{0}$ and manipulated. This is called *feedforward optimization* or feedforward extremal value control. If, however, $\partial Q/\partial \underline{u}$ is directly determined in dependence on process in- and outputs, and $\partial Q/\partial \underline{u} = \underline{0}$ is feedback controlled, this is called *feedback optimization* or feedback extremal value control, Fig. 4b. Feedforward optimization has the drawback that because of inaccurate process models and nonmeasurable disturbances the real optimum is not found. This is avoided by feedback optimization. However, then oscillations around the optimum may occur.

In the past most proposals for on-line optimization assume steady-state conditions to obtain Q and $\partial Q/\partial \underline{u} = \underline{0}$. A survey of literature on on-line optimization is given by Bamberger (1978). Recent applications of on-line optimization are given by Larmon (1977) and Baxley (1977).

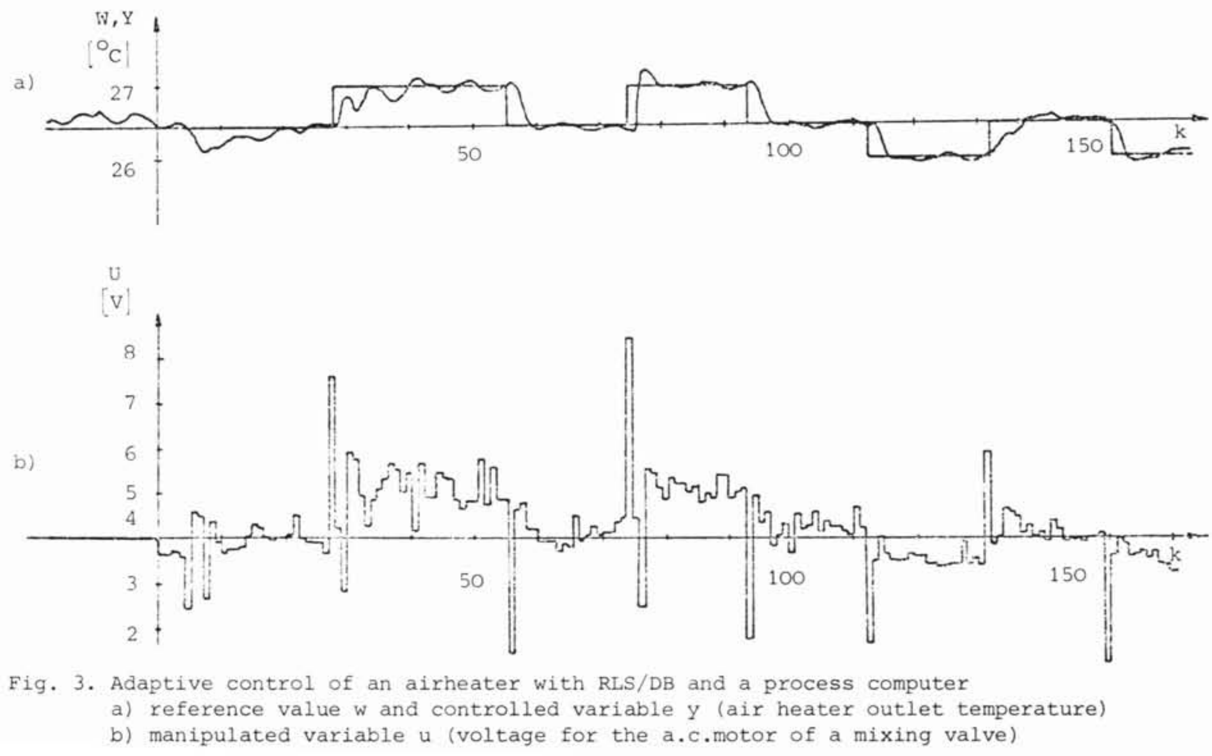

Fig. 3. Adaptive control of an airheater with RLS/DB and a process computer
a) reference value w and controlled variable y (air heater outlet temperature)
b) manipulated variable u (voltage for the a.c.motor of a mixing valve)

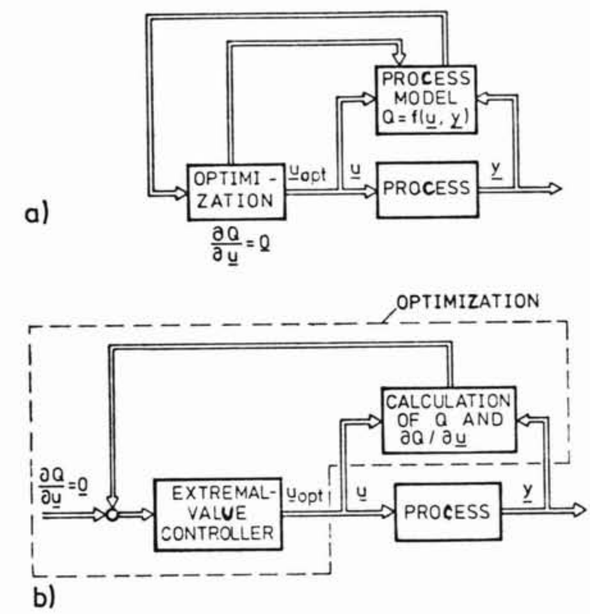

Fig. 4. Basic approaches for steady-state on-line optimization
a) feedforward optimization
b) feedback optimization

For on-line optimization based on measured steady-states one has to assume that really steady-states are reached, which is not often the case for many industrial processes. Furtheron, it needs a long optimization time to step from one steady-state to another until the optimal steady-state is obtained. To shorten the optimization time which is absolutely necessary for time varying processes, the process dynamics have to be taken into account.

The application of a steady-state optimization on a distillation column which regards the transients of the process is shown in Sawaragi and colleagues (1971). A dynamic version of steady-state optimization is described in Østergaard (1976) and its application to a heat exchanger in Østergaard (1975). Random search methods are used together with nonlinear first order dynamic models with fixed parameters.

An *adaptive on-line optimization* method with higher order nonlinear dynamic models $\underline{y}=f(\underline{u})$ which finds optimal steady-states for processes with multi inputs in relatively short time using simultaneously methods for on-line identification and on-line optimization has been developed by Bamberger (1977, 1978). An objective function $Q = f(\underline{u},\underline{y})$ is calculated. Based on measured input and output signals, a nonlinear dynamic process model $Q = f(\underline{u},\underline{y})$ is identified by least squares parameter estimation or correlation analysis. The nonlinear process model is linear in the parameters and can be regarded as an extended Hammerstein model which allows an approximation of a Wiener model. The model contains a static part $\overline{Q} = f(\overline{\underline{u}},\overline{\underline{y}})$. Only this static model (obtained in a transient process state) is applied for seeking the optimal inputs $\underline{u}$ by use of gradient and search techniques. To start the optimization run, a test signal $\underline{u}_s$ which has to satisfy certain conditions is used to accelerate the process identification, Fig. 5, phase 1. After obtaining a rough model, the optimization starts, leading to additional changes of the inputs, phase 2. These input changes improve the still continuing process identification so that the amplitude of the test signal can be diminished. Finally, if the static process model and the hill climbing procedure have converged, $\underline{u}_{opt}$ is known and can be fixed and the process settles into its optimal operating point Q_{opt} according to the (slow) process dynamics, phase 3. This is done by feedforward control in order to avoid oscillations around the optimum. Then, a monitoring phase starts.

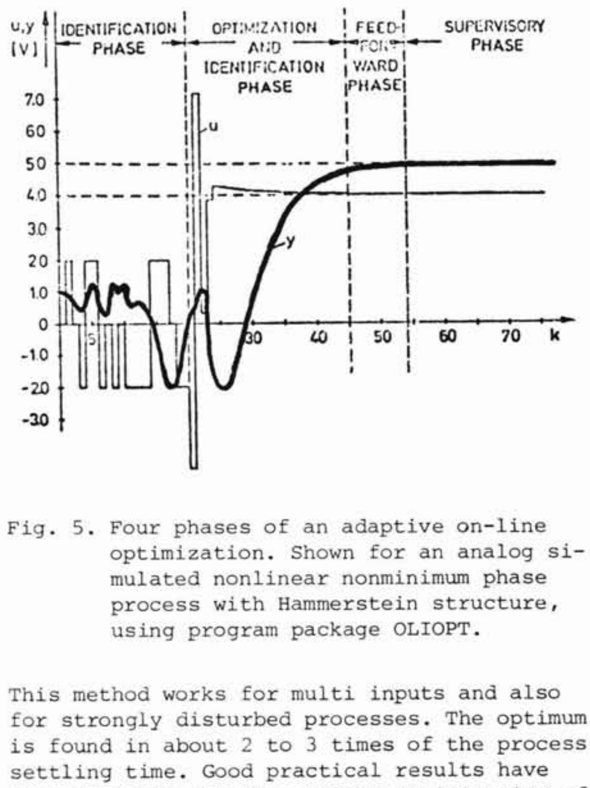

Fig. 5. Four phases of an adaptive on-line optimization. Shown for an analog simulated nonlinear nonminimum phase process with Hammerstein structure, using program package OLIOPT.

This method works for multi inputs and also for strongly disturbed processes. The optimum is found in about 2 to 3 times of the process settling time. Good practical results have been obtained for the on-line optimization of a pilot process for the cooling water circulation of a thermal power plant, Bamberger and Isermann (1977). Only some few parameters have to be known a priori to start the optimization. Adaptive on-line optimization can be regarded as a 'higher level analogy' to self adaptive direct control..

7. PROCESS MONITORING AND FAULT DETECTION

Process monitoring and succeeding actions in general consist of following steps; indicating the closed loop character:
(1) Checking if the process is in a normal or

unnormal condition (binary decision, alarm)
(2) Analysis of disturbances (fault detection and localisation, cause and source of faults)
(3) Control action to keep or to make the process normal ('security control', 'fault tolerant system')

Most important is to detect faults as early as possible, so that there is a chance to undergo a break-down. In many cases disturbances respectively faults are indicated by changes of measurable or nonmeasurable process variables. Here, only some remarks to steps (1) and (2) are made.

7.1 Monitoring of Measurable Variables

Improvements in the monitoring of measurable variables are possible by not waiting until the variables or their trends exceed a certain limit value, but by *predicting the signals* and acting before the limit is reached. Then limit values can be moved further away from the nominal value and unnecessary alarms, resulting from short time exceeding, are avoided. Signal prediction can be performed by using signal models, e.g. as stochastic difference equations, which are obtained by on-line signal identification (time series analysis). Inclusion of a process model and its measurable inputs can be used to improve the predicted output signal.

7.2 Monitoring of Nonmeasurable Variables

The development of monitoring nonmeasurable variables is at an early stage. Therefore, only some few examples can be given. The problem consists in estimating not directly measurable variables which indicate a fault in the process, based on measurable variables. Static and dynamic process models are required and methods of state and/or parameter estimation have to be used. Some examples are:

- Heat stresses: Based on measured pressures and temperatures dynamic models have to be used for calculation of heat stresses at definite locations of a thick wall element (turbines, steam generators, Wölfel (1974)).
- Leaks in pipelines: Small leaks can be detected and localised by pressure and flow ratio measurements only at the beginning and the end of a liquid or gas pipeline, using special correlation techniques and dynamic process models, Siebert and Isermann (1977).
- Faults in actuators and sensors
  Some work has been done to detect abrupt changes in dynamical systems as aircraft control systems, Willsky (1976). Based on state space process models sudden changes in the parameter or state values, or their derivatives have to be estimated. Then for example actuator faults, sensor faults or controller faults can be indicated.

Further examples are rents in mechanical elements, unassembled elements, pollution of mechanical filters, heat exchangers or chemical apparatus.

CONCLUSIONS

It has been tried to show how advanced methods of process computer control, optimization and monitoring can be developed on the basis of mathematical process and signal models. Characteristics of these advanced methods are the estimation of not directly measurable parameters and variables and the use of computer aided designed and self-adapting algorithms. Methods of parameter and state estimation are combined with design methods for control, optimization and monitoring algorithms. Once realized in software packages, they can be applied manifold within process or micro computers.

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