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ADVANCES IN INDUSTRIAL MODEL-PREDICTIVE CONTROL

by

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Abstract. Due to the economically sensitive condition of the chemical and petroleum industries, we can no longer afford to operate with the inefficiencies of the past. Over the last 15 years we have found that on-line optimization implemented with model-predictive control recognizing process and operating policy constraints, provides the best means for achieving the profit potential of our plants. Only model-predictive controllers permit the flexibility required to handle the constantly changing performance criteria, in particular the enforcement of operating constraints. However, the performance criteria of today's problems are becoming harder to quantify, while optimization systems are driving the processes over a wider range of operating conditions than ever before. Therefore, there is a need to improve the model-predictive control techniques so that practical performance criteria based on engineering judgement can be transparently specified, and that model inaccuracies are considered explicitly in the problem formulation. In this paper the state-of-the-art in industrial model-predictive control is presented. An attempt is made to propose a path of evolutionary development in process control that will converge to a **Unified Theory** replacing many of the ad-hoc solutions developed over the last thirty years. New techniques for multi-objective optimization and robust control are described that have the potential to allow us to improve the current technology in order to solve the control problem at hand. It is concluded that the complex control problems of today can only be

solved through the development of a **Unified Theory** along the concepts of model-predictive control. This **Unified Theory** of process control will then allow for the application of the **Integrated Technologies** of process optimization and control.

Keywords. Model Predictive Control; Dynamic Matrix Control; optimization; constraints; performance; robustness.

PREFACE

It is the purpose of this paper to determine a future direction for process control research within the context of model-predictive control methodologies that will allow for the evolution of a consistent, unified approach to problem solving in our field.

We recognize that history includes many ad-hoc solutions that did not pass the test of time. However, we have learned as much from historical failures in approach as we have from successes. Over the last thirty or more years there have been many significant contributions to our technology. Some were not appreciated because of the truly innovative nature of the contribution and some were overly praised but did not withstand the scrutiny of time. We wish that our paper be accepted in the sense of a contribution that is very dependent on the work of those that came before us. In presenting this paper we wish to acknowledge this work and credit our contribution to the fine work done by our predecessors, the large number of whom preclude individual recognition without the probability of omitting some. With the benefit of observation of the work of all our predecessors we therefore propose this forward plan for the development of a **Unified Theory** of process control as our contribution to the field.

INTRODUCTION

In order to ensure a competitive edge in today's economic climate the chemical and refining process industries need to extract the maximum profit from their processes in the face of constantly changing market conditions. An expensive way of realizing the achievable profits is to modify the process design and install modified equipment to take account of these changes. One then hopes that the changed market condition is maintained long enough to recoup the capital cost and also generate a resultant net profit. Alternatively, or in conjunction with modified equipment, plant profitability can be achieved with minimum capital costs by applying broad-based technology to on-line optimize our chemical plants and refineries.

On-line optimization systems relentlessly realize the achievable performance of the existing equipment by driving the process to its operating constraints while constantly updating the operating conditions based on the process economics. Its successful implementation generally involves two phases (Garcia, 1982) (Fig. 1):

- Optimization Phase:

  Steady-state process representations are used to optimize the process based on an economic objective function subject to equipment and operating policy constraints; the process representations include the effect of disturbances of economic impact as are feedstock quality, equipment degradation, etc. which are assumed to occur with larger period than the inherent residence time of the process; the operating point is updated with a frequency comparable to the disturbance frequency.

- Control Phase:

  Dynamic process representations are used to optimize a performance objective function which penalizes deviations of process variables from their optimum values given by the optimization phase; since the optimal operating point generally lies at the intersection of constraints, this phase has the responsibility of dynamically enforcing those constraints while rejecting fast disturbances; the control system updates manipulated variables at a faster frequency than the optimization phase executions.

One can argue about the justification of the division between the phases. It is obvious that in cases where the disturbances of economic impact change faster than the inherent plant dynamics both phases coalesce therefore requiring frequent dynamic on-line optimizations. Even in those cases where separation is not advisable, it has been done because it is not possible with today's hardware to solve on-line optimization problems with detailed dynamic process representations. Therefore, the two-phase on-line optimization approach is widely used.

Detailed process representations of large collections of algebraic and differential equations based on first principles avoid the issue of pre-biasing the solution of the optimization problem caused by the use of so-called simple models. Since there exists no technique today for choosing, a-priori, the correct degree of detail for optimization models, large computation requirements are inevitable. The field of expert systems is beginning to contribute significantly in providing a framework that allows us to collect the modelling skill of practitioners as new systems are implemented. Also, the great improvements in computing power provided by parallel processing might make this issue of model rigor disappear in the near future. More will be said about these two areas of research effort later.

Since the optimization problem is more tractable than the control phase and conceptually easier to understand, there exists a temptation to "implement" only the optimization phase without regard for the control phase. However, one must recognize that optimization problems are relatively easy to solve but the results are extremely difficult to implement. The control phase makes this implementation possible. Therefore, the achievable profits of optimization cannot be realized without good control and one cannot divorce one technology from the other. We have chosen to define this synergism of technologies as the **Integrated Technology** approach to process control. It is only in this realm that process control methodologies can even be considered for industrial application, and therefore, we have a clear way of assessing current technological advances and of directing future research efforts. Let us review the current state of the process control area in the light of this approach.

Over the last 25 years we have experienced a tremendous evolution in the techniques used to control our chemical and refining processes. If there is a single explanation for the changes observed it is that the applications have always been influenced by the control hardware available for concept implementation. Academicians as well as practitioners have been discussing for years the so called "gap" between theory and practice, giving what we consider to be an imprecise picture of the real situation. As we see it, from the researcher's side there exist two main reasons for the lack of solutions to the real problems. On the one hand, some theoreticians have either totally ignored the real problem and gone into theoretical developments that cannot be applied to chemical and refining processes, or when applicable the solutions have resulted in being practically impossible to implement with the available hardware . On the other hand, many researchers (both in industry and academia) have focused their attention on ad-hoc solutions to problems so that they fit the capabilities of the most commonly available hardware implementation modes, therefore necessarily limiting the scope of their research. While this may have been justified in the past it is hard to understand why this is still practiced to the present when on-line computing power has become relatively inexpensive and provides a framework for generalized solution conception replacing the ad-hoc approach.

However, we as practitioners should not be so quick as to completely blame theoreticians for such failure. Our greatest sin is to have led them to believe that ad-hoc solutions were all that were acceptable to us. Even when these techniques have failed, their failure was usually excused resulting in the development of "more advanced" ad-hoc solutions. As a consequence, this has created a situation where these pseudo-successful ad-hoc solutions have become the accepted theory. Although no significant economic penalty has been paid so far for these misdirected efforts, the current economically sensitive condition of our industry dictate the need to search for a **Unified Theory** of process control in order to ensure a competitive edge. It is our estimate that the profitability of our industry could be significantly improved through application of the **Integrated Technology** approach of optimization and control.

In recent years we have observed the surge of a new generation of researchers who have courageously made significant advances and proposed solutions to control problems which tend to provide some unification. It is interesting to realize that the catalyst for these advances has been provided by developments in industry. As early as the mid-seventies some visionary corporations realized the potential of a **Unified Theory** and embarked in the development of their own control algorithms in order to address the real problem of achieving improved profitability. By then process control practitioners had already abandoned the "modern control theory" approach to multivariable control. Except in few notably successful implementations (Ray, 1981) the Linear Quadratic Optimal Controller (LQC) so successful in aerospace control applications (Kwakernaak and

Sivan, 1972) was generally found to be difficult to tune and exhibited poor robustness to plant changes. Therefore the interaction problem was handled by the use of decoupling techniques for multi-loop systems (Ray, 1981). Independent developments in the USA by Shell Oil Co. (Cutler and Ramaker, 1979; Prett and Gillette, 1979) and in France by ADERSA/GERBIOS (Richalet et.al., 1978) brought forth new techniques based on a linear model prediction: Dynamic Matrix Control (DMC) and IDCOM, respectively. One can show that in the absence of process constraints these techniques are mathematically identical to LQC except that a simpler formulation allows easier on-line tuning and transparent specification of control objectives. However, it is the explicit inclusion of process constraints in the algorithm what has made these techniques so successful in the industrial environment. The development of DMC marked the first time a control technique was devised which could successfully handle process constraints, thus allowing the realization of achievable profits via implementation of results of on-line constrained optimizations. In fact, in the particular case of fluid catalytic cracking control no technique previously published had provided the performance required in the face of constantly changing control objectives and active constraints (Prett and Gillette, 1979; Morari, 1981).

One significant contribution associated with the introduction of DMC to the control literature was in setting a new tone by communicating industry's needs in a language that both industry and academia could understand, i.e. the language of mathematics and control engineering. It was hoped that this would lead to a renaissance of control research along more unified lines. Such renaissance has happened and we have witnessed numerous theoretical developments in the chemical engineering process control area over the last seven years which appear to be on the right track for finally achieving the desired unification.

Our objective in this paper is to define where we presently are technologically, and then point out what is necessary to promote a continuance of the current efforts toward solving the control problem. We strongly believe that the model-predictive control methodology provides the only framework for achieving this. In addition to its constraint handling capabilities, model-predictive control has performed reliably in applications because of its:

- multivariable features
- stability properties
- inherent deadtime compensation

These properties have been analyzed in the control literature (Garcia and Morari, 1982).

But the most important feature of model-predictive controllers, and in particular of DMC, is that they solve a new problem and thus produce a new controller **at each execution.** This makes the algorithm capable of taking measures on-line which could not be foreseen at the design stage therefore having unique constraint handling capabilities. In this sense, **model-predictive** controllers must be uniquely distinguished from other controller designs. For lack of a better terminology, in this paper we will classify as **recursive** controllers those techniques that use a fixed relationship between error and manipulated variable which is solved for only once, during the conceptual design phase.

The algorithm as proposed did not explicitly deal with the issue of model accuracy. The best available model was determined and the control engineer designed a control system to meet implementation performance standards. Robustness was achieved by an intuitive process of relaxing performance standards to recognize inherent model inaccuracies. Of course, as time went on, the model might become increasingly inaccurate due to changing process conditions. This was handled by having an expert work force in the field to perform on-line detuning until such time as a new model determination was demanded. However, in today's business environment it is not possible to justify the field assignment of such expert manpower. For this reason, as well as for control efficiency, we must begin to deal with the performance/robustness issues more methodically.

As a result of an increased number of installations of on-line optimization systems, recent experiences have indicated that even though the model-predictive control approach is still the best tool for multivariable constrained control, the traditional approach that assumes an exact, fixed, linear model does not allow us to achieve the desired control performance objectives. We are finding that the performance objective and constraints of modern plants are changing more frequently than before and are more difficult to translate to solvable mathematical forms. In addition, processes are being operated over a wider range of conditions than ever before. Since we can no longer afford the costs associated with maintaining these complex loops, we have to improve our control methods so that the desired performance is achieved with minimum demands on manpower.

In this paper we discuss some of the many areas of research which we are currently exploring in order to solve these problems while at the same time pointing out where the future developments in this area should be directed.

The paper is organized as follows. First we give a brief description of the current state-of-the-art in model predictive control as practiced in Shell pointing out the special properties that make it suitable for solving practical control problems. The issue of specification of control performance is discussed next in the light of the **Integrated Technology** approach. Finally, in the last part we deal with the issue of the effects of model error on performance loss and list the several methods currently under study to address the problem at hand. The conclusion will contain an assessment of the process control area as we see it, indicating where the technological breakthroughs need to happen in the light of the current and future condition of our petrochemical industry.

ELEMENTS OF MODEL-PREDICTIVE CONTROL: THE LINEAR CASE

The model-predictive control methodology consists of the following elements:

- Linear model relating the manipulated variables and measurable disturbances to the outputs of interest

- Prediction of the outputs of interest over the future time horizon, corrected via feedback

- Computation of future manipulated variable moves to make the prediction of the outputs and manipulated variables satisfy some performance criterion.

It is assumed that the model is open-loop stable, and that the algorithm is implemented in a sampled-data system. Therefore, a discrete-time model of the process is considered where values of variables are known only at discrete intervals of time k:

$$kT \leq \text{time} \leq (k+1)T$$

where T is the sampling time of the system.

A "moving horizon" approach is used where at every sampling interval the prediction is updated and the future manipulated variable moves are computed. However, only the manipulated variable move corresponding to the current sampling interval is implemented. One step of this approach is illustrated in Fig. 2 where the prediction of a single manipulated variable m(k) and output variable y(k) is obtained at the end of the computation phase in order to, for example, bring the prediction to a target value.

In this section all three elements are discussed based on current practice. This will allow us to point out where the advantages in the method may lie as well as where improvements are necessary.

The Model Formulation

Model-predictive control algorithms employ a linear model of the process to predict the effect of past changes of manipulated variables and measurable disturbances on the output variables of interest. In practice an input-output model description is used as follows:

$$y(k) = \sum_{\ell=1}^{\infty} a_\ell \, \Delta u(k-\ell) + d(k) \tag{1}$$

where a_ℓ is a matrix of unit step response coefficients, Δu are the changes or moves of the system inputs (manipulated variables and measurable disturbances) and d(k) is a term containing all the contributions to the outputs that the model cannot describe as are unmeasurable disturbances. An equivalent model form is the impulse response model :

$$y(k) = \sum_{\ell=1}^{\infty} h_\ell \, u(k-\ell) + d(k) \tag{2}$$

where h_ℓ is a matrix of unit impulse-response coefficients, and

$$a_\ell = \sum_{j=1}^{\ell} h_j \; .$$

The only difference between models (1) and (2) is that the step-response model contains an implicit integrator.

Of course, the properties of the method should not depend on the particular model formulation. One could even use a state-space model as follows:

$$\begin{aligned} x(k+1) &= A\, x(k) + B\, u(k) \\ y(k) &= C\, x(k) + d(k) \end{aligned} \tag{3}$$

Since the system is stable, successive substitutions of the state $x(k)$ should yield exactly model (2). In order to obtain (1), we add an additional state which acts as our integrator as follows:

$$\begin{bmatrix} \Delta x(k+1) \\ q(k+1) \end{bmatrix} = \begin{bmatrix} A & 0 \\ CA & I \end{bmatrix} \begin{bmatrix} \Delta x(k) \\ q(k) \end{bmatrix} + \begin{bmatrix} B \\ CB \end{bmatrix} \Delta u(k) \tag{4}$$

$$y(k) = q(k) + d(k)$$

where Δx denotes a change in the state. The resulting input-output model of (4) is the step-response model (1).

The Prediction Problem

Any of the model descriptions can be used to predict future values of the outputs $y(k)$ over a time horizon. For this discussion only model (1) will be considered. For any future interval of time ℓ the output prediction is given by:

$$\hat{y}(k+\ell) = \hat{y}^{*}(k+\ell) + \sum_{i=1}^{\ell} a_{mi}\, \Delta m(k+\ell-i) + \hat{d}(k+\ell)\,, \qquad \ell = 1,2\ldots P \tag{5}$$

where the contribution of past inputs to the projection is given by the term

$$\hat{y}^{*}(k+\ell) = \sum_{i=\ell+1}^{\infty} a_i\, \Delta u(k+\ell-i) \tag{6}$$

and $\hat{d}(k+\ell)$ is the prediction of unmodelled effects. Note that equation (6) contains the effect of all past inputs: both manipulated variables and measurable disturbances while the summation in (5) only goes over future manipulated variable moves. The step-response coefficients a_{mi} relate manipulated variable moves to the outputs.

An important term in (5) is the prediction of the unmodelled effects $\hat{d}(k+\ell)$. This term can be obtained by using the most recent output measurement $y_m(k)$. Using equation (1) we can calculate d(k) as follows:

$$d(k) = y_m(k) - \sum_{\ell=1}^{\infty} a_\ell \, \Delta u(k-\ell)$$

The predictions $\hat{d}(k+\ell)$ can then be estimated by filtering d(k) appropriately.

In the particular case of DMC the prediction most commonly used is

$$\hat{d}(k+\ell) = d(k) \quad \text{for } \ell = 1,2..P. \tag{7}$$

This estimator is satisfactory only when the measurement noise level is small and the deterministic part of the unmeasured disturbances has fast dynamics and is infrequent. Otherwise, significant errors in the prediction could ensue.

One way to resolve this problem is to use optimal filtering theory (Kwakernaak and Sivan, 1972) to design an observer/estimator for $\hat{d}(k+\ell)$ if some knowledge of the noise dynamics of the process is at hand or if the deterministic part of the unmeasured disturbance model is available through some identification method. Such approach would not only provide the filtering of noise but also good estimation of slowly varying disturbances. However, one should be aware of the fact that these techniques are valid only under very stringent assumptions about noise dynamics (namely, zero mean Gaussian noise) and therefore, one is forced to resort to ad-hoc selection of the noise covariances for tuning. In the absence of noise the use of a model for the disturbances should improve the prediction.

The Structured Singular Value theory of Doyle (1982) gives a comprehensive controller design method under uncertainties in both model parameters and disturbance description. One advantage is that the analysis is not restricted to a Gaussian description of the noise. Consequently, it seems to be the best approach to date to resolve this issue of disturbance prediction. This is a topic of current research in our group.

The Control Problem

Once a model prediction of the outputs is obtained the following generalized control problem is solved:

> Find the sequence of M future manipulated variable moves $\Delta m(k)$, $\Delta m(k+1)$, ... $\Delta m(k+M-1)$ so that the prediction of the manipulated variables and outputs satisfy a set of performance criteria.

This problem is solved at every sampling time when a new prediction is updated based on the most recently obtained feedback measurements. The first move $\Delta m(k)$ is the only one that is implemented although the others could be used in case of loss of measured variables. However, the main reason for computing future moves is to allow for the imposition of desirable performance objectives and constraint handling on manipulated variables as well as on output variables.

Except for the linear model assumption, this control problem is general enough to allow the solution of most foreseeable control problems of industrial relevance. The challenge consists in being able to translate the desired performance objectives into an equivalent mathematical form that allows computation of the moves. One convenient form that we have used with success is the Dynamic Matrix Control algorithm (Cutler and Ramaker, 1979; Prett and Gillette, 1979) and more recently the Quadratic Dynamic Matrix Control (QDMC) algorithm (Garcia 1984). The QDMC formulation solves for performance objectives expressed as a sum of squared deviations of controlled outputs from target values and inequality constraints of outputs and manipulated variables.

In the particular case of QDMC the following quadratic program is solved on-line:

$$\min_{\Delta m(k)\,\ldots\,\Delta m(k+M-1)} \tfrac{1}{2} \sum_{\ell=1}^{P} \{ \| \Gamma_\ell [\hat{y}(k+\ell) - y_S(k+\ell)] \|^2 + \| \Lambda_\ell \, \Delta m(k+\ell-1) \|^2 \}$$

$$\begin{aligned}
\text{s.t} \qquad \hat{y}(k+\ell) &= \hat{y}^*(k+\ell) \\
&\quad + \sum_{i=1}^{\ell} a_{mi}\, \Delta m(k+\ell-i) \\
&\quad + \hat{d}(k+\ell) \\
y_L(k+\ell) \le \hat{y}(k+\ell) &\le y_H(k+\ell)\ , \quad \ell = 1,2..P \\
m_L(k+\ell-1) \le m(k+\ell-1) &\le m_H(k+\ell-1)\ , \quad \ell = 1,2..M \\
\Lambda_\ell &= 0\ , \quad \ell > M
\end{aligned} \tag{8}$$

where the prediction in equation (5) is used and $M \le P$. Since a linear prediction is used, the resulting inequality constraints are linear in the solution variables $\Delta m(k)\ \ldots\ \Delta m(k+M-1)$ and therefore (8) is indeed a quadratic program.

Comparison with Classical Approaches

It is important at this point to reflect on what the predictive control problem methodology allows us to do and compare it with standard approaches which might appear similar to the uninformed observer. Here we will compare the QDMC algorithm with the LQC methodology on the basis of industrial control applicability. The observations on LQC should equally apply to most other classical algorithms.

Model-Predictive type controllers (QDMC). QDMC assumes one objective function to be minimized which reflects some of the desired performance criteria of the control system. Different objectives for each of the projections of variables are lumped into one objective function. The relative importance of each objective is specified by appropriate selection of weights. These weights are closely tied up with the variable scaling.

Additional performance criteria are specified by the use of inequality constraints in the predictions. These constraints impose hard bounds on the predictions of the variables in order to keep them within acceptable operating limits. For these hard constrained variables the corresponding weights in the objective function are zero.

Since the problem is solved at each sampling time, the controller is able to account for different scenario sets of active constraints which were not foreseen at the design stage. The transfer from one set of active constraints to the other is done smoothly and optimally by the quadratic programming algorithm. Therefore, it is in practice an on-line intelligent system albeit still with some limited capabilities.

In terms of numerical solution, a quadratic program can be customized to efficiently solve problem (8), which in the absence of constraints reduces to a simple least-squares problem (Prett and Gillette, 1979). Although complex by historical standards, a simple interface allows easy implementation of the algorithm.

Recursive type controllers (LQC). The discrete optimal control algorithm as described in Kwakernaak and Sivan (1972) employs a state-space model of the process as in (3) in order to solve the following optimization problem:

$$\min_{\substack{m(k)\,\ldots \\ m(k+P-1)}} \ \tfrac{1}{2} \sum_{\ell=1}^{P} \{ \ || \Gamma_\ell \, y(k+\ell) \ ||^2 + || \Lambda_\ell \, m(k+\ell-1) \ ||^2 \ \}$$

$$\text{s.t.} \qquad x(k+1) = A\,x(k) + B_m\,m(k) \qquad \qquad (9)$$

$$y(k) = C\,x(k)$$

LQC also minimizes a weighted quadratic objective function of the model predictions of the outputs and manipulated variable values and assumes M=P. As formulated, the resulting LQC controller is not suited for handling non zero targets, measurable disturbances and non zero mean unmeasurable disturbances since it does not provide integral action (Garcia and Morari, 1982). However, several modifications can be made to resolve these issues. For example, one can formulate the objective function as in QDMC (equation 8) and perform the prediction using the state-space model (4) and the estimate of $d(k+\ell)$ in (7). As a result, the two problems become identical in the absence of process constraints.

The solution of problem (9) (or equivalent) produces a set of manipulated variable values. By using the LQC method, a set of Riccati equations can be solved to obtain a simple expression where the manipulated variable to be implemented is a linear combination of the states. Such relationship lends itself to a simple implementation which can be represented in the form of block diagrams and easily realized with standard hardware. The computational burden consists of calculating the controller gain matrix, which is done off-line. After the computation is performed, the controller is fixed.

Even though one can minimize the same objectives as in QDMC and influence them by using weights, the LQC formulation does not allow for the specification of constraints. In fact, the only way constraints can be handled by LQC or any other recursive type of controller is to add an intelligent decision maker on top that will decide which constraints become active and therefore restructure the control problem accordingly. Such approach has been suggested before by Arkun and Stephanopoulos (1980).

In this respect most controllers are similar to LQC and consequently different than model-predictive type controllers. In QDMC the computed set of moves in the manipulated variables depend not only on past history of plant dynamics but also on predicted violations of constraints. This is not possible to represent in any recursive / transfer function / block diagram type of formulation. At the same time one must also realize that if constraints are removed and future target trajectories are linear transfer functions, then QDMC is essentially no different than any other control method. In these cases, the manipulated variable moves depend exclusively on past plant history and therefore it is possible to analyze with classical techniques familiar to most control engineers.

It is in this constraint-free environment that QDMC was found to have an Internal Model Control structure (Garcia and Morari, 1982) and therefore enjoy many important properties, in particular, that it does not require a stability analysis. These important properties by themselves provide enormous incentive for the use of model-predictive controllers over other designs. However, as explained above, in the constrained on-line optimization framework the added feature of on-line updating of the moves based on predicted process constraint violations is what allows model-predictive controllers to realize the achievable profits.

After comparing the two main methodologies of process control as we see them, one can now start to see where the important theoretical developments are necessary in order to solve the real problem at hand. We have identified two important areas where significant advances in model-predictive control are needed before we can attempt to solve the real control problems:

1. Performance Specification:

   In the cases above we have assumed that the mathematical objectives solved represent the true objectives we want the control system to satisfy. Even then, we have arbitrarily lumped several unrelated objectives into one single function by assigning appropriate weights to the individual objectives. In addition, we have imposed hard constraints even on variables for which no significant penalty is paid for violations; although there is provision in QDMC to weight these "soft" constraints into the objective function in the event of a predicted violation. However, this brings up the more practical issue of how to distinguish between objectives to be optimized and constraints to be satisfied and, in turn, which constraints are hard or soft. These decisions need to be based on engineering judgement and can change during the operation of a unit.

Therefore, there is a need to develop on-line systems which translate the qualitative decision making into quantitative problems to be solved by the control system.

2. Robustness to Modeling Errors:

Most methodologies for process control do not handle the issue of model inaccuracy in a satisfactory way. In the event of mismatches in the assumed process model and disturbance description a "tuning" procedure is employed which consists in modifying the true performance objectives so that the controller obtained assuming a perfect model will perform as desired on the true plant. There is a definite flaw in the design when we know that model errors exist but insist on design methodologies that use a perfect model description. The new Structured Singular Value (SSV) approach of Doyle (1982) was developed to address this particular issue of design in the face of uncertainties. However, it assumes a transfer function type of implementation. Therefore, there is a need to tie these new results with model-predictive type controllers.

In the rest of this paper we will discuss in some depth these two issues and show some research efforts currently in place to address them.

SPECIFICATION OF PERFORMANCE CRITERIA FOR PROCESS CONTROL

The most important step in process control design is to determine what the control system is meant to do and what performance is expected from it. Even though we can attach some monetary or economic value to every criteria, there is usually not enough data to allow us to assign costs for every situation. Therefore, it is seldom the case that the performance is given by a single criterion (i.e. cost) nor that it remains invariant with time.

As explained above, we will assume a two-phase approach to process control as illustrated in Fig. 1. Therefore, the function of the control phase must be not only to move the process to the new operating point dictated by the optimizer but also to keep it operating there despite disturbance changes. In order to achieve this, there are multiple criteria to be satisfied by the control system. In this framework we will classify all **practical** process control criteria as belonging to one of the following kinds:

- Economic:

  These can be associated with either maintaining process variables at the targets dictated by the optimization phase or dynamically minimizing an operating cost function.

- Safety and Environmental:

  Some process variables must not violate specified bounds for reasons of personnel or equipment safety, or because of environmental regulations.

- Equipment:

  Physical limitations of equipment must not be exceeded by the control system even when not directly related to safety.

- Product Quality:

  Consumer specifications on products must be satisfied.

- Human Preferences:

  There exist excessive levels of variable oscillations or jaggedness that the operator will not tolerate. There can also be preferred modes of operation.

It will be assumed that every variable needed to evaluate the practical criteria stated above is measurable or can be inferred by secondary measurements or operating policy. Then it follows that any practical criteria can be stated as being one of two types of **mathematical** criteria:

- Objectives:

  Functions of variables to be optimized dynamically where optimal means best satisfaction of the criterion.

- Constraints:

  Functions of variables to be kept within bounds which in turn can be of two kinds:

  - Hard constraints: no dynamic violations of the bounds are allowed at any time.
  - Soft constraints: violations of bounds can be allowed for satisfaction of other criteria.

The challenge for the designer consists in the selection of the actual functions and in the evaluation of trade-offs between criteria for solving the problem. Also, confusion between constraints and objectives must be avoided at the design stage. In the following we explore each of these issues and give examples of proper selection of performance criteria for practical problems.

Selection of Objective and Constraint Functions

Different methodologies in process control are based on assumptions about the functionalities of objectives and constraints in order to simplify the solution of the problem. Besides making the problem mathematically manageable, the main reason for simplification is to allow implementation in the existing hardware.

For example, in QDMC a quadratic objective function is used for mathematical convenience since it yields a simple least-squares control problem in the absence of constraints. When constraints are added, a quadratic program results which can be solved very efficiently and conveniently with standard software. However, for some applications a quadratic objective might not be the appropriate criterion to use. Also, there might be some advantage in using frequency response objectives instead of time domain objectives.

Although these issues have enough relevance to merit further discussion and analysis, in our opinion there are other assumptions which have a more significant impact on performance. For instance, the most typical assumption made in process control is to "convert" constraint criteria into objective criteria. The reason is that problems with constraints are difficult to solve with the available hardware. On the other hand, conveniently formulated objectives can yield concise control designs which can be implemented easily with simple blocks. However, the performance of the control system will generally degrade when a true criterion is compromised for mathematical convenience.

For example, quality criteria in the form of composition specifications is a constraint criteria. However, in many situations it is changed into an objective that minimizes deviations from a target, having the predictable consequences. On the one hand, composition is kept at a target even when deviations away from the real bound and into the feasible region are not critical and might even be necessary in order to satisfy other conflicting criteria. On the other hand, since the constraint limit is not enforced, violations can occur and therefore the target must be kept within some tolerance of the bound. Therefore, there is a performance loss directly related to the mathematical simplification of control criteria.

There seems to be a need to develop methods for not only specifying the correct function to be used as a criterion but also for making the choice between expressing a practical criterion as either an objective or as a constraint.

Evaluation of Trade-offs and the Solution of the Control Problem

Once a satisfactory set of functions is chosen as objectives and constraints, there remains the problem of evaluating the trade-offs between criteria. It is obvious that by making a constraint hard it is understood that it takes precedence over any other objective or soft constraint. In the case of soft constraints, they can be handled as objectives when they become active during the operation of the controller. Since there exist many quantitative as well as qualitative reasons for the designer to prefer one criterion over another, the control technique must provide a way to allow the designer to influence the solution. This can be done in several ways.

Single objective function. One can lump all objectives and all active soft constraints into a single objective function by using weights. The importance of each objective is then influenced by the relative size of the weights. This objective is then optimized subject to the hard constraints. Such approach is done by QDMC as described in the previous section. In addition, in QDMC we have been able to add other objectives that can be expressed as quadratic functions to solve economic optimization and enforcing targets for manipulated variables (Prett and Gillette, 1979).

Although computationally convenient, there are some difficulties with this approach. First, the selection of weights is dependent on the particular scaling of the variables, therefore making the enforcement of an objective difficult. For example, selection of weights for the satisfaction of a target for a temperature vs. that of a composition will depend on each variable engineering units. Second, even when there are no scaling problems, the relative importance of different kinds of objectives cannot be exactly quantified for most problems (i.e. economic cost vs. variable deviations). Third, since the objectives are lumped together there is no guarantee that by increasing the corresponding weight of one objective the other objectives will not be affected, due to an inherent interaction between objectives through the lumping. And finally, those weights chosen today may not be appropriate later on when operating conditions have changed.

Despite these difficulties, the single objective function approach has worked satisfactorily in many practical cases. The reason is that it is computationally so simple that one can afford to be imprecise with the initial weight selection. Then the weights can be updated on-line according to the observed performance. Such approach has been followed in Shell since the initial applications of DMC. However, its success has been achieved at a high maintenance cost. Although this was cost effective in the past, it is becoming increasingly difficult and costly to maintain the current large number of QDMC loops. Recent technological advances indicate that these difficulties can be overcome through better formulation of the problem. This then allows for less control expert personnel being assigned to the loop maintenance role. Gradually, our technological advances are allowing for the entry of more advanced loops into the world of general control loop maintenance. This is of course the objective of the pursuit of the **Unified Theory**.

Multiple objective functions. From the above discussion it follows that the exact mathematical formulation of the control problem to be solved is a multi-objective optimization algorithm subject to multiple constraints, with the ability to distinguish and to handle hard and soft constraints. By performing a suitable multi-objective optimization (also known as vector-valued function optimization) the issue of assigning weights for each criterion can be removed.

One such algorithm solves the following generalized optimization problem at each sampling time (Nye and Tits, 1985):

$$\min_{x} \{ \max_{j} \quad f_j(x) \mid g_i(x) \leq 0 \} \tag{10}$$

where j=1,2... are the number of objectives and active soft constraints, i=1,2... are the number of hard constraints and the solution vector consists of the manipulated variable moves. This problem minimizes the maximum of the objectives subject to the hard constraints. Since each objective has its own level of importance and satisfaction to the designer, one has to somehow influence the solution of (10) based on the designer's desires. One way of achieving this is to normalize the set of objectives and soft constraints conveniently as follows:

$$f_j' = (f_j - fgood_j) \;/\; (fbad_j - fgood_j) \tag{11}$$

where the "good" and "bad" values of the objectives and soft constraints are specified by the designer. Note that values of 0 and 1 correspond respectively to the specified good and bad values. This implies that these normalized objectives are to be always minimized.

By normalizing individual objectives with respect to their good and bad values all the criteria can be compared on the same basis. For example, two objectives having the same normalized value equally satisfy the designer; both would be equally "good" or equally "bad". Therefore, the problem of selecting weights when the objectives are lumped in one function is replaced by the problem of selecting the good and bad values for each objective. Even though still requiring some effort to select, compared to weights these values will make more engineering sense and will be directly related to the actual problem.

In the original paper where this optimization technique is presented (Nye and Tits, 1985) the authors make the point that such an algorithm must be supported with a good man-machine interface so that the designer can evaluate the trade-offs and influence the solution accordingly based on engineering judgement. In an on-line environment (as we propose to use such a technique) these decisions will necessarily need to be automated so as to achieve a maintenance-free operation. The best technology available at present to achieve such automation is the expert system technology. As we see it there will be an intelligent decision maker on top of the optimizer updating the criteria (Fig. 3). These criteria will be updated based on quantitative as well as qualitative information about the operation.

Some Examples of Selection of Performance Criteria

In this section two examples of problems where correct specification of performance criteria is critical are presented.

The surge level control problem. Distillation column trains where the product flow(s) of one column feed a downstream unit pose an interesting situation in control objective specification. It is common practice to balance the material in these columns by controlling an accumulator level through manipulation of the outlet flow. Since the manipulated variable for controlling the level in one column is in turn a disturbance to the following unit, any upset can easily propagate downstream. In olefin plants, for example, there is a fractionation train as shown in Fig. 4.

If only one column in this train is considered, the practical criteria for this problem are:

1) Minimize variations in the outlet draw.
2) Maintain the level within the upper and lower bounds of the tank over a future time horizon.
3) Maintain the outlet flow within its upper and lower bounds over a future time horizon.
4) Bring the level back to the middle of the tank at the end of the time horizon.

Satisfaction of these criteria will minimize the propagation of upsets, will keep the level within the equipment constraints while manipulating the outlet flow within its limits, and bring the level back to the middle of the tank in order to guarantee surge capacity for the next upset.

Several issues are of importance here. First, if the control problem is designed individually for each column in the train, there might be a loss of performance. Note that the downstream columns will be perturbed with known inlet flow changes and therefore one could feedforward the predicted moves. More elegantly, however, one could solve for the set of criteria for the entire train yielding a multivariable control problem.

Second, let us consider the traditional control setup for this problem. Since the level in the tank must not exceed its bounds the common practice is to design a controller for keeping the level at the middle of the tank usually very tightly. As a consequence, any disturbance change to a column will propagate downstream with equal intensity or possibly amplified if the loops are not adequately tuned. In the particular case of an olefins plant, a furnace trip will cause a severe step decrease in the feed to the first column (Fig. 4) which can upset the process for several hours. Thus, a high price is paid for substituting the true criteria for an alternate criteria of minor relevance, namely, tight control of the level. In this problem, it is more important to minimize outlet flow changes regardless of the level, except when it violates the upper and lower bounds.

Finally, from criterion 4) it is obvious that we are assuming every inlet flow disturbance change to settle faster than the horizon chosen. Should a dynamic representation of the inlet disturbance be available, this information would allow the controller to make moves to conserve surge capacity for future upsets without having to design the controller to satisfy criterion 4). This illustrates the effect of model error in forcing the modification of performance criteria. This issue will be covered in the next section.

A semi-batch reactor control problem. The process discussed here is the block polymerization of synthetic rubbers (Garcia, 1984). The final product consists of a polymer composed of several blocks of different monomers. A sequence of batch operations is performed to produce the blocks. Since the polymerization proceeds via an anionic mechanism, chain termination follows an Arrhenius type decay whose rate increases with temperature. Successful polymerization of all blocks demands that a only a small fraction of the molecules terminate at every reaction step.

These reactions are carried out in the vessel depicted in Fig. 5. The heat of reaction is removed by circulating the reactive solution through exchangers which use refrigerated water. In addition, there is the capability of manipulating the rate at which monomer is added for control of the heat release. The initial batch charge and recipe for the reaction are assumed given. In general, there is a desired temperature target at which the reaction is to take place.

Following this description, the criteria to be satisfied are:

1) The cooling water flow must be within its upper and lower bounds.

2) The monomer addition rate must be within its upper and lower bounds.

3) The reaction temperature must be close to the target over the whole batch.

4) The fraction of terminated chains must be smaller than a given bound at the end of the batch.

5) The batch reaction time must be minimized.

It must be noted that satisfaction of these criteria guarantees that other important properties of the polymer are satisfied, and therefore these criteria cover all possible aspects of the problem. The last criterion is purely economic.

In order to solve this problem, a multi-objective constrained optimization of the type described in (10) is required. In the absence of constraints and transforming criterion 1) to an objective criterion, then an optimal control approach can be used. Alternatively, due to computing limitations, the method reported by Garcia (1984) consists in defining alternate criteria which indirectly satisfy the true criteria. These alternate criteria are then solved for by using the standard QDMC algorithm (although with some modifications due to the nonlinearities in the model). These are:

1) The cooling water flow must be within its upper and lower bounds.

2) The monomer addition rate must be within its upper and lower bounds.

3) The reaction temperature must be close to the target over the whole batch.

4a) The monomer addition rate must be at its maximum possible value during the batch.

In order to satisfy these criteria, a control problem can be set up with the reactor temperature as the controlled variable. Also, a target can be imposed on the monomer addition rate equal to its maximum bound. This forces the controller to add monomer at the maximum possible rate. The manipulated variables are the cooling water flow and the monomer addition rate.

Note that satisfaction of alternate criterion 4a) indirectly satisfies criteria 4) and 5), since adding monomer at the maximum rate possible minimizes the reaction time. This in turn minimizes the chain termination rate due to the properties of the anionic mechanism. Note that by doing this we have substituted a constraint criterion by an objective criterion while having to lump both target criteria 3) and 4a) into one single objective. As a result, there is a need to tune the weights in the objective function in order to satisfy the true criteria.

In the following section the important issue of robustness to model uncertainties is discussed as it affects the satisfaction of performance specifications.

MODEL INACCURACY CONSIDERATIONS IN PROCESS CONTROL

In previous discussions, we have not explicitly dealt with the issue of accuracy of the model of the process and of the disturbances in designing model-predictive controllers. An important property of model-predictive controllers is that no stability problems exist under perfect model conditions, even in the face of constraints on the manipulated variables (Garcia and Morari, 1985). However, there exist inherent limitations in satisfying arbitrary criteria due to specific process characteristics. As discussed by Garcia and Morari (1982) system zeroes outside the unit circle and deadtimes impose limitations on the satisfaction of targets which cannot be removed by any control system. Since satisfaction of active output constraints can be thought of as a target satisfaction criteria, output constraint criteria satisfaction will also be limited by the same process characteristics. As a result, these limitations must be taken into account when formulating the objectives and constraints. The factorization method (Garcia and Morari, 1982) takes care of this problem for target criteria and therefore, for most practical cases these limitations do not impose additional difficulties in the design.

However, the most important limitation to satisfying control criteria is imposed by inaccuracies in the model assumed for design. Models used for design will not be accurate for several reasons:

- The model is assumed linear when the process is nonlinear and therefore, the model will not describe the process when the operating point changes beyond a certain amount. This problem is exacerbated by the presence of optimization systems which generally increase the frequency of operating point changes.
- The equipment degrades or is changed (e.g. catalyst change, heat exchanger fouling, tray collapses, etc.).
- Disturbance characteristics are unknown and therefore assumptions are made at the design stage on their dynamic behavior.
- Techniques used for identification are not accurate enough or the measurements are not of enough quality to produce the model detail wanted.

In the face of significant model inaccuracies the control system is generally unable to satisfy all of the true performance criteria specified for the process. In this event, the designer (before the implementation) or the tuner (after implementation) is faced with the decision to trade one performance criteria for another.

For example, two commonly specified criteria for single variable control systems are to maximize the setpoint tracking speed while exhibiting smooth manipulated variable response. The tuning parameter selection (e.g. controller gain) influences the trade-off between these criteria. In the absence of model error it is possible to achieve any desired speed in setpoint tracking behavior (within some inherent system limitations as are deadtimes and system zeroes outside the unit circle (see Garcia and Morari, 1982)). However, the faster the response, the more "power" will the manipulated variable need to have. In order to satisfy the smoothness criterion on the manipulated variable the designer can detune the controller until an acceptable response is obtained. This tuning procedure yields the fastest tracking speed possible for the desired manipulated variable smoothness in the absence of model error.

Let us now assume that the controller designed as explained above is installed and a significant change in the process occurs. Invariably, the fastest speed of tracking achieved by the designer when the model is perfect will not be achievable in the face of model error without an increase in manipulated variable jaggedness. Therefore, the tracking speed must be sacrificed to satisfy the smoothness criterion. If this slower closed-loop response is acceptable, the model error has not imposed a restriction on satisfying the criteria. On the other hand, if the closed-loop response is not fast enough for the particular application, then this inaccuracy forces the tuner to accept a higher level of manipulated variable jaggedness, or most likely, to take the loop off control.

Controller robustness can then be defined as the ability of the control system to satisfy the desired performance criteria of the true process in the face of inaccuracies in the model used for design. In the example above, an expert tuner is assumed to be present to ensure robustness, and therefore this is a drawback in the way controllers are designed and tuned today. In the particular case of model-predictive controllers, this issue is amplified by the fact that it is not possible to foresee at the design stage all possible scenarios of active constraints and tune appropriately for all of them. Our goal, that is equally shared by all practitioners, is to design a controller that stays on-line longer while requiring minimal maintenance. Let us examine the traditional methods used to achieve robustness and also discuss a new technique aimed at solving these difficulties.

Traditional Methods of Handling Model Inaccuracies

The single variable tuning example discussed above illustrates the most common procedure used to handle the uncertainty issue. Out of lack of better information about the process, most control methodologies assume the model description of the process to be accurate at the design stage. The control performance is evaluated based on this model and a set of tuning parameters is obtained. However, model inaccuracies will cause a degradation in the expected design performance when the loop is implemented. The traditional way of handling this loss of performance is by modifying the tuning on-line.

Another interpretation of the traditional tuning process is to think of it as a procedure that modifies controller criteria to guarantee robustness to modelling errors. In the QDMC method, weighted penalties on the manipulated variable moves are added to the objective function as given in equation 8. Even though in many practical cases there is a true need to minimize manipulated variable variations, the main reason for penalizing them in QDMC is to improve the robustness properties of the algorithm. However, to guarantee robustness on-line tuning is required.

It is reasonable to think that if some knowledge of the uncertainties is available at the design stage, a more robust design could be obtained by, for example, performing studies on the tuning parameters. The problem with such a study is that the true process performance would need to be evaluated by performing simulations over all possible process representations generated by the uncertainty description. In addition, in the model-predictive environment, innumerable studies would be required to consider all possible scenarios of active constraints.

The issue is then to be able to easily measure how model inaccuracies limit the satisfaction of true process performance criteria (both objective and constraint criteria) given an uncertainty description. This measure can then be used in two ways. First, to evaluate the trade-offs at the design stage for the most typical scenarios of active constraints. This would indicate whether or not the controller will work for expected uncertainties without having to perform extensive simulation studies. Second, during the implementation, changing criteria can be evaluated on-line in the face of inaccuracies. As a result, a design can be produced which will stay in operation longer with minimum maintenance. These issues are central in a newly developed robust control theory discussed in the following.

Methods to Solve the Model Uncertainty Problem

We are currently investigating several methods to handle the issue of model inaccuracy in the design of model-predictive controllers. In this section we give a short description of each and propose how they can be used to solve the problem at hand.

Robust control techniques. We have found recent developments in the area of control to have promising possibilities in solving the model-predictive control problem in the face of uncertainties. Although its implementation assumes a recursive type of controller with no constraint handling, the Structured Singular Value (SSV) approach of Doyle (1982) employs the correct philosophy of approaching the robustness issue: use an uncertainty description of the process at the design stage to obtain a controller that will not perform worse than desired on the true process, therefore, minimizing on-line tuning. In this discussion we briefly describe this technique as applied to recursive type controllers and point out what research topics need to be addressed in order to extend these ideas to model-predictive controllers.

The SSV provides a measure of true process performance satisfaction in the face of model inaccuracies. The result is a refinement of the Singular Value result (Doyle and Stein, 1981) where now structured uncertainties can be considered. This means that it allows the designer to specify uncertainties in the gains, time constants, etc. in given elements of the system transfer function matrix. As a result, a less conservative stability criterion is obtained.

In Doyle's formulation, performance is described by weighted frequency response functions that reflect the designer's desired closed-loop characteristics. The trade-offs are influenced by the selection of these weights. Model inaccuracy is described in any form desired as long as it can be represented in block diagram form suitable for linear processes. In addition, an uncertainty description of the disturbance dynamics in frequency response is used making the method more appealing than LQC where disturbances have to be described as Gaussian noise.

Under these assumptions, the method consists of the solution of two important control problems:

The Analysis Problem: given a controller, one can evaluate a criterion (the SSV) whose value indicates whether or not the desired performance is achieved for the true process in the face of the described model and disturbance uncertainties.

The Synthesis Problem: given the desired performance of the true process and a description of model and disturbance uncertainties, a controller transfer function is found so that the SSV criterion is met.

The first problem involves an optimization procedure to evaluate the SSV where the second involves another optimization to compute the controller.

Even though the methodology has been developed for a recursive type of control implementation, we see much promise in it, particularly in the way model and disturbance uncertainties are described. Of course, this description is not always available. However, it is our experience that the designer has enough knowledge about the process to be able to specify ranges of values for gains and time constants. Even such crude description would produce a more intelligent and consequently more robust design than assuming the parameters to be accurate.

At present, this technique is useful to solve the analysis problem of QDMC at the design stage, but only if constraints are removed. Using the nominal model one can design QDMC for a set of tuning parameters (as is done presently). Then the SSV is computed for such controller to evaluate whether or not the desired closed-loop properties of the control system (e.g. disturbance rejection, manipulated variable smoothness, etc.) are satisfied for the given model and disturbance uncertainty description. Such analysis would give the designer a tool for tuning his controller, without having to perform simulation studies. We are currently incorporating such analysis tool in our design techniques.

Since it is not possible at the design stage to consider all possible scenarios of active constraints and other criteria, and therefore, all possible controllers generated by QDMC, the best we can hope for with the current SSV theory is to perform analysis studies on the most common operating conditions. This would involve substituting a constraint criteria for an equivalent objective criteria. For example, if we expect some variable constraint to be active, it could be considered as a controlled variable with the target as its bound and the analysis performed on the resulting controller. This would hopefully reduce the situations where on-line tuning is required to a minimum.

However, in an environment of changing criteria that do not translate easily to frequency response functions (as are inequality constrained responses in the time domain) this methodology would likely need to be modified. As discussed above only the on-line solution of the problem provides such flexibility. We must realize that at the design stage there seems to be no comprehensive way of evaluating all the possible operating scenarios and consequently, case studies must necessarily be performed.

Among the possible modifications, one could remove the weight selection process by using a multi-objective optimization method that allows direct evaluation of the performance criteria based on engineering judgement. The technique described previously seems to be a convenient tool for this (Nye and Tits, 1985).

But the best extension of this technique to the model-predictive framework is to solve the synthesis problem on-line for the manipulated variables moves directly rather than off-line to obtain a transfer function. This has the potential of producing a controller which can accept changing objective and constraint criteria. These criteria are then traded on-line in the face of model inaccuracies to produce the best moves of the manipulated variables. Although possibly computationally prohibitive with today's computers, this appears to be a sound approach to solve the real problems at hand.

<u>Adaptive Control Methods.</u> Much attention has been given in the literature to adaptive control schemes. These methods handle the model inaccuracy problem by on-line identifying the process model based on measurements of inputs and outputs of the plant (Astrom and Wittenmark, 1973). Besides solving for only an objective criteria, namely the minimum variance objective function, this is done under the assumption that a perfect model is obtained at every execution time.

Besides being limited in the criteria that are solved, the assumption of perfect model can create problems. Even though the model is updated continuously, on-line experiments have inherent limitations which do not allow complete identification of all process modes or of all disturbance characteristics. Therefore, the model updates might not be good enough to allow the control system to satisfy the specified objective and therefore a tuning procedure is inevitable.

In the framework of model-predictive control, we have already discussed how to best handle the criteria formulation problem, and therefore, out of adaptive control theory we will only be concerned with the on-line model identification aspects. In light of the robust control theory described above, two research topics are of interest:

- Use robust control analysis to find out which model parameters lack enough accuracy to allow the satisfaction of the desired criteria. Then an on-line identification procedure can be used to refine the estimates of such parameters.

- Develop on-line identification methods that not only find the nominal model but also identify the uncertainty bounds on plant and disturbance models.

Current work consists in finding suitable on-line identification schemes for dealing with these issues.

Nonlinear model description. In case a dynamic nonlinear model of the plant is available, the model-predictive control problem can be solved assuming perfect model description. Numerical problems aside, this seems to be the best approach to take. However, model inaccuracies will inevitably be present even using nonlinear models and therefore, a nonlinear robustness analysis is needed. An advantage of using nonlinear models is that now the parameters can have definite physical significance as for example, fouling rates, kinetic rate constants, etc.

We have had good success using nonlinear models for solving complex control problems. The reactor control problem described in the previous section was solved by using nonlinear ordinary differential equations to generate the predictions and step response coefficients (Garcia, 1984). The solution method assumed linear superposition of future predictions to compute the moves and therefore was not optimal. However, one can easily formulate a dynamic optimization problem which solves the problem exactly. In this particular application, computing power limitations prevented us from using a more rigorous solution method on-line.

CONCLUSION

In this paper an attempt was made to formalize a rigorous approach to research in process control. The pursuit of a **Unified Theory** was introduced within the context of the need for our industry to apply an **Integrated Technology** philosophy to maximize the synergism of separate component technologies such as control and optimization. The field of process control has been pursued in an ad-hoc fashion for many years. Many so called solutions have not stood the test of time nor have they been translatable nor generalizable to cover more than the immediate application. In technical developments too much attention has been paid to implementation constraints, such as hardware capability, leading to the situation we have today wherein much of our industry is not capable of exploiting the rapid growth of computing power available at the field level. Hence we have the sad state of choosing between ad hoc solutions that really do not meet the requirements of the application, or so called advanced technology that really does not address the real problem.

The concept of an **Integrated Technology** refers to the recognition that a control system, besides having to perform in the load rejection mode, will also most probably experience some manipulation of setpoints which is generalized here in the term **Optimization**. Whether this is performed using a rigorous first principles approach or in a more ad hoc fashion is really beside the point. Our control design methodologies must incorporate this fact and hence be able to recognize and deal with constraints. Ad-hoc approaches to constraint handling superimposed upon so called advanced techniques are no better than overall ad hoc problem solutions themselves. It is time to recognize this fact and get on with the pursuit of research activities that will lead to a continually evolving series of problem solutions growing in technical sophistication. Over time it is hoped that this will lead to a **Unified Theory** of process control that will be generally applicable to most all our problems. The authors feel that the Dynamic Matrix Control technique is an excellent first step down this path that incorporates many of the requirements discussed. It is however just a beginning. It is a beginning that at least provides the framework for evolutionary growth. We must deal with the following issues:

- Nonlinear model requirements
- Constraint handling
- Detailed performance analysis and multi-objective solution techniques
- Dynamic problem structuring techniques
- Requirement for low maintenance

and furthermore deal with them in a generalized framework so that long term we can look to a **Unified Theory** incorporating all aspects.

While involved in this endeavor it is also important for us to suitably exploit the growing areas of Artificial Intelligence and Super Computing. The field of Artificial Intelligence will facilitate the synergism of qualitative and quantitative knowledge bases. Much of our historic problem with specification of performance requirements has been due to the qualitative nature of the input information. Difficulty has been experienced in effecting the appropriate level of interaction between this and the more quantitative solution techniques available. This is being rapidly addressed by the new developments in Artificial Intelligence and process control researchers are well advised to stay up to date with this work. One caution in this area is that there has been a tendency to shroud the old traditional ad-hoc solutions discussed earlier in the mantle of respectability by framing them within the context of Artificial Intelligence Systems. This is considered unacceptable. The real contribution of Artificial Intelligence will be as a complementary aid in solving the real problem and not in facilitating the implementation of ad-hoc solutions.

The field of super computing is also very exciting as a prospective aid in implementing our proposed approach. It is reasonable to expect that within the next five years low cost high performing computer power will allow us to consider removing artificial boundaries between the areas of control and optimization and so allow us to truly achieve an **Integrated Technology** approach.

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NOMENCLATURE

a_ℓ step-response coefficient matrix with respect to process inputs for ℓ^{th} time interval.

a_{mi} step-response coefficient matrix with respect to manipulated variables for i^{th} time interval.

A state-space model state matrix.

B state-space model input matrix.

B_m state-space model manipulated variable matrix.

C state-space model output matrix.

d unmodelled contributions to the output

f^j j^{th} objective in a multi-objective optimization problem.

g^i i^{th} hard constraint.

h_ℓ impulse-response coefficient matrix with respect to process inputs for ℓ^{th} time interval.

k discrete interval of time.

m process manipulated variable vector.

M number of discrete time intervals when manipulated variables are allowed to move in the controller computation.

P number of discrete time intervals in the controller horizon.

q integrator state vector.

T sampling time.

u process input vector (manipulated variables and measurable disturbances).

x vector of system states.

y process output vector.

y_m process output measurement.

y_S output setpoint vector.

Greek

Δ denotes a change in a variable over a time interval: $\Delta x(k) = x(k) - x(k-1)$.

Γ_ℓ matrix of penalty weights on outputs.

Λ_ℓ matrix of penalty weights on manipulated variables.

Subscripts

L variable vector of low limits.

H variable vector of high limits.

Superscripts

$\hat{}$ predicted variable.

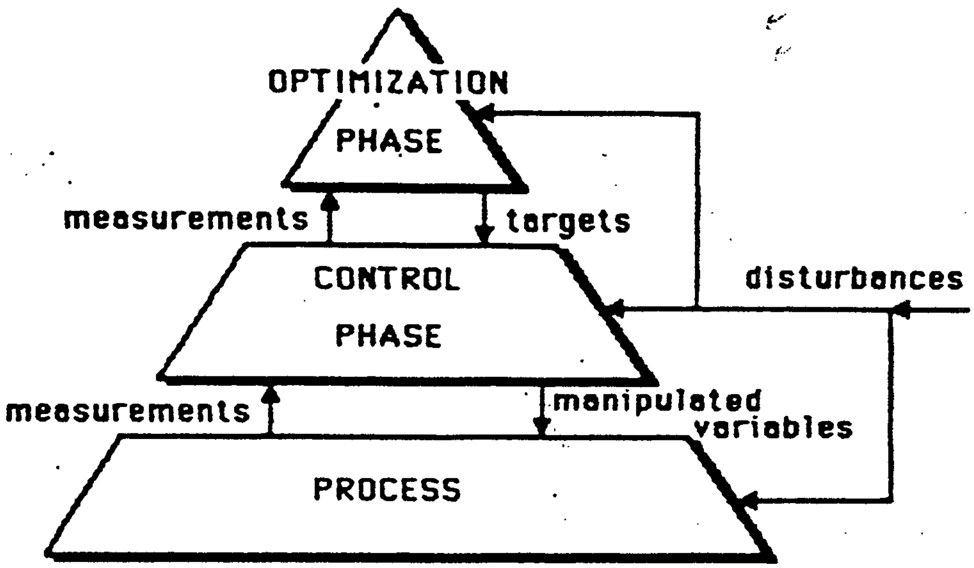

Fig. 1. The Integrated Technology Approach to process control.

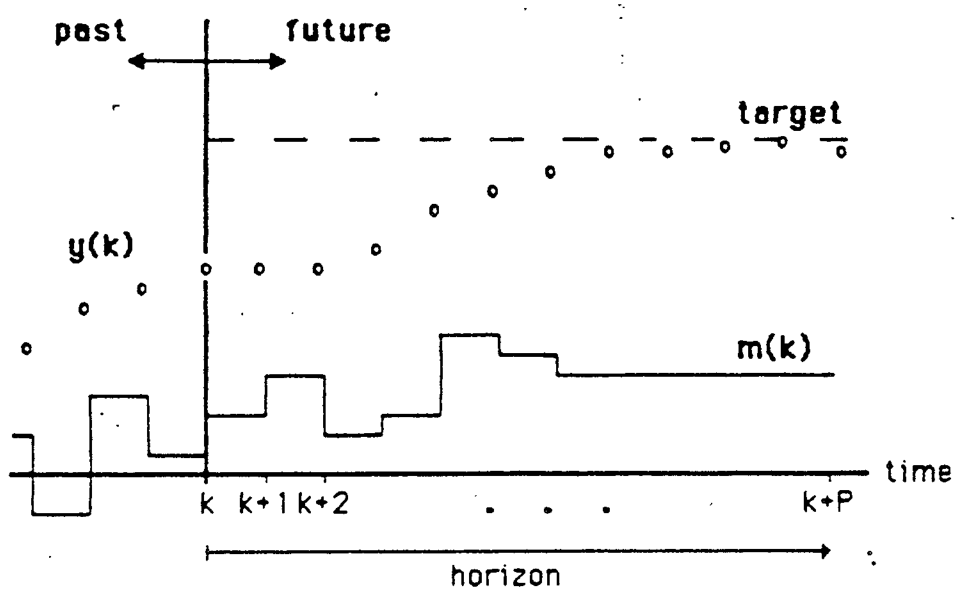

Fig. 2. The "moving horizon" approach to model-predictive control.

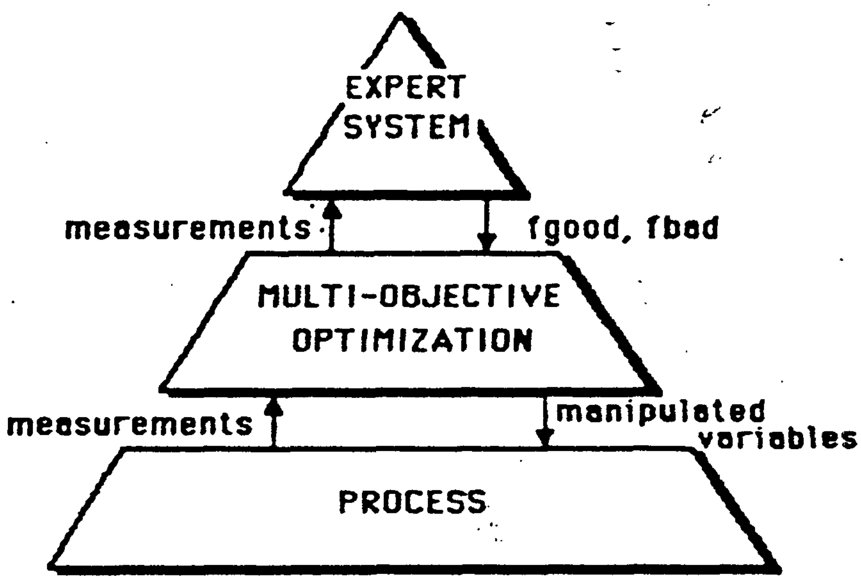

Fig. 3. On-line updating of the multi-objective optimization criteria by an expert system.

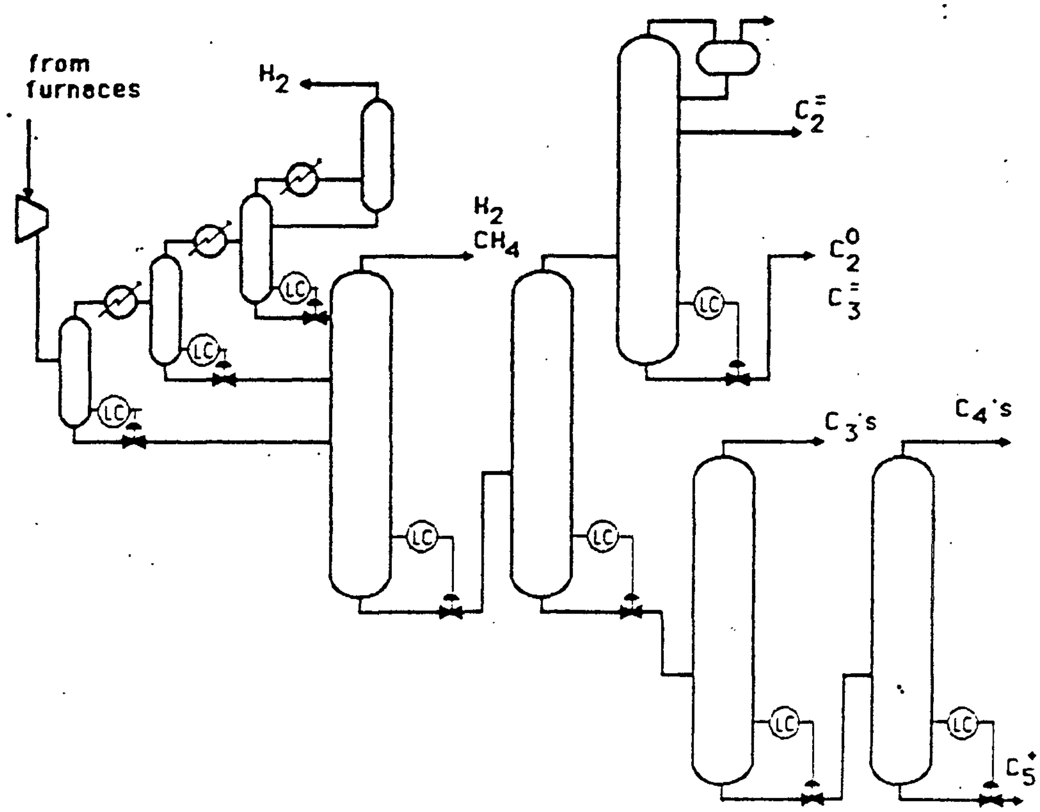

Fig. 4. Olefins plant fractionation train

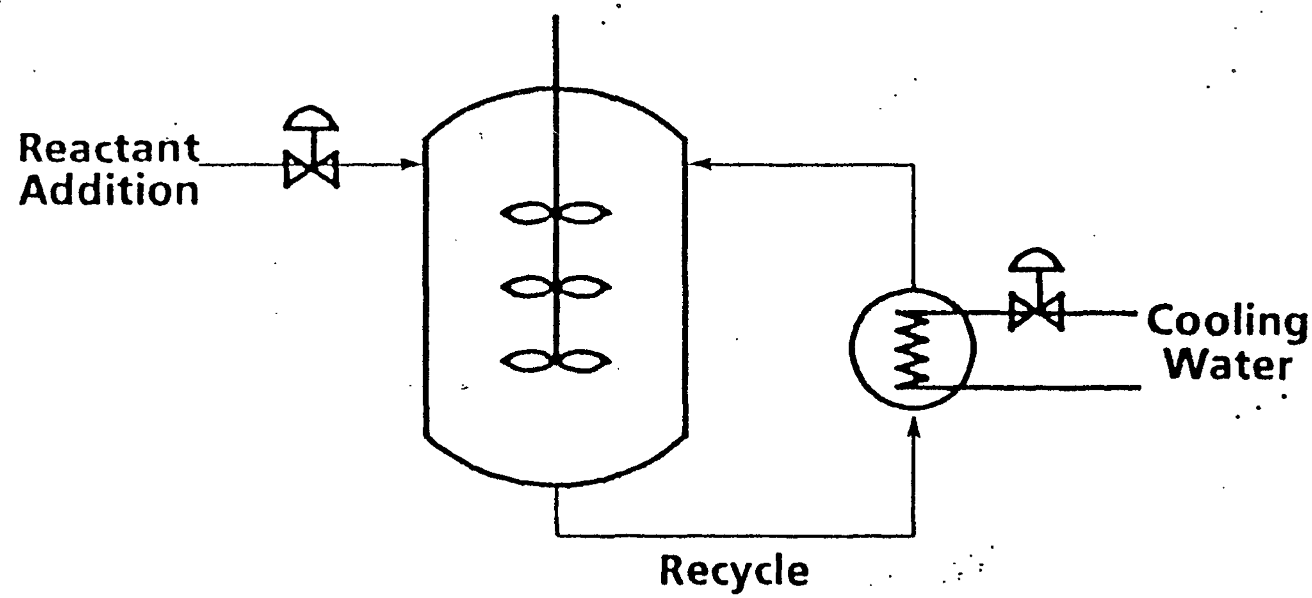

Fig. 5. Semi-batch polymerization reactor.

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