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Industrial Applications of Model Based Predictive Control*

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Two typical applications of Model Based Predictive Control (MBPC) are presented. One deals with a slow process unit: a typical crude oil distillation tower with dynamic control and local constrained optimization; the other one with a two degree of freedom follow-up servo turret. The connection between the identification uncertainty and the control robustness is presented.

Key Words—Model based predictive control; distillation; tracking systems; global identification; robustness; concurrent engineering.

Abstract—In this paper we describe two classical applications of MBPC which enhance the advantages of the method: feed-forwarding, constraints handling, no-lag error on dynamic set points, easy trade-off between robustness and dynamics specifications. We insist more on the project procedure than on the control algorithms which are presumed to be known from references. Practical difficulties appear to come more from the selection of the model and from the formulation of the specifications than from the strict controller design. To be efficient with a good economic pay-back, MBPC should be used at the optimization level, embedded in an appropriate environment. These requirements nowadays, due to efficient control packages, demand more time and effort than the control algorithm *per se*.

1. INTRODUCTION

In the last 10 years Model Based Predictive Control (MBPC) has achieved a significant level of acceptability and industrial success in practical process control applications. During the same period, as classical research topics on self-tuning theory seemed to dwindle, the academic community devoted more attention to MBPC (Clarke *et al.*, 1987; Soeterboek, 1990; De Keyser, 1991). Thus, it is to be noted with some satisfaction, that theory and practice supported each other quite efficiently in this methodology. Progress, which has consequently been steady, is now accelerating.

This paper aims at giving a comprehensive report of two typical applications of MBPC:

(a) in the 'slow process' field, typically the petrochemical industry which still remains the main end-user and promoter of 'advanced control';

(b) in the 'fast process' industry which has a more diverse background, where each company has its own specific corporate understanding of control problems.

The first case-study relates a typical, though sophisticated, application of MBPC to a crude oil distillation unit. The target is not to demonstrate that MBPC works satisfactorily, since it is proven in field. Among today's 300 industrially commissioned applications of advanced control in the petrochemical area, IDCOM-HIECON (Richalet *et al.*, 1978) and DMC (Cutler and Ramaker, 1980); roughly sharing the same application niche (Babb, 1991), have the largest number of economically successful applications. Thus we will concentrate on three other areas:

—for the industrialist who has not (yet) used MBPC: what are the technical economic and human requirements for a successful application?

—for the industrialist who already applies MBPC: what are his needs? How can application be improved?

—for the control scientist: what are the needs for the future, where do possible new developments lie, what can be brought back as a research topic, where might theory contribute positively and allow progress on a safe theoretical basis?

The second case-study relates an application of predictive functional control (PFC) (Richalet *et al.*, 1987) to a severely constrained follow-up servo system in mechatronix, where the process

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to be modelled is not at all 'well-behaved' and where both robustness and performance are needed.

Both applications are relevant to MBPC which has a universal and open nature and thus can cope with the specific requirements of practical applications. The foundations of these two control strategies are well described elsewhere and can be found in the bibliography.

Applying advanced control requires some effort. When contemplating practical applications, the academic community might have a somewhat distorted point of view in overemphasizing the relative importance of the control algorithms (Aström, 1991). Certainly, without them, no added value will be gained, and nothing will work out well; they are definitely the gist of the applications. However, other parts of the whole application procedure are also essential. Moreover, most time and effort is nowadays spent precisely on the non-control strategy part, since we now have efficient computer aided design control methodologies.

Before any evaluation of MBPC, a basic question is to be raised: is advanced control necessary? What is it?

Definitely the answer cannot be given in terms of a list of particular selected strategies. Advanced control is not a restricted club, composed of self-styled 'optimal, general, universal' control algorithms. From the application point-of-view, which is under consideration in this Special Issue, the difference in control approaches comes with the necessity of modelling. The situation in industry seems to be clearer nowadays: either a model is or is not needed. If it is needed then advanced control is the answer.

The instrumentation industry proposes already implemented control techniques, which are to be tuned locally, for example PID. One can consider that tuning a PID controller is theoretically equivalent to modelling a second-order system, but explicit modelling is not performed. Rules and tuning aids can be provided and the performance to cost ratio of the procedure, if it works, is well appreciated. That is why PID is to be considered first, systematically. Fortunately for the production industry, 80–90% of all control problems can be executed elegantly with this procedure. Now it appears that the remaining 10% are multivariable and deal with interactive processes which are not easy to decouple, which are constrained, nonlinear, and where 'optimality' is looked for in terms of error variance or closed-loop time response, disturbance rejection, *etc.* To achieve these performance characteristics, the PID controller loses its superb efficiency and a simulator is needed, where more complex control strategies have to be evaluated (Grosdidier *et al.*, 1988; Latour, 1976).

The workplan is then thoroughly transformed and local staff need to have a different background. There lies the difficulty of penetration of advanced control in industry, either at the decision level or at the execution level.

Specific tuning is always necessary. In the first case it is the controller which is tuned; in the second the model is to be matched to the actual process. Once this effort is made, the controller should be obtained almost automatically, with only specification parameters (*e.g.* time response, robustness). MBPC's popularity comes in great part from the fact that a suitable model being given, the controller can be easily implemented with a direct physical understanding of the parameters to be tuned (reference trajectory, disturbance rejection, *etc.*) and easy constraints handling (Abu el Ata-Doss *et al.*, 1991; Soeterboek, 1990; Tzang and Clarke, 1988).

Figure 1 shows the relative effects of control design with and without modelling.

Modelling does not just allow a simulator to be designed, it gives such a profound insight into the process that a company's technical attainment can be assessed nowadays by the number and the quality of identified dynamic models of its processing units. Process assessment and instrumentation guides are the basis for diagnosis, and predictive maintenance, a simulator for operator training and control will all come along with the model. Control is to be embedded in system engineering and this more comprehensive approach marks the true difference between advanced control and the classical instrumentation approach. They should not be opposed since they are quite complementary; they are to be used at the appropriate time and place. Thus advanced control involves more than simply

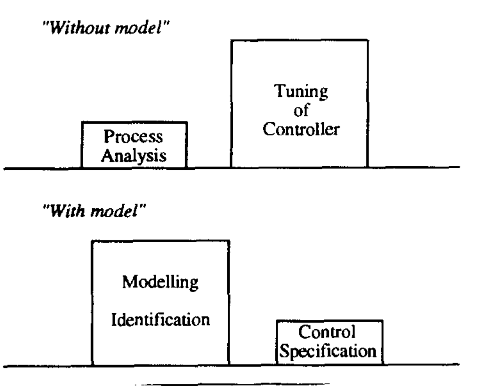


FIG. 1. Relative effects of control design with and without modelling.

implementing a control algorithm—it requires a comprehensive approach based primarily on a model.

2. APPLICATION 1: DISTILLATION

2.1. *Control in the petrochemical field: some general remarks*

In 'slow process' industry, 2/3 of the control problems occur in the petrochemical plants, where 2/3 of the units are distillation columns. That is why control of distillation is unavoidable for all advanced control methodologies (Stephanopoulos, 1984).

The crude oil distillation unit stands at the front end of the refinery. The unit performs the distillation of the crude oil into boiling range fractions which are characterized by distillation properties such as 'end-points', 'cloud-points' *etc.* delivered on-line by dedicated analysers.

Specifications of products vary continuously and depend on the downstream requirements and on the type of crude oil available at a better price on the market. This technical and commercial variability is the major motivation for implementing advanced control on these processes. Crude switches come every few days and upset operating conditions. Nevertheless, the qualities of the products should remain within strict limits.

Control is thus justified by:

—improvements in the quality of products, and variance reduction;

—fast adaptation to frequent qualitative and quantitative changes of raw material;

—minimization of pollution problems and hazards by stock reduction; and

—the increase in the mental workload of human operators.

Depending on the size of the units, earnings may be worth up to millions of dollars a year, and pay-out times are quite often less than a year. Advanced control progress is hindered, neither by computing capabilities of hardware (more reliable, cheaper and easier to program), nor by methodology (always to be improved although it already solves many problems), but by the lack of knowledge and understanding of personnel: what is advanced control and how is it to be implemented? Training of appropriate staff is the key issue. In many production industries, corporate management would like to move forward to integrated control but classical instrumentation experts lack modelling and process know-how, while process experts are not accustomed to hierarchical dynamic control. Advanced control necessitates a global comprehensive approach and suffers from too much partitioning of professional capabilities.

A typical control project. How to proceed? Three steps are to be followed:

1. *Strategy.* What is the effectiveness of the actual different elementary ancillary loops including sensors, actuators and controllers (PID type)?

What does the company want to improve? It may wish to

—reduce the variance of the products' quality, make it less dependent on operators' qualifications, working conditions and raw feed nature;

—decrease the duration of off-specifications periods during changing loads. Profit is to be gained from a flexible production unit able to follow up more variable scheduling requirements (just-in-time, zero stock);

—reduce polluting effluents or warehousing of hazardous products with high insurance policy fees;

—reduce personnel, although in these industries it is not a major issue as in discrete manufacturing.

Most of the time there is a combination of these requirements but their relative weights will induce different solutions (Pirie and Grimble, 1991).

2. *Work team.* Computer technology and information processing are useful tools, but a willingness to work with peers in other functional areas is fundamental. A taskforce is to be assembled where everybody should be informed and will contribute when necessary. Instrumentationists and process experts should collaborate closely. The design of test protocols is, for instance, a typical critical moment where everybody should be involved. Acting on the process to get data while operating perturbs the whole plant and might appear to be a useless nuisance if not clearly explained.

Information and some training on the state-of-the-art of the disciplines of the other partners involved might be useful. Is the job to be done by in-house personnel or subcontracted, and if the latter, then to what extent? What is intended—a 'turn-key' project or full independence and understanding? Training, maintenance and documentation need effort and time. What kind of project handling methodology and software is to be used? What norm (ISO 900i)?

3. *Technical and technological tools.* Methodology: What type of technical approach is to be considered? What kind of models are already available? What are the interactions between static optimization and dynamic control? What is the proper mixture of techniques to be used: classical control, MBPC, knowledge based, rule based? What are the available methodologies?

Computers: What type of control system—distributed control systems (DCS) or dedicated units? Cascaded supervisory computers or PCs on a bus? What are the necessary computing power and the memory requirements? Reliability and back-up systems?

The temptation is great to start with the easiest part and to buy the computer first, although a wrong selection of target is more critical at the strategic level than at the computer selection level.

2.2. *Atmospheric unit*

Process description. The topping unit is at the Mobil Oil Notre Dame de Gravenchon refinery (France). It is a 50 trays, two beds column with four pumparounds and four side draws. This refinery is mainly lube oil oriented and the atmospheric residue is processed by a vacuum unit. Vaporized crude oil is fed into the distillation column, and its components are extracted from a side stripper unit ranging from heavy product (residue $\approx 50\%$) to light product (naphtha $\approx 10\%$). The product qualities which were measured and that were selected for the control application are the heavy naphtha '95% point', the '90% point' and 'flash-points' of the light kerosene, and the gas oil 'pour-point'.

Among the input variables that can be manipulated, the draw-off flowrates were considered for use by the dynamic controller; others such as pumparound duties, stripping and furnace outlet temperature are adjusted by a local static optimization procedure (Fig. 2).

Three disturbances appeared to have a significant effect on the qualities of the products (the top temperature, one stripping steam ratio and the top pressure) and were taken into account by the controller as feedforward variables.

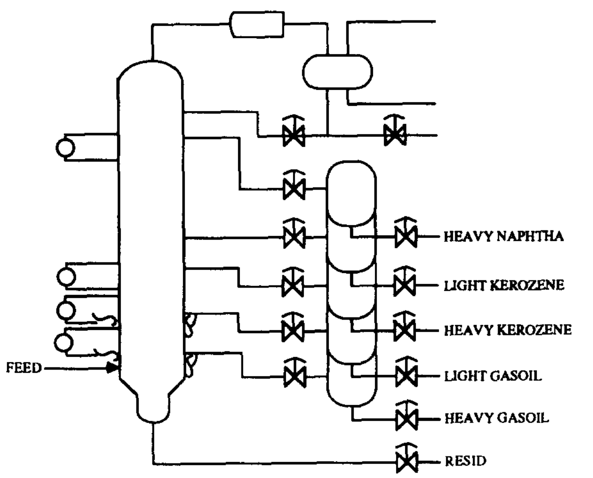


FIG. 2. Topping crude oil unit distillation.

Control strategies and requirements. Three main operating modes were considered: maximization of the kerosene or naphtha cut yield and an intermediate strategy between these two. In the case of yield maximization, these quality specifications were given in terms of constraints. The objective was then to draw as much kerosene or naphtha as possible while respecting the quality constraints. A secondary objective was to maximize also the yield of the nearby product as long as the main objective was satisfied. Constraint handling was thus a strict necessity.

In an intermediate working mode, the draw-off yields were not to be maximized and the qualities had fixed set point values. In regard to operating conditions, other situations were also to be considered, such as keeping the light and heavy kerosene sidestreams segregated; the kerosene qualities ('90%' and 'flash-points') were specified for the light kerosene in the 'segregated' case, and the mixed kerosenes in the other case. The controller was then required to change automatically the control strategy depending on the production mode, and to allow bumpless switching from one mode to another.

Since quality analysers are not fully dependable sensors, control should be permanently active through back-up control substructures in case of some analyser failure. The same procedure should work also if one of the manipulated variables is switched to manual.

2.3. *Vacuum unit*

Process description. The vacuum distillation column processes the atmospheric residue and produces four distillates, whose viscosities are to be controlled. The duties of the three pumparounds were adjusted from time to time for the global optimization of the unit. Four variables (the distillates' draw-off flowrates and the top reflux) can be manipulated for viscosity control purposes. Five disturbance variables have been selected after plant tests. The feed cut-point which reflects the composition and the flowrate of the last distillate (C3) was not available for control although it can be modified manually for reasons other than viscosity control (Fig. 3).

Control structure and requirements. Three viscosities (V1, V2, V3) can be controlled around the prescribed set-points with some given tolerance. The controller must take into account the main disturbances as feedforward variables. The vacuum unit operates mainly through three operating modes, corresponding to different flowrates of the intermediate cut CI with their

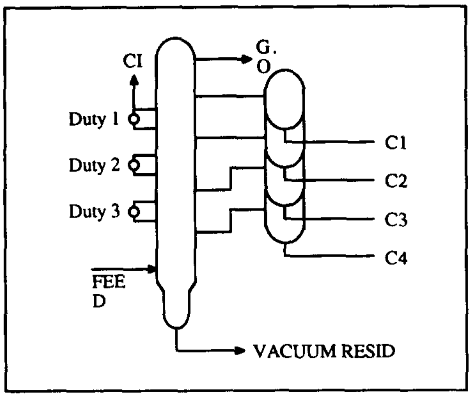


FIG. 3. Vacuum unit distillation.

corresponding set-point values specified by the viscosities.

It is well known (and was verified during the plant tests) that the temperatures of the draw box are strongly correlated to the viscosities. The idea was then to build a cascaded control structure, considering that a first control level should be concerned with the temperatures and a second one with the viscosities (Fig. 4).

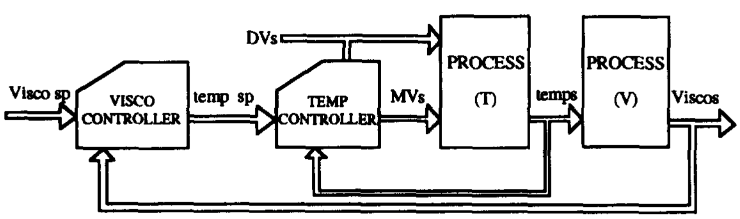
Such a control structure has several advantages:

—Disturbances: when unmeasured disturbance variables affect both temperatures and viscosities, controlling the temperatures rejects the perturbation before it affects the viscosities.

—Dynamics: the time response between the manipulated variables and the temperatures (from one to three hours) is shorter than the time response between these same manipulated variables and the viscosities (from two hours to four hours and a half, including the time delay). The control strategy can take advantage of this by using a faster feedback.

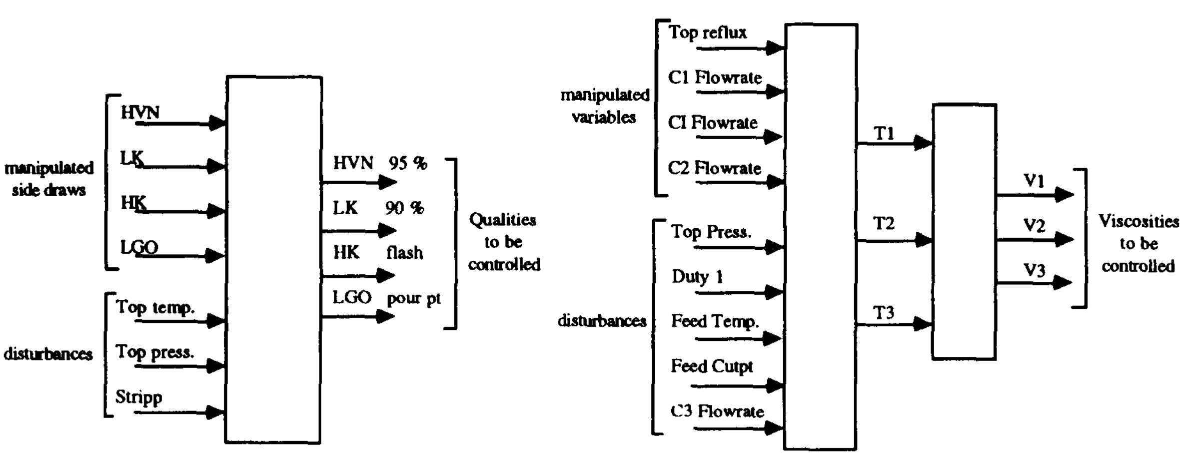
—Sensors: the thermocouples are more reliable than the viscosity analysers. If they fail, the temperature controller keeps on working. The actual viscosities may not be right at their set-points but the unit is at least stabilized during the maintenance period.

Model. Regarding the temperature controller, the internal model has been identified from the nine selected inputs and the temperatures. This model is strongly multivariable: only two static gains were considered as negligible. Concerning the viscosity controller, experiments were optimized and applied once the temperature controller had been implemented. This was done to ease the application of the temperature variations which are needed to identify the temperature–viscosities relationships. In practice, several constraints limiting the actions of



The viscosity controller computes a set of temperatures set points (temp sp) to satisfy the viscosities set points (visco sp). The temperature controller satisfies these set points by acting on the manipulated variables (MVs). Measured disturbance variables (DVs) are taken into account.

FIG. 4. Cascaded temperature quality control.



Full atmospheric distillation control structure

Full vacuum distillation control structure

FIG. 5. Control schemes.

the temperature controller made it difficult to apply all the planned plant tests. However, a rough model has been built from the collected data and implemented into the viscosities' control structure. One temperature–viscosity model is needed per operating mode depending on the intermediate cut operation rate.

2.4. *Description of the control strategy and its implementation*

2.4.1. *Control algorithm.* IDCOM-HIECON is a basic model based predictive controller designed for multivariable processes. A 'black-box' model is defined by a set of step responses corresponding to each input–output relationship. Step responses were defined by 50 parameters. Such a representation is very convenient for multivariable processes and for non-well-behaved transfer functions (*e.g.* non-minimum phase systems). Convolution representation has been criticized in the past for its over-parametrization. Indeed, convolution should not be used for fast processes with tight computing time restrictions. However, in the case of slow processes, the advantages of having a representation which is linear with the parameters (weights of past MVs uncorrupted by noise), surpass the drawbacks. An iterative quadratic Lyapunov minimization of the structural distance, with an appropriate relaxation matrix, yields smooth responses with no bias. It can be used on-line in a open or closed-loop procedure. This model is used to predict the behaviour of the outputs to be controlled and to compute the corrective actions to be applied to the manipulated variables (MVs) (Roat *et al.*, 1991).

Some of these features were very useful for this application, for example:

—each output variable to be controlled can have its own closed-loop time response (to a set-point change) specified by the user at a constant value or at a value depending on the set-point–measurement deviation (reference trajectory):

—constraints may be specified and changed in real time on the manipulated variables and on the controlled qualities as well (absolute and speed limits);

—an ideal resting value (IRV) may be given to some manipulated input variables: these inputs tend to their IRV as long as the other manipulated inputs can satisfy all the outputs specifications. The maximization of a given product yield is done by using this feature, which is of great economical interest.

Minimization of quadratic criteria between the reference trajectory and the predicted output is ensured by a complex iterative strategy which permits in degenerate cases (more MVs than CVs) the IRV procedure, based on linear programming (dual) and quadratic programming (Wolfe, 1959).

TABLE 1. ATMOSPHERIC DISTILLATION CONTROL STRUCTURES CORRESPONDING TO THREE DIFFERENT OPERATING MODES

Modes outputs and inputs attributes	Maxi naphtha	Mini naphtha	Intermediate
Heavy naphtha 95%	* < Max	< Max	Set-point
Light kero 90%	Min < * < Max	Min < * < Max	Set-point
Light kero flash	> Min	* > Min	Set-point
Gas oil pour-point	Set-point	Set-point	Set-point
HVN rate	MAXI 1	MIN 1	Free
Light kero rate	MAXI 2	MAXI 2	Free
Heavy kero rate	IRV	IRV	Free
Gas oil rate	Free	Free	Free

Depending on the mode, the symbol (*) shows which constraints are active. The objectives on the manipulated inputs are ranked: i.e. MAXI 1 is more important than MAXI 2.

The control structure is designed through a special table: the FCS (flexible control structure) describing the set of inputs with their attributes (manipulable/feedforward, constraints, IRV) and the set of outputs to be controlled with their own specifications (set-point/zone, constraints, closed-loop time response). Fifty-three control structures were defined in this way as required by different operating modes.

Table 1 gives an example of such a FCS table on the atmospheric unit for three different operating modes in the case of segregated kerosenes.

The IDCOM-HIECON defines the control strategy in the terms through which the problem is addressed by end-users. Robustness was carefully assessed as a trade-off between model uncertaintly due to identification and changing working conditions. In the case of some detected (or declared) failure of a sensor or actuator, the control supervisor module switches to a predefined back-up control substructure. If no substructure has been defined, then the algorithm does its utmost to find a trade-off (lack of manipulated input) or to minimize the input's moves (missing analyser). Most of the 53 structures were designed in the topping unit application to cope with all these situations; for instance, if an analyser fails, then the sum of two sidestreams should be kept constant.

2.4.2. *User's interface.* The operators need to understand how the controller works and to evaluate the pertinence of all MV moves. It is rather difficult to comprehend what goes on in a multivariable controller because:

—all the manipulated variables move simultaneously and the future effect on the controlled variables is quite impossible to estimate (operators' intuitive thinking is insufficient);

—predictive constraints handling is unfamiliar;

—feedforwarding produces unexpected actions for someone familiar with regular PID controllers;

—introducing objectives such as yield maximization though the IRV procedure into the control strategy, makes the behaviour even harder to analyse.

The degree of acceptance of this new process control depends on the design of the interface and on the training of operators. Three different screens were to be developed for each unit to display information concerning the measured values, the control strategy and their specifications, the status of the sensors, *etc*.

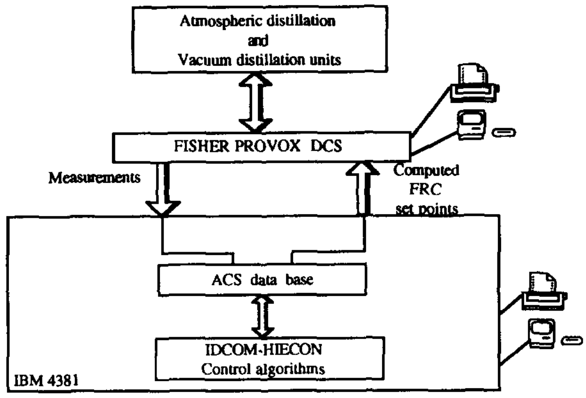
From the 'control screen', the operator can change the displayed values of the specifications and constraints. The system checks the measurements and the links between the actuators, the distributed control system (DCS) and the process computer: the analysers' and the actuators' status is set to 'off' and displayed in case of a problem. The operator can set them to 'out of order' for whatever reason. Through this screen, the operator can also fix the control strategy like 'mixed keros and mini-naphtha mode'.

A second screen, 'help screen', explains in full sentences in natural language what the objectives are, for example: 'minimize the naphtha yield with flash constraint, maximize the keros yields with the '90%' constraint, keep the heavy kero yield around its IRV and satisfy the gas oil pour-point set-point'.

The 'help screen' displays the actual performances regarding the products' qualities but, using the internal control model, it also gives predicted behaviours of the CVs and MVs. This screen also shows which manipulated variables are on their constraints in order to help the user analyze a situation (Kassianides and Macchietto, 1990).

The third screen mainly displays the variables that are not part of the control structure but that define the working conditions of the unit, like duties and top pressure.

2.4.3. *Hardware architecture.* A DCS (Fisher Provox) system receives the measurements from the sensors and sends the computed control actions to the actuators. It manages 'level zero' control, alarms, historical data and data logging, and it displays trends and process pictures on colour CRTs to the operators. A process computer has been installed to manage upper level controls, global optimization using physical models, and other programs needing some computation facilities. This computer (IBM 4381 with Data Base software ACS) has its own industrial data base and allows the user to implement specific real-time routines that address the real-time data base (Fig. 6).



Hardware architecture

FIG. 6. Control architecture.

The IDCOM-HIECON control software is implemented on this computer and the three corresponding user's screens are displayed through the ACS facilities. Colour CRTs display the information in the control room and in other departments in the refinery.

The control algorithm gets the measurements (inputs and outputs) and the user's specifications (set-points, constraints, operating mode) from the ACS data base and sends back the computed values of the manipulated variables and a few messages to be displayed. Another routine is in charge of the communication between the ACS real-time data base and the DCS.

2.4.4. *Software architecture.* The IDCOM-HIECON software consists of three main parts:

—a supervisor module which communicates with the environment. It selects, when needed, a new control structure and its internal model;

—a module which builds the control equations and prepares the formulation of the problem in suitable form for the solver;

—a solver which computes the control inputs' moves to satisfy the specified objectives.

The first module is the only one to be adapted for any specific application; it is mainly a set of I/O statements to access the data base and the control structures' disk files, and some logics to select the most suitable control structure depending on the operating conditions (Fig. 7).

2.4.5. *Main steps of the project.* A first set of input and output variables was defined during the functional design, including a description of the main control objectives. These variables are the variables to be manipulated by the controller, the products' qualities to be controlled and the disturbance variables that may

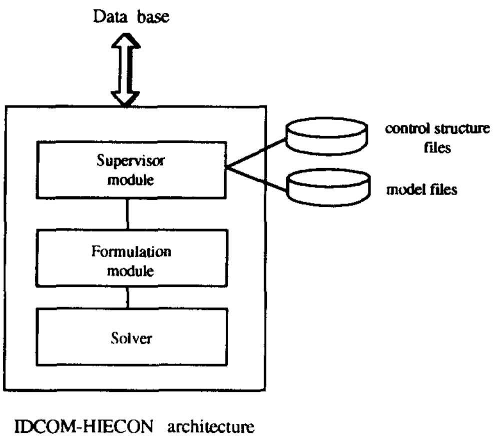


FIG. 7. Control modules.

affect these qualities. Quite a large number of input variables were considered at the beginning to avoid overlooking any significant effect. Experiments, 'a string of step changes', were carefully optimized and prepared with the plant operators and applied to the prospective manipulated variables to evaluate their dynamic effect on the products' qualities. The collected data were then used to identify the internal model required for the IDCOM-HIECON predictive controller. The most active measured disturbances to be taken into account by the controller as feedforward variables were ultimately selected:

—top pressure, top temperature and one stripping steam ratio on the atmospheric unit;

—top pressure, duty of the first pumparound, feed temperature and cut-point draw off of the heaviest distillate in the vacuum unit.

After the usual pretreatment of data:

—selection of a sampling period $T_S = T_R/40$, where T_R is the open-loop 95% response time;

—high-pass and low-pass parallel filtering for drift and measurement noise elimination, with the classical practical rule: band pass of filter is 3 times and 1/3 of the band pass of the open-loop process;

—two types of model structure are used: impulse response for processes *a priori* 'non-well-behaved' with non-minimum phase effect, time delays, *etc.*; and first-order with delay $\{Ke^{-\theta s}/(1+\tau s)\}$ for more classical processes.

For the first type (convolution), the identification scheme used is the well known normalized least mean square algorithm (Abu el Ata-Doss *et al.*, 1985) which is an iterative algorithm based on the Lyapunov minimization of the structural distance

$$D_s = \|\boldsymbol{a}_M - \boldsymbol{a}_P\|^2$$

where $\boldsymbol{a}_M$ and $\boldsymbol{a}_P$ are vectors representing the convolution parameters of the model and the process, respectively (see also Bershard, 1986; Bitmead and Anderson, 1980).

For the second type (first-order model), the parametric global identification technique is used. This gives the full uncertainty domain of the model, ensuring that the robustness of the model is compatible with the robustness of the controller (Richalet *et al.*, 1991; Richalet, 1991).

In both cases the identification procedure ultimately provides the model in terms of a step response to be used by the controller. The identified model was then implemented on the PC workstation with the control algorithm for control structure design. Some adaptations were necessary to transfer the control software from the design workstation to the IBM 4381 host process computer (communication with the ACS real-time data base). A user's interface was designed and implemented in the same hardware environment. During the sustained performance tests, the controller was operated continuously to evaluate the defined control structures and substructures. All the project partners were closely involved in these different phases, sharing experience and knowledge of process, operating conditions and control.

2.5. *Results*

The performances can be considered in terms of control, local optimization and operation rate.

Regarding the control objectives (satisfaction of set-points and constraints) two figures have been estimated from collected data: the deviation between the mean value of the measured qualities with their objectives, and the corresponding standard deviation.

The performance evaluation is shown in Table 2.

The second aspect concerns the way the controller manages the dynamic yield maximization while respecting quality constraints. The following trends (Fig. 8) show the behaviour of the main variables over 24 hr. The control structure being used during this period corresponds to a maximization of the light kerosene yield, which decreases the heavy naphtha yield. In this control structure the objectives and means are:

—three manipulated variables: heavy naphtha, light kerosene and light gasoil with their own minimum, maximum and speed constraints. The heavy kerosene drawn is not manipulable in this configuration.

—three qualities must satisfy constraints:

the heavy naphtha '95% point' constraint is far above the operating point,

TABLE 2. PERFORMANCE EVALUATION

Qualities (°C)	Measured objective deviation	Standard deviation
Heavy naphtha: 95% point	0.1	1.6
Kerosene: flash-point	0.1	0·8
Kerosene: 90% point	0.5	1.8
Gasoil: pour-point	0.1	0.75

the kerosene 'flash-point' is against its low limit,
the kerosene '90% point' is against its high limit.
—the light gasoil 'pour-point' satisfies its set-point.

During the first part, up to 17 hr, the kerosenes are segregated and the target is to minimize the heavy virgin naphtha and to maximize the light kero yield through the ideal resting value procedure: a local dynamic permanent optimization which can be considered as a permanent 'give away' minimization procedure.

Action is limited by the '90% point' of kero quality constraint and by the gasoil 'pour-point' which are within the acceptable limits. Note that DVs are active and induce MVs variations.

At time 17 hr, the kero 90% 'pour-point' is not in use. The cut between heavy and light keros is then controlled by insuring that the sum of the upper distillates is kept constant. The gasoil 'pour-point' becomes a set-point.

It is to be pointed out on this example that dynamic control includes optimization and strategic logical decisions to have a chance to bring any payback.

Vacuum unit:

After implementation of the control strategy, the variations of the viscosities ($\pm 2\sigma$ around the set-point) appeared to be smaller than or equal

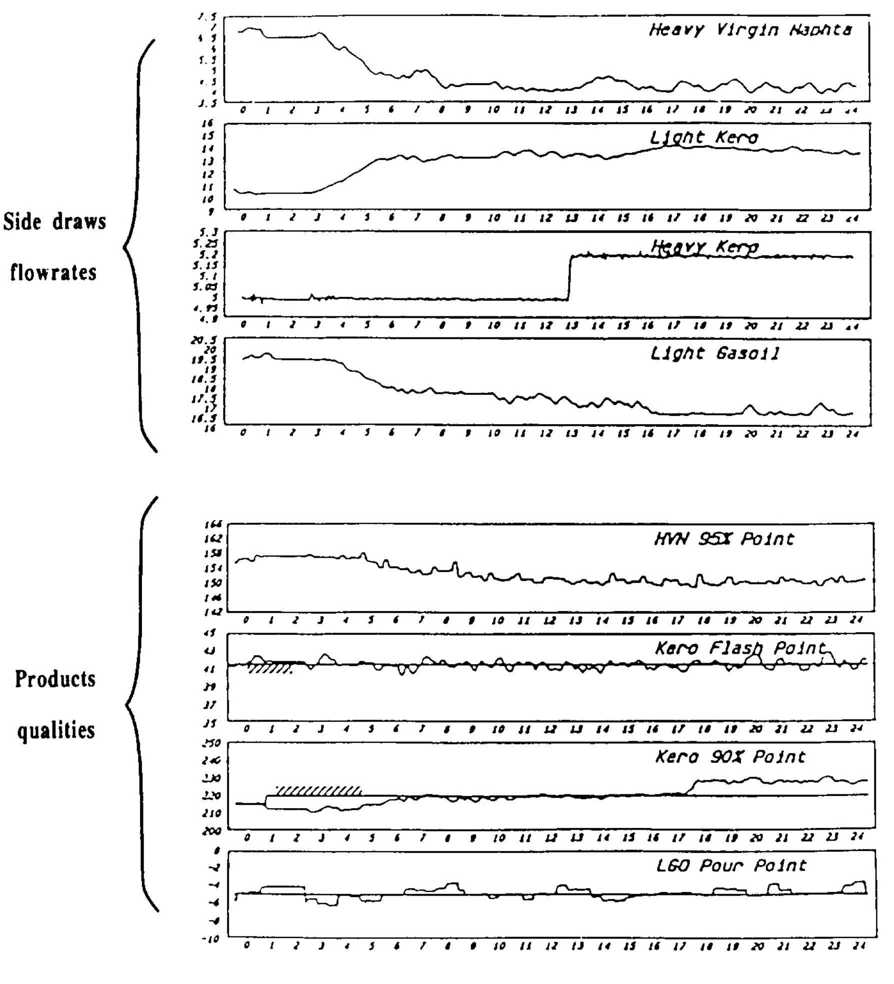


FIG. 8. Real-time behaviour.

TABLE 3. STANDARD DEVIATION OF VISCOSITY

Cuts	V1	V2	V3
Standard deviation	0.15 cst (40°C)	0.15 cst (100°C)	0.23 cst (100°C)

to the range specified by the refinery. Handling of the unit appeared to be improved when switching from one operating mode to another, and in cases of viscosimeter failure. Thanks to the reduction of the viscosity (V_i) fluctuations, the severity of the Furfurol processing was then also reduced (Table 3).

Depending on the operation mode, the yield increase varies between 0.26% and 1.24% due to variance reduction and target shift. The last aspect of the results to be considered is the controller operation rate: due to the flexibility of the control structures, on-line time was better than 98%.

In conclusion, the system was operational by the end of 1989 on the atmospheric unit and by June 1990 on the vacuum unit and has been running ever since with a very good acceptance by operating people. The tight collaboration between control and process experts during the project made possible the design of other control strategies and structures by the local staff. Due to permanently changing operating conditions, this required feature is compulsory if some perennial effect is looked for, thus clearly demonstrating the limits of turn key projects with no know-how transfer, in a 'hit and run' approach.

The reduction of the qualities' variations around their specifications has brought the benefit of automatic yield maximization. The significant increase of the yield, translated into financial terms, corresponds to a pay-out time of less than a year.

2.6. *Time and effort*

Including some feasibility study, the procedure extended to 2 years calendar time, due to the necessary coordination of task force availability. It is not possible to work continuously on such a project, because the availability of the unit is not permanent.

The existence of efficient identification and control CADs shifts the effort on to specific issues. Modelling, experiments and identification cover in fact more than half of the effort (Fig. 9).

- GENERAL SPECIFICATIONS	10 %
- MODELLING	30 %
- PROTOCOL DESIGN - EXPERIMENTS - DATA PROCESSING	20 %
- IDENTIFICATION	5 %
- FINAL SPECIFICATIONS	5 %
- CONTROLLER DESIGN	10 %
- SOFTWARE IMPLEMENTATION	10 %
- COMMISSIONING TESTS TRAINING DOCUMENTATION	10 %
	100 %

FIG. 9. Workplane of advanced control.

General specifications. What are the targets?

—variance reduction: minimization of the error between mean value and set-point or, which is not strictly equivalent: should error stay within limits?

—maximize production while ensuring quality constraints;

—change production modes rapidly to minimize off-specification production;

—respect a list of constraints with a predefined hierarchical order (see Bradys *et al.*, 1989).

Modelling. This is the qualitative part of the building of a simulator. What are the MVs, CVs and DVs? What is the nature of the different processes? Is a physical 'first principles' static model available? Is the process locally linearizable? What kind of model is to be used: parametric or not? Rough parameter estimation: time response, pure time delays, efficiency of actions, *etc.* A first draft of the context diagram with some hints on the dynamics is to be obtained from this mainly qualitative investigation.

Protocol design. The target is to stimulate the process without disturbing the production. Optimal test signals are then needed to find the proper trade-off between these conflicting objectives. From a previous model, optimal deterministic test signals should be designed. This procedure is connected to 'global identification' techniques, and it is now quite feasable to design such a test protocol in order to decrease the uncertainty of a prescribed parameter or feature of the model.

To get out of the vicious circle aspect of that procedure, an iterative approach is needed: model→control→test signal, *etc*. Typically, an open-loop identification will be followed by several closed-loop sensitizing tests with different working conditions. Closed-loop identification then appears necessary:

—small amplitude test signals are needed, in order that production is not perturbed. They induce a long test duration to extract signal from noise, which induces the necessity of working under closed-loop conditions, which induces optimization of extra-set-point signals.

—identification is nowadays becoming more a problem of synthesis of optimal test signals rather than data analysis.

Identification. After the appropriate signal processing (visual inspection for artefacts, drift elimination with parallel high-pass filters, etc.) a string of identification methods is used leading to the domain of uncertainty of the parameters.

Final specifications. From the identified simulator new questions arise. Working on complex processes, with optimality in mind, specifications depend on the possible solution. Feedback between the end-user and the control designer is definitely necessary. That is particularly true when 'industrial robustness' (resistance to sensor failure) is at stake. A partnership attitude is then needed.

Controller design. With CAD packages, controller design may appear easy but great care should be devoted to the evaluation of the resistance to model mismatch, noise, high amplitude jerky disturbances which bring the process outside its constrained field. Tuning, in the classical acceptance of the term, almost disappears, once the model is obtained. Specification parameter values are fed into the CAD package and the designer has to select, among possible tunings, his own appropriate trade-off: *e.g.* gain margin vs closed-loop time response.

Software implementation. Interfacing with the local real-time signal database is the key problem on one side, while information display on the other side leads to ergonomy and training of the operators. If not trained, they will be baffled by the weird decisions taken by constrained multivariable controllers. Explicit documentation, partly based on PC diskets is a must if some durability is looked for (Sheridan, 1987).

3. APPLICATION 2: A FOLLOW-UP SERVO

3.1. *Control in the fast process field: some general remarks*

Methodology. In the field of mechanical processes with electric or hydraulic drives, many problems arise at the control level or at the implementation phase. Several authors have already pointed out all the difficulties. Processes become less controllable:

—flexibility appears with mass and stiffness reduction. High frequency lightly damped modes are numerous (Balas, 1975, 1978) and ill-defined, and vary with operating conditions.

—gear box elimination removes backlash effects but accuracy specification increases.

—unstationary dry friction is difficult to identify.

—direct drive generates a greater sensitivity to perturbations and inertia changes, thus greater robustness is needed.

—follow-up servos with zero lag on polynomial set-points to ensure high speed reproducibility are more often encountered.

—band-pass specifications increase and limitations of energy resources appear. Manipulated variables are mostly on constraints.

—the target is to embed the control procedure into the whole mechanical and control design procedure. CAD of control needs to be interactive, and understandable by mechanical engineers (Kuntze and Hirsch, 1989; Richalet, 1990).

Implementation. Control sampling periods of less than a millisecond are frequent. Computer technology is improving: clock frequencies go higher than 33 MHz at low cost and specific DSP boards are accessible, but a competitive race between flexible mechanics and computer speed will not end, whatever the possibilities of the computer may be.

Model reduction is thus a major topic of research in this area. This is a vast problem since reduction is to be performed for a specific target. A dangerous attitude seems to be appearing: MBPC is known to be very robust though not conservative, and temptation is strong to rely on this robustness and to select models which are too elementary. Control theory should dampen its pendulum swing between robustness and dynamic response objectives.

Reliability of software is the major problem. In 'slow process' industry it is necessary but not too critical because back-up systems can have time to react. In fast processes, logics takes a greater part and software should be totally safe. Integration of logical control and dynamic control is a difficult and useful research topic. Specification languages which can produce source codes automatically in a thoroughly safe way are to be encouraged (Benveniste, 1991; Benveniste and Berry, 1991). Note that 'synchronous languages' which pretend to perform this integration seem to give a satisfactory answer to

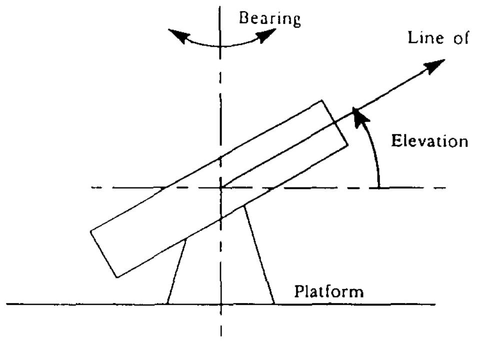


FIG. 10. Two axis optical turret.

the reduction of man-hours and the reliability of control software problems.

3.2. *Fast follow-up servo system: presentation of the application and its issues*

3.2.1. *Problem description.* The object of the study is to realize the digital control of a two axis (elevation and bearing) turret (Fig. 10) to track manoeuvred targets (Cuadrado *et al.*, 1991).

The system includes electromechanical structures and electronic parts, within *a priori* unknown characteristics. Numerous nonlinear elements were identified after measurements on the actual system (saturation, backlash, *etc.*). High performance requirements (robustness, stability, disturbance compensation, tracking accuracy, *etc.*) lead to the need for improved identification and control methods. Computer aided design tools (GLIDE for identification and PFC for predictive control) were used for this application. However, in order to simplify the on-line implementation, a unique linear model was looked for.

3.2.2. *Modelling the physical structure of the system.* All the components (load, motor, electronic loops, nonlinear elements, *etc.*) of the hardware system were separately modelled to build a modular representative functional model. A computer simulator was then designed from it. The simulator was used as a reference at all the steps of the study identification and control design, so that implementation in a real-time control processor was done with no risk (Fig. 11).

3.2.3. *Mechanical structure of the turret.* A representative model with three dumbbells was chosen. The main mechanical components of the chain are the motor, the gear box and the load (Fig. 12). Symbols belong to classical bond-graphs representation.

The chain characteristic are:

—the motor, gear box assembly and load inertias;

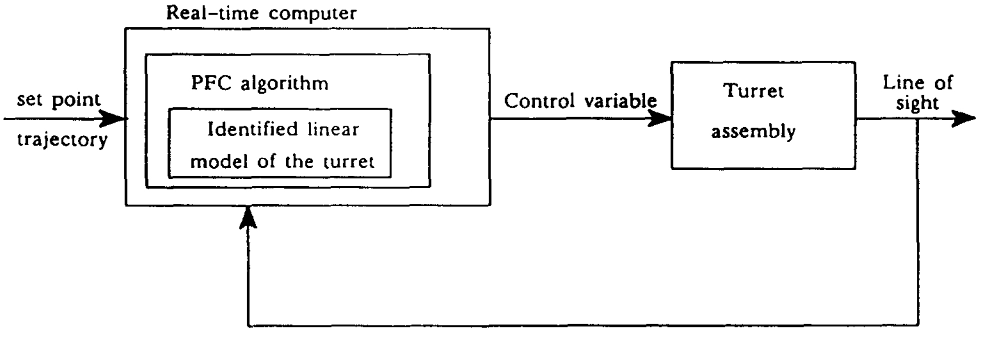


FIG. 11. Functional scheme of the turret control.

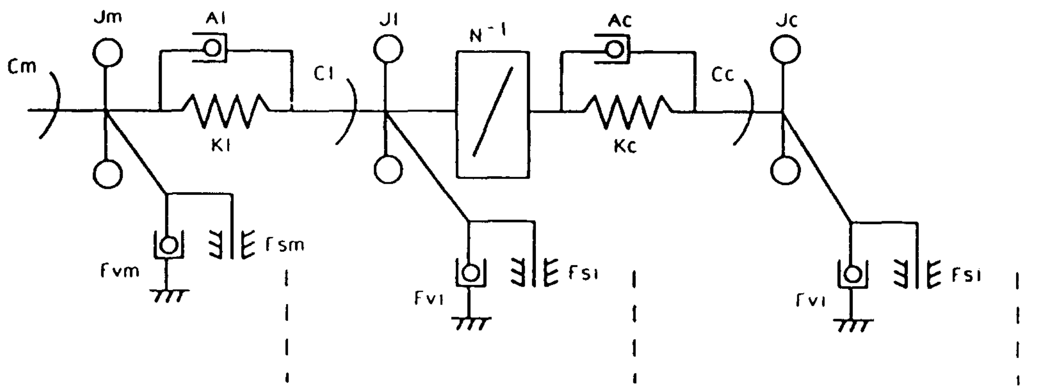


FIG. 12. Three dumbbells model.

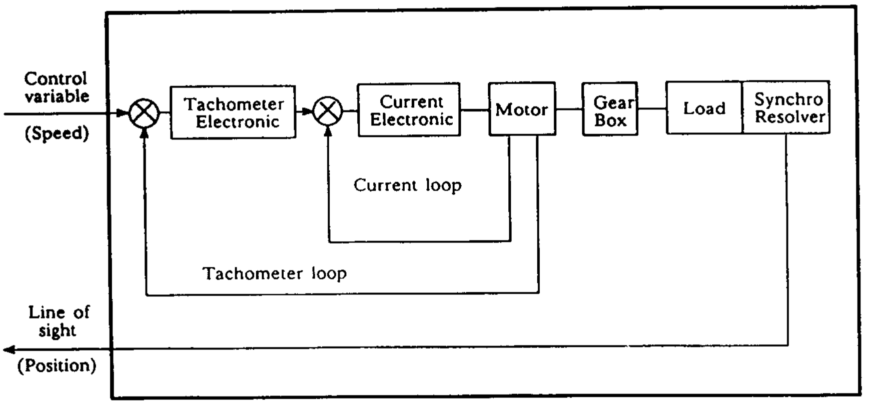


FIG. 13. Turret assembly (one axis).

—the flexibility and the damping of the transmission gear;

—the free motions, frictions and hysteresis;

—the gear ratio.

3.2.4. *Electronic regulators and sensors.* Electronic loops are included in the turret assembly hardware:

—regulation loop for the motor current;

—tachometer loop for regulation of the motor speed.

Synchro-resolvers give the angular positions (elevation and bearing) of the load with respect to the platform (Fig. 13).

All the components, of the electronic loops (operational amplifiers, saturations, thresholds, *etc.*) are represented in the simulator, which is a complex nonlinear dynamic system of order larger than 15 including all components (friction, backlash, *etc.*).

3.3. *Modelling and linear identification*

3.3.1. *Determination of the model structure.* Due to computing time restriction a simplified linear model was needed. Selection of the model structure came from the following considerations:

—To obtain an efficient control, the assumed structure of the model should be complex enough to be able to reproduce the process behaviour within its stochastic environment.

—To reduce the uncertainty of the parameters and to avoid parameter compensation, the model must be over-parametrized. Moreover, the model must remain valid for a wide operating range without pretending to represent nonlinearities and noise characterisation.

—Trade-off between model selection and control robustness was the key problem, so great care (and the interest of this application) was given to parameter evaluation.

Considering the above criteria and the fact that the process is physically integrative (Fig. 13), the resulting structure, after several attempts, was finally selected as

$$H(s) = \frac{K}{s(1 + \tau s)}.$$

Flexible modes were counteracted by an inner loop velocity controller and damper, and by a gradient constraint on the position set-point, in order not to trigger torque spikes which have almost no effect on the position but which uselessly excite the modes. The amplitudes of these modes were such that this procedure was efficient enough. The choice of this model may appear naive after a lot of time and man-hours have been spent in the construction of a very accurate and detailed 'first principles' based simulator. It is in fact an economic restriction imposed by available limited computing power: the matched robustness of control thus appears to be a strict necessity (Davidson *et al.*, 1990; Anderson and Liu, 1989).

3.3.2. *Identification method.* For this application, a method that evaluates the accuracy of the identified model was necessary. The different steps of the identification phase are described below.

3.3.2.1. *Data pretreatment.* In order to improve the signal/noise ratio, the input and output measurements are treated with a parallel filter technique:

—The high frequency noise on the measurements which does not contain any useful information is eliminated by a low-pass filter (spill-over of high frequency flexible modes was eliminated).

—MBPC needs an incremental local model, so a high-pass filter is used to suppress initial conditions and low frequency disturbances.

If an identical parallel filter is applied on the input and the output of a locally linear process, the same transfer exists between the initial and filtered data. In the case of an integrative plant, a low-pass filter on the input, and the same low-pass filter with a derivative term on the output will identify a model where the output data do not integrate offset errors.

3.3.2.2. *Global identification.* The global approach treats the identification as an informational problem and not as one of simple minimization. Instead of determining just one model in the parametric space (one coordinate for each parameter) as is done with the classical local approach, it determines an iso-distance (iso-D), *i.e.* all points (models) corresponding to a possible error level D^*, which represents all types of modelling errors and perturbations. This means that, if D is the state distance defined by

$$D(\mathbf{p}) = \sum_{n=1}^{N} \{y_M(\mathbf{p}, n) - y_P(n)\}^2$$

where $\mathbf{p}$ is the vector of model parameters to be estimated, global identification will consider all models ($\mathbf{p}$), such that

$$D(\mathbf{p}) \leq D^*.$$

To determine an iso-D, many analytic, heuristic and random methods exist. A simple procedure consists of limiting the problem to the determination of the parallelepiped circumscribed to the iso-D, as shown in Fig. 14 for a two dimensions case, thus giving the variation intervals of the parameters related to the considered iso-D level. This procedure is iterated and initiated with a model identified with a method based on the minimization of the above mentioned state distance (e.g. Gauss–Newton). It is to be noted that for this distance, y_M is generated uniquely by the input to the process and does not depend on the past output values as in the least squares-type identification methods (no bias).

The structure of the iso-D can be analysed through the spectrum of the 'information' matrix which is computed by using the sensitivity functions of the model with respect to the parameters.

If λ_{max} defines the greatest eigenvalue of this

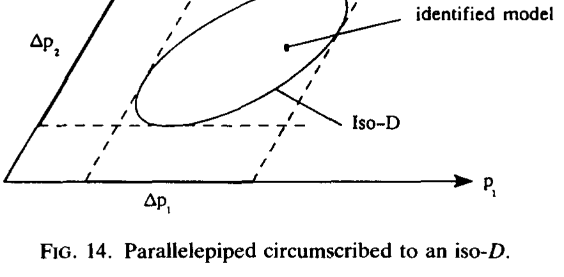


FIG. 14. Parallelepiped circumscribed to an iso-D.

matrix and if λ_i is any other eigenvalue, then λ_i/λ_{max} evaluates the sensitivity in the direction corresponding to λ_i with respect to the most sensitized direction (that corresponding to λ_{max}). Actually, if this ratio is small (less than 0.1), we can consider that the direction is poorly sensitized and if it is too small, the iso-D is too stretched in this direction and can even be open. In that case, either test signals or the structure of the model have to be reconsidered, and true overparametrization thus appears clearly.

So, the global approach allows us to test the model validity. Using the same representation with different data sets, the corresponding iso-Ds have to intersect. The iso-D structure allows the evaluation of the relative distribution of the information brought by the data in the different parameter directions; this gives an indication of the sensitivity of the different parameters to the experiment. This indication can be very useful in designing sensitizing protocols which will respect all the specific constraints of application and will match the closed-loop signal sensitivity effects. It is obvious that the richness of the information content of the protocol will affect the ultimate quality of the model, irrespective of the merits of the identification method to be used.

3.4. *Experiments and results*

3.4.1. *Context.* The experiments have been realized with a computer which has generated the test protocols for the process input by way of its analog output. The computer also gets the process output. Figure 15 shows the experimental configuration.

Then, it appears that identification allows the existing plant dynamics between the control variable u and the measured θ_m to be obtained. Not only the load, the motor and its control loops, but also the transmission delays and the sensor plants will be identified and lumped in a simple model (Fig. 15).

3.4.2. *Input protocol design.* It is obvious that the 'richness' of the information content of the protocol will affect the quality of the identified model. A signal formed by successive steps ($\pm m$) would be a rich enough protocol input, but the process constraints prohibit abrupt variations of the signal from $+m$ to $-m$. The protocols used, which are close to the real operating inputs, are made of triangles or trapezoids. Figures 16 and 17 show the different parameters which define the two types of protocol, respectively.

Experiments with four different protocols (P_1 to P_4) have been used for the bearing axis plant identification (Table 4). They correspond to

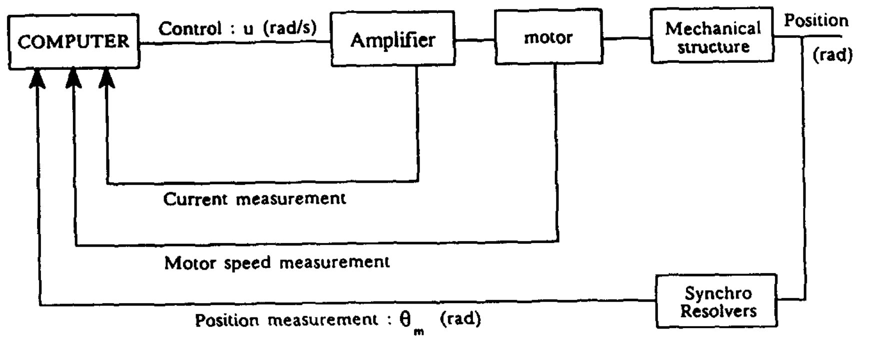


FIG. 15. Experimental configuration.

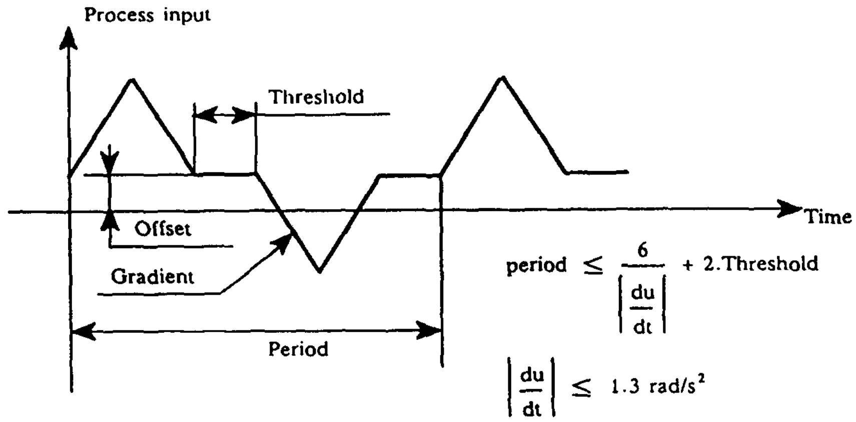


FIG. 16. Triangle protocol.

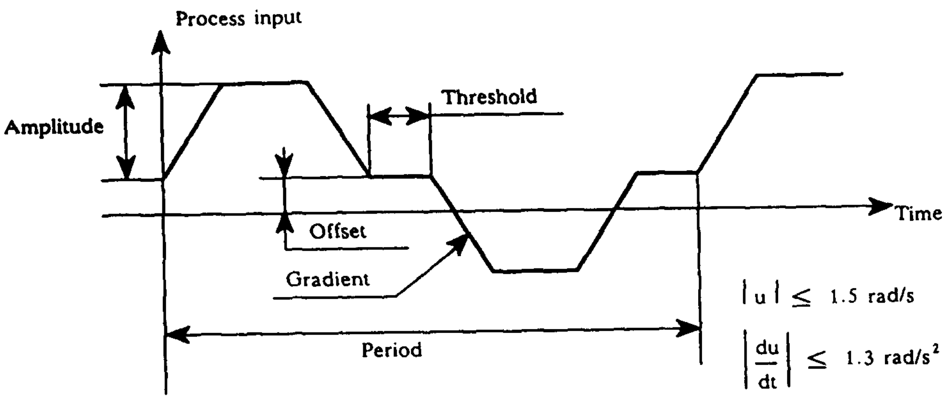


FIG. 17. Trapezoid protocol.

different operating ranges of the identified process especially with regard to the signal amplitude (Fig. 17).

The experiment with protocol P_1 (Table 4) clearly shows a friction phenomenon: the input evolves while the output remains quiet. We can also notice that for each experiment, there is a small output drift, while the input has no offset (Fig. 18).

3.4.3. *Utilizsation of the experimental results for identification.* Identification goes through the following steps: data pretreatment; local identification; and global identification.

3.4.3.1. *Data pretreatment.* In order to improve the identification quality, the input and output signals have to be pretreated. This step consists of filtering these data to suppress useless components: mean value; drifts; noise; and integration between input and output.

The parallel filter technique described in paragraph 3.3.2.1 is used here; first-order filters are sufficient. The time responses of the different

TABLE 4. EXPERIMENT RESULTS WITH FOUR DIFFERENT PROTOCOLS

Protocol		Amplitude (rad/s)	Period (s)	Threshold (s)	Offset (rad/s)	Gradient (rad/s^2)
P_1	Triangle	—	4.5	0.25	0.0	0.01
P_2	Triangle	—	2.5	0.25	0.0	1.3
P_3	Trapezoid	0.1	3.0	0.1	0.0	0.5
P_4	Trapezoid	0.5	3.0	0.1	0.0	1.3

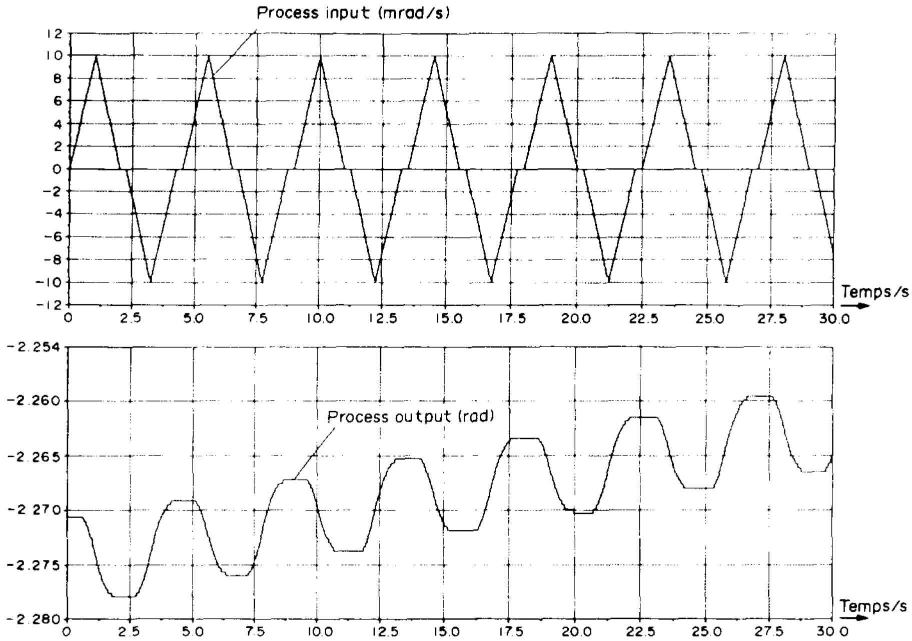


FIG. 18(a). Experiment results with protocol P_1.

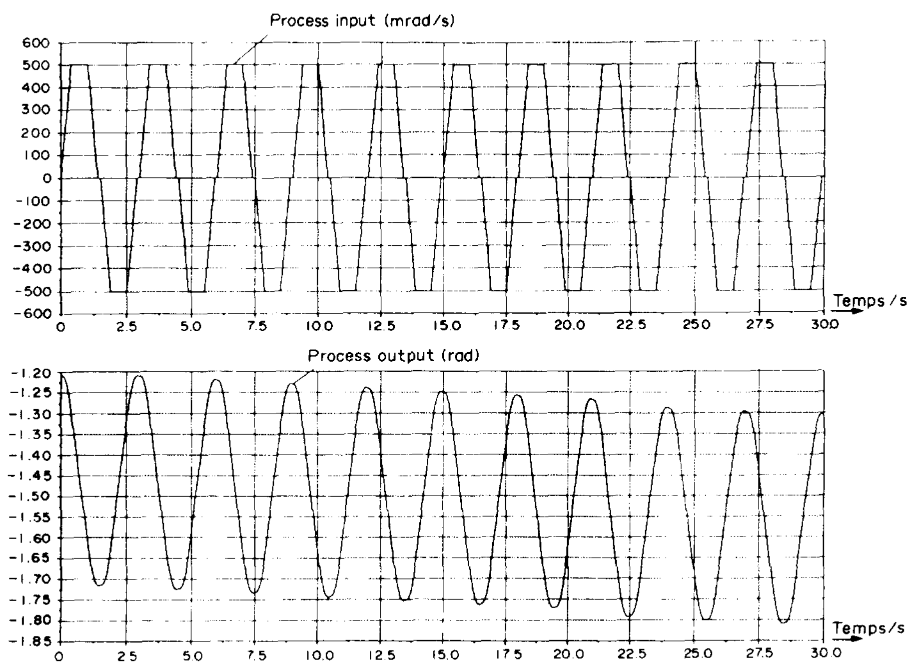


FIG. 18(b). Experiment results with protocol P_4.

TABLE 5. PARAMETERS OF PRE-PROCESSING FILTERS

Protocols	Low-pass	High-pass	Derivative/low-pass
P_1	0.06	0.6	0.05
P_2, P_3, P_4	0.02	0.2	0.03

filters, justified by physical considerations, are shown in Table 5. Figure 18 shows filtered input and output signals for the protocol P_4.

3.4.3.2. *Local identification.* Since the least squares method is biased, the 'model method' was used, where model output is computed with past values of model output and input. It requires an initial value for each parameter to estimate. A harmonic analysis made on the actual process allowed estimation of an initial value for each parameter:

$$K = 1$$

$$\tau = 0.03.$$

The parameters obtained with local modelling technique are shown in Table 6.

3.4.3.3. *Global identification.* The process being nonlinear, local linear models depend on the value of the state vector, a 'trade-off model' among all local linear models is therefore necessary. One has to find a unique model which is compatible with all test signals. If such a model is given by a unique set of parameters there is no possible compatibility. If the model is described by its whole uncertainty domain then there is possibility for a non-void intersection of the different domains. GLobal IDEntification (GLIDE) then yields a possible solution. For each of the previous local identification results, the GLIDE package informs about the validity of the obtained model by way of two criteria:

—the parameter sensitization criterion, which should be as close as possible to the value 1: $\lambda_{min}/\lambda_{max}$, λ_{min} and λ_{max} being the smallest and greatest eigenvalues of the information matrix, respectively.

—the mean error

$$\sigma = \frac{1}{N}\sqrt{\sum_{n=1}^{N} \{y_M(n) - y_P(n)\}^2}$$

where N is the identification horizon and $y_M - y_P$ is the difference between the model and the process outputs.

TABLE 6. THE PARAMETERS OBTAINED WITH LOCAL MODELLING TECHNIQUE

Protocol	K	τ
P_1	1.23	0.084
P_2	1.06	0.027
P_3	1.03	0.033
P_4	1.02	0.023

TABLE 7. QUALITY OF TEST SIGNALS

Protocol	$\lambda_{min}/\lambda_{max}$	σ (mrad)
P_1	0.595	0.58
P_2	0.812	12.94
P_3	0.767	3.97
P_4	0.852	11.43

Table 7 gives, for each experiment, the obtained values of the above criteria.

The standard deviation of the output difference equivalent noise depends on the input value. This difference will be withstood by the control law self-compensator and by passive robustness.

The GLIDE tool permits the evaluation of parameter dispersion for the obtained model. This consists of determining in the parametric space the set of points corresponding to a particular value of the stated distance (iso-D). This has been done with the estimated $\sigma = 15$ mrad. The results are given in the synthetic Fig. 19. The selected model is such that its parameters are in the iso-D intersection.

The selected model is

$$H(s) = \frac{1.043}{s(1 + 0.03s)}.$$

Figure 20 shows the filtered protocol input, the filtered process output, the model output and the difference between the process and the model outputs.

3.5. *Control law*

3.5.1. *Constraints and required performances.* The most important specifications that the control law has to withstand are:

—large system parameter variations (for example: the turret inertia depends on the load, the range is from 60 to 120 kg/m^2). These variations have an effect on the process time response (30%) and on the process time delay (50%);

—nonlinear effects due to friction, threshold, backlash, *etc.* (non-stationary).

For a tracked flying target, the set-point trajectories are unknown. Nevertheless, most of them correspond to a rectilinear uniform flight at a constant altitude. Set-points can be approximated by

$$\theta = \tan^{-1}\left(\frac{Vt}{d}\right)$$

where V is the target speed, d is the shortest distance between flight and turret, t is the current time, and θ is the bearing position.

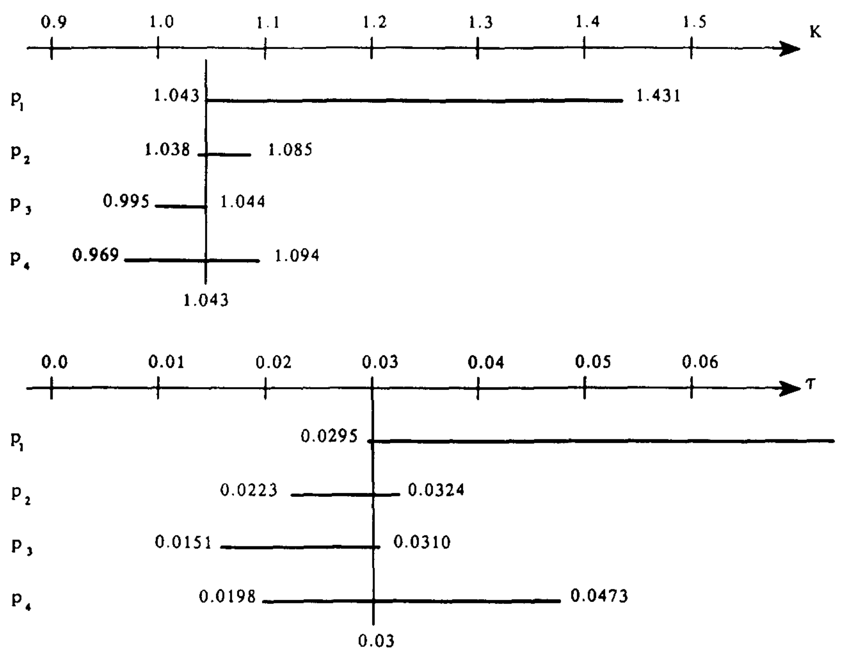


FIG. 19. K and τ determination.

The allowed tracking error in the previous conditions should not exceed 5 mrad with a rise time response which is as short as possible. In order to preserve the electromechanical parts and respect power limitation, the control is subject to the following constraints:

$$|u|_{max} \le 1.5\,\text{rad/s} \quad \text{and} \quad |du/dt|_{max} \le 1.3\,\text{rad/s}^2.$$

As the real-time computer is not only dedicated to the turret control, the sampling time cannot be less than 20 ms, which is a severe restriction; but due to MBPC efficiency, a large sample period can be used.

As the required performances are very strict, in spite of the simplicity of the model, a classical control technique would have been insufficient for the following reasons:

—the set-points to follow without tracking error are second-order polynomials;

—the manipulated variable constraints are very strict and are often hit (the model evolves with constrained control);

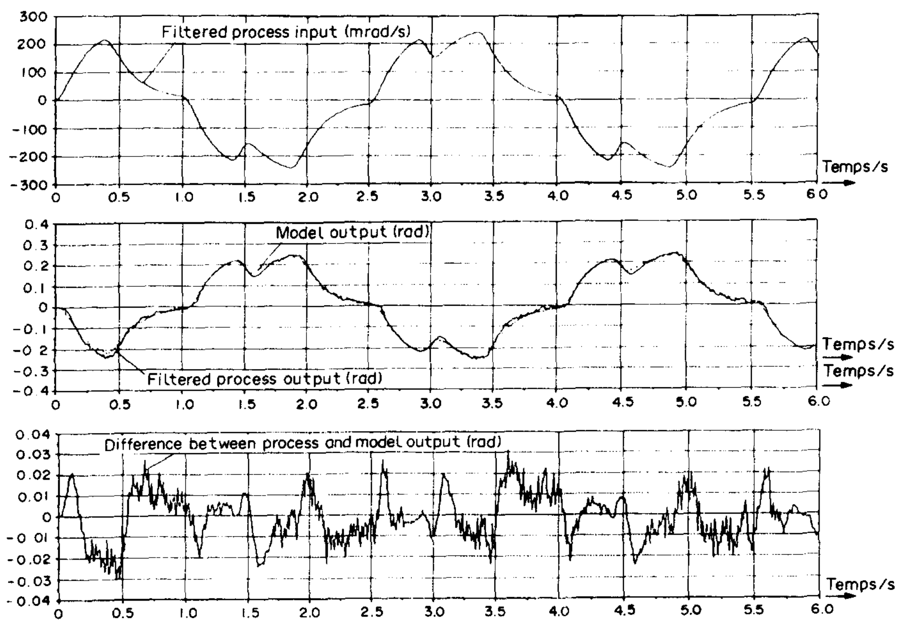


FIG. 20. Identified model behaviour with protocol P_4.

—the sampling time (20 ms) is quite long with respect to the process time response;

—the process is highly nonlinear (friction) and classical control laws did not achieve the required robustness performances.

3.5.2. *Predictive functional control—tuning.* Descriptions of PFC can be found in the References. The elaboration of a PFC technique control law requires the tuning of a few parameters. They are:

—the base functions

—the reference trajectory

—the coincidence points

—the self-compensator parameters

—the set-point extrapolator parameters.

Tuning is done off-line on the simplified model to set all parameters, and for a final verification, on the complex simulator. If modelling is done properly, in particular with the control strategy in the loop, the model is well adapted and no local tuning on site is necessary, though some factors can be tuned (reference trajectory, constraints).

The reference trajectory was selected to be exponential. It is defined by the closed-loop dynamic specification. This trajectory is initiated at the current process output. Since the manipulated variable gradient is constrained, the rallying time was limited to 1.4 s. Selection of a shorter time is useless but still jeopardizes robustness.

90% of unknown set-points can be approximated by parabolic arcs. The number of base functions has been set to two (step and ramp) since for an integrative process this choice allows tracking of a second-order polynomial without tracking error. For set-points of higher orders, an error would appear.

In order to solve the system, the number of coincidence points must at least be equal to the number of base functions. If it is greater, the system is solved with a pseudo-inverse. The number of coincidence points has been set to the minimum (two). Their location affects the robustness and also has some effect on the control dynamics. If they are situated close to the current instant, the band-pass is large; if far away, the dynamic is quite poor. These considerations and an on-line help procedure of the CAD package yield the selection of the following coincidence points:

$$h_1 = 0.2s \quad h_2 = 0.3s.$$

As indicated above, most of the set-points can be considered as second-order polynomials. This gives the degree of the set-point extrapolating polynomial. The number of past set-point values used in the extrapolation results from a trade-off between the following considerations:

—the noise on the set-point is quite important ($\sigma = 25$ mrad). Taking a large past horizon will have filtering and delay effects.

—10% of the set-points correspond to very highly evolutive targets. If the fitering effect is important, the extrapolation will be poor and will lead to the loss of the target.

The number of past set-point values has been set to five. As the difference between the process and the model outputs is evolutive, it has been necessary to take into consideration the first derivative of this difference by way of the self-compensator. The linear control law equation is of the following form where no division or inversion appears:

$$u(n) = k_0\{c_0(n) - y_P(n)\} + k_1\{c_1(n) - e_1(n)\} + k_2c_2(n) + v^T x_M(n)$$

with

$$k_0 = 2.02189$$
$$k_1 = 61.3447$$
$$k_2 = 190.279$$
$$v^T = (0.0 - 0.268).$$

The control law has easily been implemented in the control computer.

3.5.3. *Results.* The obtained results for a tracking sequence are presented. Figure 21 shows a step response of the turret and a non-moving target tracking. The tracking error remains in the specified values. The rise time (without overshoot) fulfils the specifications. Figure 22 shows the tracking of a rectilinear uniform flight at a constant altitude. Here, the target is more evolutive, but the tracking error always remains within acceptable values.

3.5. *Conclusion*

The application of global identification and MBPC has been discussed. It was shown that good performance and robustness could be obtained under wide operating conditions, in spite of the fact that the controller used a simple second-order internal model. A low-pass filter was applied on the set-point extrapolator in order to decrease the energy of the manipulated variable. In case of high evolutive targets, it results in a tracking error which is not prohibitive. Robustness of control was matched to robustness of identification.

Compared to a pre-existing control strategy already applied on this process, robustness and closed-loop dynamics have been increased by 50% and 20%, respectively. The practical implementation has confirmed the technical

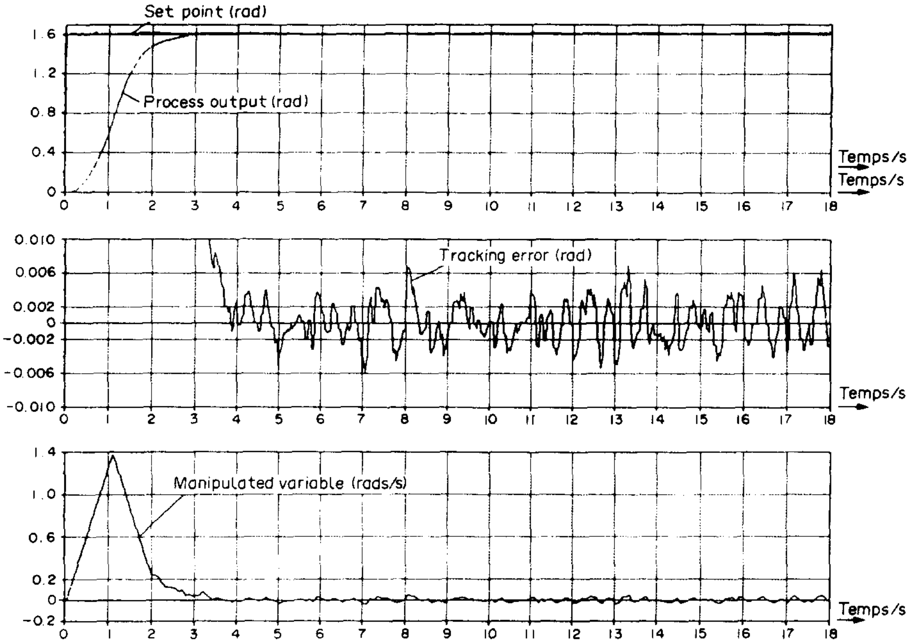


FIG. 21. Non-moving target tracking.

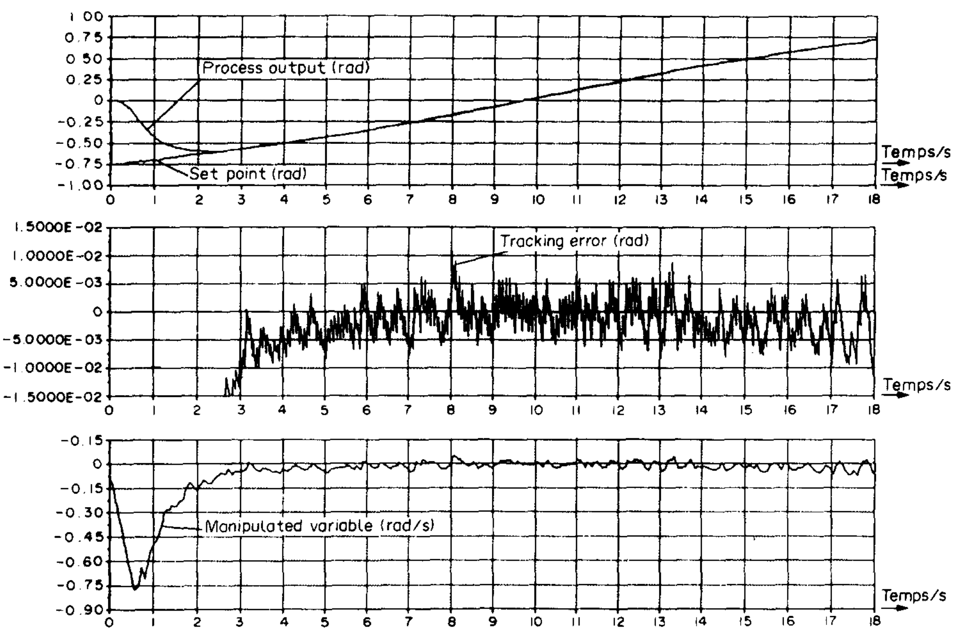


FIG. 22. Evolutive target tracking.

choices made at the CAD phase. The most interesting aspects of the whole procedure lie in:

—the global identification approach which yields a simplified model with an uncertainty domain that will be used to partly specify the control robustness;

—the ability of MBPC to handle a high order tracking servo-system with no lag error in a constrained field;

—the ease of tuning for project engineers who do not need to be experts in control.

4. GENERAL COMMENTS ABOUT CONTROL SYSTEMS DESIGN: LESSONS FROM INDUSTRIAL EXPERIENCE

4.1. *The need for a concurrent engineering approach*

These two typical applications, though very different, have common features.

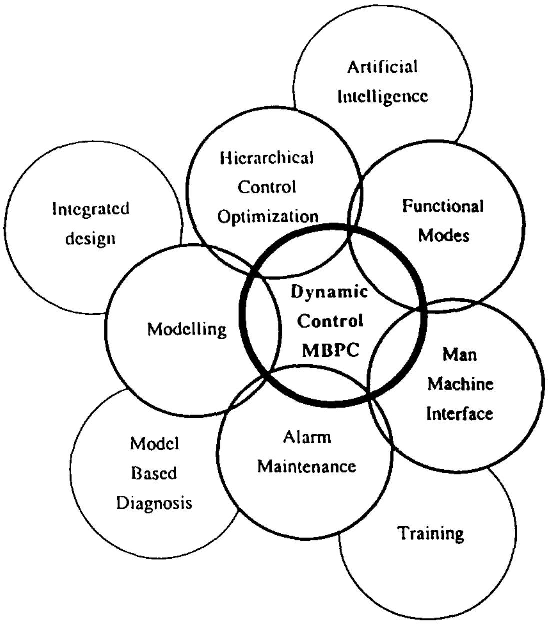


FIG. 23. Concurrent engineering—MBPC.

Dynamic control acts on the actuators of the process in order to fulfil prescribed objectives mandated by a supervisory hierarchical system. Control is not an isolated discipline and a concurrent engineering approach is needed.

From industrial experience some needs can be formulated and proposed as research topics to control and associated methodologies. Such links with the ancillary disciplines are expressed by the graph in Fig. 23, where side-by-side interactions are also to be considered, e.g. 'diagnosis' is between 'modelling' and 'alarm-maintenance' (Bainbridge and Beishon, 1991; Isermann *et al.*, 1990).

Analog data are acquired and coded into digital values with the necessary physical units. A real-time database is then made up and from its information content, a control module will, at prescribed sampling instants, deliver to some ports the increments to be applied to the manipulated variables. This continuous control part constitutes 10–20% of the whole software workload. Technology is becoming more and more reliable due to the increase of component reliability and to the possibility of redundancy now accessible because of low cost hardware, therefore more responsible duties are now imposed to the controller. Control melts into supervisory management, becoming powerful and smarter. The logical part increases as the decision level becomes more important and sophisticated. It is a paradox: since the continuous control part becomes more efficient and straightforward, it becomes just a component of the whole management system.

200 loops to be controlled by a slow process operator was a classical rule of thumb in process man–machine interface design (Sheridan, 1987). This rule is not enforced anymore and artificial intelligence-based systems tend to take over some of the operator's role, and to have access to higher levels of responsibility. What is to be done at that level? How can the validity and coherence of information coming from different sensors be checked and cross-checked? How should an operator react after detection of a sensor failure? (Johansen, 1991).

Robustness has two meanings:

(a) Control theory: resistance of the control strategy to structural changes of the plant to be controlled, *e.g.* gain variation. The robustness will then be evaluated by stability boundaries. Robustness is of great interest for the end-user; *e.g.* should the controller's parameters depend on the load or be constant? In the second application, resistance to structural changes was a definite advantage.

(b) Industrial application: a sensor status is declared 'out-of-order' either by the operator's decision or by an equivalent expert system. Can the system reconfigurate itself and select another appropriate control scheme?

The success of the control of the crude oil distillation tower presented here came from this possibility of supervisory control which deals with poorly reliable on-line analysers. It remains operational with an on-line time in excess of 98%, even with analysers with an on-line time of 90%. To ensure good economic pay-back, control should react on quality given by on-line analysers, but due to their poor reliability, an automatic change of control structure should be performed in case of failure. Thus control and diagnosis are necessary components of true industrial optimization (Basseville, 1988).

As stated earlier, MBPC needs models. Modelling is an endless problem since variety of processes, control targets and operating conditions are constantly changing. Optimization induces a larger field of action which means more variables to be taken into account, thus leading to multivariable systems; and a larger range of amplitude of variation leading to nonlinear systems.

Modelling and identification procduce a predictive simulator of the plant. Efficient tools are needed to shorten the time spent on this part, which is always risky (abstract equations on a complex, noisy, changing actual world). If a control CAD is available and if implementation can be done in symbolic languages (automatic code generation) most of the time is now spent in the elaboration of a simulator.

Design of test protocols is critical because, apart from the final implementation, it is the only contact with the process that perturbs production and operating people and may induce product losses.

Robustness of identification, *e.g.* model uncertainty, is necessary; all the more so as not to perturb production, signal/noise ratio of data tends to be poor. Model uncertainty determination is a true industrial need. Test durations become shorter and so the assumption that on a finite horizon the noise is independent of the running signal becomes less valid; the signal/noise ratio being already poor, most identification methods give biased estimates.

Model robustness is to be matched with robustness of control (Gevers, 1991). A parametric global identification technique which delivers the whole parametric domain of acceptable models is to be encouraged in connection with the determination of stability boundaries of the controller.

Production planning is now embedded in a 'zero stock' environment and control modes change more often. Even for an elementary PID, it has been noted (Aström, 1991) that a large number of functional modes are dependent on some supervisory logic. Artificial intelligence techniques, with the use of expert systems, is a remarkable tool that has not yet been used to its full potential even though there is an urgent need expressed by practical users.

Dynamic control receives set-points, and constraints specifications form a higher hierarchical control level. Upper levels are in charge of static and dynamic optimization. Some cost function is to be minimized in a constrained domain. In the past, there was a clear separation between dynamic control and static optimization where physical process models were used by process engineers (Roberts and Lin, 1991). Nowadays optimal scheduling of production tends to change set-points at a rate close to the time response of units. Therefore the separation between 'dynamic control' and 'static optimization' is not so clear anymore. Start-ups, load changes dealing with varying models and varying control targets is a good research topic.

When significant thresholds are crossed, signal based alarm processing is a basic need to ensure the safety of operators and the preservation of units. However, they come too late and requirements go much further: the goal is to avoid state alarms occurring. Model based diagnosis tends to warn operators of any structural change occurring between measurements (Basseville, 1988).

We have to face a somewhat paradoxical situation: the more automatic control becomes, the more 'advanced' should be the human operators. There should be a shift from a pure logical activity (failure prevention) to a more integrated and permanent action (optimization and diagnosis).

Machine tools drastically need such systems, and any process working in a 'zero stock' type of production needs these predictive maintenance tools. A whole year's optimization (2%, 3% reduction of marginal costs) can be absorbed in a few days of 'out-of-order' status of a unit (Isermann *et al.*, 1990).

Signal processing experts and control scientists have most of the mathematical tools to attack all the problems related above. It is recommended that they also devote some time to the needs of practical users. Adaptive control on-line is indeed the most enticing problem of control theory, but extracted from its true industrial environment (functional modes, diagnosis, *etc.*) it can be extremely dangerous and industrial end-users resent this partial approach to their actual problems (Morari and Prett, 1986).

4.2. *The impact of MBPC*

The success of MBPC in industry demands some explanations. MBPC is:

—easy to explain and understand, at least at the level needed by industrialists or end-users;

—an open strategy, adaptable to all follow-up or regulatory problems;

—able to handle constraints, since it deals with the far-away future behaviour of the process. Constraints handling is needed either in 'slow process' industry because it appears as a quality restriction, or in 'fast process' because of actuators limitations;

—CAD compatible and easy to tune with 'specification' and not with 'tuning' parameters. The dynamic performance–robustness trade-off is easy to formulate.

But there should be no naive assertions: MBPC also has drawbacks and thus it is fortunately not the only control possibility. It increases the number of arithmetic operations greatly (mul/add) and requires more memory allocation. Theoretical results need also to be strengthened.

Pro and con arguments are summed up in Table 8.

Altogether MBPC is a good candidate for overall industrial control on a large basis. It is definitely not a fixed or even fully mature approach but the academic and industrial communities involved are sensitive to both practical and theoretical problems. The fact that, in some cases, it can be understood in terms of

TABLE 8. ADVANTAGES AND DISADVANTAGES OF MBPC

Advantages	Disadvantages
Mono or multivariable control of open-loop stable or unstable non-well-behaved processes: universal approach	Needs a dynamic black box model of the process: test signals have to be applied, a simulator is to be identified
No explicit derivative: no effect of measurement noise	Demands more computing power: memory allocation and computing time. Not a problem for slow processes but can be critical for mechatronics
No explicit integrator: antiwind-up is not necessary	
Handle constraints on MVs and CVs (over-ride)	'New method'
Feed-forwarding is made easy	Needs technical staff with training in: modelling, identification digital control hierarchical control new concepts
No lag error on polynomial set-point	
CAD approach: no 'witch tuning', fewer personnel needed	
Trade-off between robustness and dynamics is clearly negotiable	Engineering approach is different
Easy to maintain	
Modelling on-line opens the way to monitoring and diagnosis	

elementary PID or as a specific LQG control strategy is quite a comfort and encourages the community to go further (Bitmead *et al.*, 1990).

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