SYSTEMS CONTROL OF CHEMICAL AND RELATED PROCESS SYSTEMS

Irving Lefkowitz

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INTRODUCTION

The traditional concept of control, in application to chemical and related process systems (CRS), concerns the problem of how to manipulate inputs to the system so that (a) designated output variables follow predetermined time trajectories (which may be constants over finite intervals) or (b) the state vector of the system is transferred (optimally) from some initial value to a specified final value. However, there has been an increasing tendency to consider control from a broader and more general perspective. Strong contributing factors in this trend are (a) the increasing application of computers in process control, providing the hardware and software means for implementing more sophisticated control concepts, and (b) the growing awareness and acceptance of a "systems approach" in the design and control of industrial process systems.

The objective of Systems Control, in a very general sense, is to achieve most efficient utilization of resources (e.g. material, energy, environmental, labour, capital) in the production of products satisfying quality specifications and consistent with goals and constraints which may be imposed by society. Thus, Systems Control is concerned with the broad spectrum of decision-making and control functions (e.g. process control, operations control, scheduling, planning, etc.) which play a role in the effective operation of the system with respect to its production goals.

Performance of the processing system depends on a variety of factors including; (i) product specifications and process design; (ii) the nature of resources available and environmental constraints; (iii) the choice of processing conditions, allocation of resources, scheduling of operating sequences, etc. Thus, we distinguish two phases of system evolution with respect to information processing and decision-making functions.

a) Design Phase. This phase concerns implementation of overall system objectives through the design of the production means. It is characterized generally by very long time horizons and by high costs for implementation (e.g. analysis and design effort, capital investment). There are a variety of disturbances which affect the design process and hence can stimulate consideration of a design modification or even reinitiation of the design process. These include: major changes in product specifications or quality requirements, technological developments with respect to a new product or a new method of production, equipment failure, major changes in resource availability, and the imposition of a new constraint (e.g. stricter environmental standard, etc.).

Decisions at the design phase tend to be strongly conditioned by subjective and non-quantifiable factors, hence the human traditionally plays a dominant role. Methods and techniques of computer-aided design are becoming increasingly important, however, in coupling the capabilities of the computer (rapid computation, handling of large data bases, fast-time simulation of the consequences of alternative policies, etc.) with the judgment, experience, and intuitive aspects of the design process, in which the human designer makes the best contribution.

b) Operating Phase. Here decisions and control actions have to do with determining operating conditions, throughput rates, sequencing of operations, etc. so that product specifications are satisfied along with the constraints imposed by environmental interactions, technological factors, etc. Further considerations then include the optimization of performance with respect to production efficiency, utilization of resources, etc.

The decision-making and control functions tend to be: (i) continuing and repetitive and based on real-time processing of information; (ii) strongly conditioned by feedbacks which describe the present state of the system and the results of prior operating experiences; (iii) based on technologically oriented deterministic models which lend themselves to computer-implemented algorithms. Further, the decision-making processes cover time scales ranging from very short span control operations to long-range planning processes.

The decision-making and control actions are carried out in response to disturbances which correspond here to the effects of: (i) variations in input conditions (e.g. changes in product demand, order sequence, raw material compositions); (ii) time-varying characteristics of processing units (e.g. fouling of heat transfer surfaces); (iii) changes in the objective function due to economic factors, environmental constraints, etc.; (iv) errors and inadequacies of the models used in determining optimal decisions and control actions.

We note that the boundary separating the design and operating phases of the evolution of the system may not be sharp and, indeed aspects of long-range planning associated with the operation of the system may well imbed aspects of the design functions, e.g. replacement of production units or modification of process design. Further, there is a strong coupling between plant design and operation, and, in order to achieve the maximum overall performance of the system, these interactions and the trade-off factors involved must be appropriately considered.

SYSTEMS CONTROL AND MULTILAYER STRUCTURE [1-3] *

The multilayer control concept provides a convenient basis upon which to formulate a systems control approach to CRS. First, we classify the variables associated with the controlled plant into three disjoint sets as follows:

a) *disturbance inputs* - these are inputs, independent of the control, that cause the system to deviate from desired or predicted behavior and hence motivate control action. In general, disturbances represent the interactions of the plant with other plant units and with the environment, e.g. changes in composition of a feed stream, changes in ambient temperature, changes in throughput rate, etc. We also recognize a special class of disturbance called *contingency* occurrances. These refer to events that occur essentially at discrete points in time, e.g. a pump has failed, a feed supply tank has gone empty, a catalyst regeneration cycle is to be initiated. Often, a contingency event signals that the system is no longer operating according to assumptions implied by the current control model and that, as a result, it is necessary to modify the structure of the system, go into a new control mode or develop some other non-normal response.

b) *controlled inputs* - (also referred to as manipulated or decision variables) these are the results of the decision-making process carried out by the computer/controller. They are determined so as to compensate for the effects of disturbances by either directly or indirectly modifying the relationships among the plant variables, e.g. by changing the energy or material balance in the system. The compensation may be based on (i) measurement of the disturbance and prediction of its ultimate effect on the plant (feedforward action) or (ii) measurement of the effect of the disturbance on the plant out-

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* Superior numerals refer to references at the end of the report.

puts directly (feedback action), or more generally, (iii) a combination of both.

c) *outputs* - these are variables of the plant which (i) are functionally dependent on the designated input variables, and (ii) are relevant with respect to the performance measure on which control of the plant is based. The basic system is shown in Fig. 1. We assume that the output variables are deterministic functions of the inputs, i.e.

$$y = g(m,z) \tag{1}$$

where y,m,z denote vectors of output variables, controlled inputs, and disturbances, respectively.* Basically, the controller generates m according to information contained in vectors v and x

$$m = m(x,v) \tag{2}$$

where v denotes the set of external inputs which relate to control objectives and constraints, e.g. product specifications, economic factors, etc.; x denotes the set of plant variables that are measured and whose values are transmitted to the controller (in real-time), i.e.

$$x = (y_m, z_m) \tag{3}$$

where y_m, z_m are vectors denoting the measured components of y and z, respectively.

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* Equation (1) describes a static or steady-state input-output relationship for the (time-invariant) plant. To reflect the more general dynamic and time-varying case, we should write

$$y(t) = g\{t, s(t_o);\ m(t_o,t), z(t_o,t)\} \tag{1'}$$

where y(t) is the output evaluated at time t, $s(t_o)$ denotes the state of the plant at some prior time t_o, $m(t_o,t)$ and $z(t_o,t)$ denote the time trajectories of the input variables over the interval from t_o up to (and including t). However, in the sequel, we shall use the form (1) for simplicity of representation and with the understanding that in cases where dynamic effects are significant, form (1') is implied.

If we didn't consider the problems of realization and implementation, we would ideally like to determine (2) so as to achieve optimal performance; i.e.

$$\max_{m \varepsilon M} \tilde{P}(m,y,z,v) \qquad (4)$$

where $M = \{m | y=g(m,z),\ h(m,y,z,v) \geq 0\}$

and where $\tilde{P}(\cdot)$ denotes the performance measure suitably averaged over the relevant time horizon, $h(\cdot)$ denotes the set of inequality constraints applicable to the system. Of course, practical considerations dictate a suboptimal approach to the design problem (which sometimes degenerates to the problem of just finding a feasible solution!).

The multilayer structure of Fig. 2 provides a rational and systematic procedure for resolving the control problem. In effect, the overall problem is replaced by a set of subproblems which are more amenable to resolution than the original problem. Essentially, problem statement (4) is modified to

$$\max_{u \varepsilon U} P'(x',w,u) \qquad (5)$$

Where $U = \{u | y'=g'(u,z',\alpha),\ h'(u,x',w) \geq 0,\ x'=(y',z')\}$

This yields a control of the form

$$u = u'(x',w) \qquad (6)$$

The following explanatory remarks are in order:

1) The first-layer (direct control) function plays the role of implementing the decisions of the second-layer (optimizing) function, expressed as the vector $u = (u_y,u_m)$, where u_y denotes

a vector of set-points for y which, through feedbacks (and feedforward mechanisms) determines a subset of the components of m; the remaining components of m are determined directly by u_m. This implies the first-layer relationship.

$$m = m'(x_1,u) \qquad (7)$$

where x_1 denotes the information used in implementating the direct control function.

There are two useful consequences of (7); (a) various disturbance inputs may be suppressed with respect to the second-layer problem, e.g. by specifying reactor temperature as the decision variable rather than, say, heat input rate, we remove the need for explicit consideration (in the optimization) of the many disturbance variables that may affect the thermal equilibrium and heat transfer relationships of the plant; and (b) the dynamic aspects of the control problem may be effectively "absorbed" at the first layer so that static models may be used at the higher layers to good approximation.

2) The plant model (1) is replaced by the approximate model

$$y' = g'(u,z',\alpha) \qquad (8)$$

where y',z' are vectors formed by the components of y and z, respectively, that are relevant to the second-layer problem, with the information vector $x' = (y',z')$ (corresponding to x_2 in Fig. 2) generally of lower dimension than x. The functions g' are simplified approximations to g with the parameter vector, α, properly chosen to give a good representation. Note that (8) characterizes the input-output model of the combined system consisting of the plant, direct controllers and measuring elements as seen by the second layer (represented by the dotted block in Fig. 2). Further simplifications to the problem are obtained by being able to employ static functions for P' and g', as noted in 1) above.

3) The vector h' often includes, besides those constraints necessary to ensure safe, feasible operation of the physical system, various artificial constraints whose primary function is to maintain credability of the simplified model. An example of this is the placing of bounds on the temperature and rate of change of temperature of a furnace to ensure that deterioration of the refractory wall will be negligibly affected by the operating conditions to the extent that these factors can be ignored by the model.

4) The third-layer (adaptive) function provides for updating of the parameters of the model to reflect current experience with the operating system as conveyed through the information set x_3. This means that we can eliminate from the problem formulation (5), factors which are not of primary significance, which tend to vary slowly or tend to change infrequently (e.g. catalyst activity, fouling of a heat transfer surface, seasonal variations in cooling water temperature), since these factors (disturbances) may be compensated through the adaptive function.

5) The external (economic) factors contained in v are now inputted to a fourth-layer (evaluation and self-organization) function and are transmitted to the second-layer model via the vector w. Changes in v may influence the weighting of terms in P' or some of the bounds imbedded in h'. More generally, the evaluation of performance (through the information set x_4) may lead to modifications in the structure of the control system, e.g. in the definition of the constraint set U. Finally, we note

that contingency events may also lead to changes in system relationships or objective function (manifest as changes in U and/or P'), e.g. the shift from normal operation of a catalytic reactor to a catalyst regeneration cycle.

6) From the standpoint of plant performance, it is immaterial how the transformations from input information to output decisions/actions are carried out (i.e., whether by algebraic solution of a set of equations, hill climbing on a fast-time simulation, or simply table lookup) except as the method might affect the accuracy, the cost or the speed with which the controller outputs its results. By the same token, the control functions may be performed by man, by machine (computer) or by an intersection of both.

7) Although, the multilayer hierarchy was motivated by considerations of continuous process systems, the underlying principles apply equally well to control of batch processes, semicontinuous processes, etc.[3]

A case in point is the example of a batch reactor. The second layer function determines optimal trajectories of, say, reactor temperature (as the control input) and reactor composition (as the state vector) such that product yield is maximized. The trajectories may be computed prior to the start of each new batch, with inputs based on measured feed composition, estimated catalyst activity, etc. The first layer has the problem of implementation. There are a variety of disturbances that cause the actual trajectories to deviate from the computed optimal (reference) paths (e.g. changes in catalyst activity from that predicted, errors in the model used, etc.). One form the first layer control may take (to compensate for the disturbances) is to minimize a weighted mean square deviation of actual trajectories from the reference values, applying optimal control theory (linear model, quadratic criterion [4]).It is clear, in this application, that the third layer adaptive function may update the parameters of the (nonlinear) second layer model, as well as perhaps the weighting coefficient of the quadratic criterion used at the first layer (assuming the coefficients for the linearized model are evaluated at the second layer along with the reference trajectories). The fourth layer functions will be concerned with the same overall considerations as discussed previously. Some examples of application of the multilayer concept to systems involving discrete event decision processes (e.g. scheduling, contingency control) have also been described. [3,15].

8) There are a large variety of ancillary tasks normally carried out in conjunction with the control functions identified in the multilayer heirarchy. These might be looked upon as "enabling" functions that are deemed necessary or useful to the pursuit of the overall system goals. Indeed, the provision for such tasks is often a very significant factor determining hardware and software requirements in computer control applications. Among such ancillary functions we include (i) data gathering (filtering, smoothing, reduction), (ii) record keeping (for plant operator, production control, management information, accounting, etc.),(iii) inventory maintenance (e.g. keeping track of goods in process), (iv) sequencing of operations (e.g. startup/shutdown operations). The essential feature of these functions is that they are routine, repetitive and open-loop, hence can be handled by stored programs and fixed hardware. Considerations of decision-making and control may come into the picture at the higher layers, however, with respect to modifying the procedures, operating sequences, etc., based on evaluation of performance or in response to contingency occurrences.

MULTILEVEL CONTROL HIERARCHY

We consider again the optimization problem (5) reformulated* for convenience as follows:

$$\max_{u \in U(z)} f(u,y,z)$$

$$\text{where } U(z) = \{u | y = g(u,z),\ h(u,y,z) \geq 0\} \qquad (9)$$

where f is the measure of overall performance (objective function), u is the vector of decision variables (controller outputs), y is the vector of plant outputs, z is the vector of disturbance inputs, U(z) denotes the feasibility set (conditional on z), g and h denote vectors of equality and inequality constraints, respectively.

We assume that the problem (9) has a solution $u^o(z)$; however, despite the simplifications introduced into the model via the multilayer approach, the solution is still too difficult or too costly to obtain in a direct manner in a form suitable for on-line implementation (limiting factors may include excessive computation time, inadequate storage capacity of the available computer, etc.). The multilevel approach, where applicable, provides a means of circumventing the difficulty by decomposing the overall problem into a number of simpler and more easily solved sub-problems. Thus, in application to the problem (5), we assume that the functions are separable in the sense that we can decompose the overall problem into N subproblems as follows:

$$\max_{u_i \in U_i} f_i(u_i,y_i,q_i,z) \qquad (10)$$

$$\text{where } U_i = \{u_i | y_i = g_i(u_i,q_i,z),\ h_i(u_i,q_i,z) \geq 0\}$$

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* Besides slight changes in notation, we have (i) replaced x by its component vectors y and z, (ii) suppressed the dependence of the functions on w and α (i.e. assumed these are fixed over the time horizon of the optimization problem).

$$q_i = \sum_{j=1}^{N} T_{ij} y_j \qquad i = 1,2,\ldots,N \qquad (11)$$

The variables are identified with reference to Fig. 3. Except for the q_i, the notation follows that of (9) with the modification that the subscript i particularizes the vectors and functions to subsystem i. The vector q_i denotes the inputs to subsystem i which result from interactions from other subsystems. It is assumed that these interaction inputs can be expressed in the form of (11) where the T_{ij} are matrices of zeros and ones which couple the components of q_i with the appropriate components of y_j, $j \neq i$. It is assumed that,

$$f(u,y,z) = \sum_{i=1}^{N} f_i(u_i,y_i,q_i,z) \qquad (12)$$

and that a solution satisfying the constraint sets U_i, i=1,2,...N, and the interaction constraint (11) will also satisfy the overall constraint set U (in problem (9).

In the multilevel hierarchy, the subsystem problems (10) are solved at the first level. These solutions have no meaning, however, unless the interaction constraint (11) is simultaneously satisfied. This is the coordination problem that is solved at the second level of the hierarchy.

There are a number of decomposition/coordination procedures that have been developed. Since there exists an extensive literature on the subject,[5-10] we will not go into any detailed discussion, but only outline the basic ideas underlying the most common methods.

1) Price adjustment coordination (interaction balance)
Define the i^{th} first-level problem as

$$\max_{(u_i, q_i) \varepsilon \Omega_i} f_i(u_i, y_i, q_i, z) \qquad (13)$$

where $\Omega_i = \Omega_i(\lambda, z) = \{(u_i, q_i) \mid y_i = g_i(u_i, q_i, z),$

$$h_i(u_i, q_i, z) \geq 0, \; \lambda_i q_i = \sum_{j=1}^{N} \lambda_{ji} y_i\}$$

where $\lambda = (\lambda_1, \lambda_2 \ldots . \lambda_N)$ = set of Lagrangian multipliers.

The solution to (13) is of the form $u_i^*(\lambda, z)$, $q_i^*(\lambda, z)$ $i = 1,2,\ldots N$; these are transmitted to the coordinator at the second level which is concerned with the dual problem

$$\min_{\lambda \varepsilon D(z)} \sum_{i=1}^{N} f_i(u_i^*, y_i^*, q_i^*, z) \qquad (14)$$

where the starred variables are functions of λ and z; D(z) denotes the set of values of λ for which solutions to (13) exist.

The solution procedure is an iterative one which, under appropriate conditions,+ converges to the solution of the overall problem (where the result of (14) is satisfaction of the interaction constraints (11).

A limitation of this method, particularly with regard to real-time implementation, is the fact that intermediate iterations are generally nonfeasible in that the interaction constraints are not satisfied. Thus, the iterative solutions of the first and second level problems must be carried out off-line and

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+ Unfortunately, there is no assurance that the interactions will converge to a solution or if the solution is indeed the desired overall optimum. There is some theory establishing conditions for coordinability, optimality, etc.[5]; however, these results are still limited in applicability to complex systems.

only after convergence can the result be implemented on the plant. This is indicated in the realization of Fig. 4 where the couplings of the first level controllers C_1 and C_2 to the subsystems P_1 and P_2 are shown dotted. Here x_1 and x_2 denote information vectors consisting of some mix of components of y_1, y_2, and z from which the value of z can be inferred (for purpose of carrying out the optimizations (13) and (14). Note that C_o denotes the coordinator and the starred variables represent intermediate iterative values.

2) Primal coordination (interaction prediction)
In this method, the interaction variables (and hence the subsystem outputs) are set by the coordinator. The first level problems have the form, then,

$$\max_{u_i \varepsilon U_i} \quad f_i(u_i,\hat{y}_i,\hat{q}_i,z), \qquad i = 1,2,\ldots N \qquad (15)$$

where

$$U_i = U_i(\hat{q}_i,z) = \{u_i | y_i = g_i(u_i,\hat{q}_i,z),\ h_i(u_i,\hat{q}_i,z) \geq 0\}$$

where $\hat{q}_i$, $\hat{y}_i$ denote values set by the second level. The solution to (15), $u_i^*(\hat{q}_i,z)$, i = 1,2....N, is transmitted to the coordinator which solves the problem.

$$\max_{q \varepsilon Q(z)} \sum_{i=1}^{N} F_i(u_i^*, g_i(u_i^*,q_i,z),q_i,z) \qquad (16)$$

$$Q(z) = \{(q_1,\ldots q_N) | q_i = \sum_{j=1}^{N} T_{ij} g_j(u_j^*,q_j,z),\ i=1,2,\ldots N\}$$

Again, it may be shown that the iterations converage to the desired solution under appropriate conditions. In contrast to the previous method, the intermediate solutions here are feasible.

3) There are various other coordination schemes proposed, e.g. penalty function methods, etc. These are all similar to the methods outlined above in that an iterative procedure is involved wherein a set of local subproblems are solved at the first level in terms of a set of parameters specified by the second level. The methods may differ in their applicability to a specific problem, in the computation requirements, convergence speed, sensitivity to model error, incorporation on-line and other considerations. A description and comparison of various coordination methods, particularly with respect to real-time control applications is given in references(9,10).

There are an increasing number of papers describing applications of multilevel schemes for solving optimization problems in both design and control of process systems (11-15). Many of these references include some discussion of the particular features of the method employed.

Some multilevel schemes for on-line application make use of feedback in their implementation (e.g. via the x_i in Fig.4), i.e. they generate $u_i^0(y_i,z)$, i=1,2,...N. These schemes in effect incorporate parts of the physical plant into the models used in determining the local optima. This leads to simplifications in the mathematical model and, more important, reduced sensitivity to model inaccuracies and to the effects of miscellaneous disturbances not included in the model (9,10).

In essence, the coordination schemes described above serve the purpose of motivating iterative procedures for the solution of the mathematical problem of optimization of an objective function subject to constraints. As far as the plant is concerned, it is only the final result of the iterative process that is important, i.e. the functional relationship $u^0(z)$.

Thus, the entire multilevel structure is internal to the computational block generating the optimum control. However in the on-line application, the computation depends on the current value of z and this changes with time. Thus, much of the advantage of decomposition may be lost if the iterative process of coordination has to be repeated with every change in disturbance level.

If the system is decomposed along lines of weak interaction and if the coordination scheme is selected so that intermediate results are always plant feasible, then the multilevel structure provides the basis for a decentralized control wherein: (a) the first-level controllers compensate for local effects of the disturbances e.g. maintain local performance close to the optimum while ensuring that local constraints are not violated; (b) the second-level controller compensates for the mean effect of changes in the interaction variables on overall performance. The desired result is a significant reduction in the cost of achieving control through reductions in the required frequency of second-level action and in data transmission requirements.

Weak interaction linkages are readily motivated in CRS plants because they are typically an interconnection of semi-independent processing units designed in the "unit operations" tradition. The interaction may be further weakened by design: (i) use of buffer storages between units, e.g. feed tanks and surge chambers; (ii) decoupling control of key interaction variables. e.g. temperature control of feed stream; (iii) output control of preceding unit, e.g. control of distillation column which provides feed to a subsequent unit. We remark that the measures taken to decouple the subsystems are not without cost (both capital and operating) and that there are economic tradeoffs to be exploited via the multilevel hierarchy, e.g. increasing the degrees of freedom by relaxing the coupling constraints--at the expense of more frequent coordination at the second level.

We make two final remarks: (i) the multilevel structure extends in an obvious fashion to a hierarchy of three or more levels with each supremal unit coordinating the actions of a group of infimal units according to the same principles as described above; (ii) there is a strong compatability between the hierarchical control approach and the use of mini-computers in a coordinated system plant control.

TEMPORAL MULTILAYER HIERARCHY

In this formulation of the hierarchy, the layers are distinguished in terms of the relative frequency of control action or decision-making. Three factors motivate this structure: (a) basic response time or horizon for the underlying decision process; (b) frequency characteristics of the disturbances instigating control action; (c) cost/benefit trade-off between the cost of carrying out a control action versus the performance degradation of the plant resulting from not exercising control[16,17].

The structure of the system is shown in Fig. 5. The block G represents a measurement and data processing unit which transforms the raw input and output data into information vectors denoted by x_i. The vector m is partitioned to form subsets of control (decision) variables m_1, m_2,...m_L, where m_i is updated by the i-th layer control function F_i acting with mean period T_i, where it is assumed that $T_i > T_{i-1}$, i=1,2,...L. The i-th layer control implies the transformation

$$m_i = F_i(m_{i+1}, x_i) \qquad (17)$$

The function F_i may represent the result of an optimization or merely a heuristic decision rule based on operating experience. The vector x_i denotes the information set particularized for the i-th layer decision process.

There are several general features to be noted about the structure of Fig. 5.

1) The controls are coupled as indicated by (17). Thus, the action at the i-th layer depends on the prior decision at the (i+1)th layer. There is also interaction in the other direction; it is assumed, however, that the coupling is weak so that the i-th layer decision-making may proceed on the basis of averaged properties of the lower layer actions (as communicated via x_i).

2) The decision-making horizon tends to increase progressively as we proceed up the hierarchy (consistent with the increase of T_i with i). Thus, the structure accommodates very naturally the spectrum of decision-making functions typical of production systems, e.g. process control, operations control, daily schedule, weekly schedule, monthly plan, yearly plan, long range plan, etc.

3) The control functions of the multilevel and multilayer hierarchies previously described may also be encompassed by the temporal hierarchy in the sense that these functions are characteristically ordered with respect to time scale, frequency of action, degree of aggregation, and related attributes.

4) As we go from the i-th to the (i+1)th layer, the model tends to get less detailed and more based on aggregated properties of the system. Thus, in general, the information set x_i will consist of statistical parameters (mean, variance values) associated with elements of x_{i-1} averaged over the period T_{i-1}.

By example, optimizing control of a reactor will be based on a technological model; production scheduling will be based on perhaps a regression model which relates mean product output of the reactor (under the assumed optimizing control) to predicted mean input conditions.

5) The action F_i is associated with the decision horizon τ_i, where we assume $\tau_i \geq T_i$. Prediction algorithms [18] may be incorporated in the block G so that x_i reflects a prediction of mean disturbance conditions over the interval $(t, t+\tau_i)$. The effect of errors in the prediction are reduced by feedback of operating experience through (i) updating of the prediction algorithm based on observations over the preceding T_i period, (ii) updating of the i-th layer decision every T_i, noting that if $T_i \ll \tau_i$ then only the initial segment of the F_i action is actually implemented before the next opportunity for revising the decision arises. A common choice in scheduling and planning practice is to set $T_i = \tau_{i-1}$, e.g. the monthly plan may articulate with the yearly plan which is updated every month.

6) Control action may be carried out according to a periodic policy [16] i.e. every T_i units of time action F_i is performed; or an on-demand policy [17] whereby F_i is actuated by a contingency occurence or by the observation of the disturbance exceeding the bounds of the predicted range. In general, both policies would be incorporated within the system.

7) We may formalize the cost/benefit tradeoff problem to provide a rational basis for design choices regarding the multilayer hierarchy. One formulation of the problem is as a Markovian decision process [17] with the tradeoff expressed as

$$P_{net} = \tilde{P}^H - \tilde{C}^H \qquad (18)$$

where $\tilde{P}^H$ denotes average plant performance under a control policy H, $\tilde{C}^H$ denotes mean costs of control conditional on H. The design objective is to select a policy (e.g. specifications of $\{m_i\}$ and $\{T_i\}$) within a permissible set of alternative policies for which P_{net} is a maximum. The control costs may include consideration of costs of measurement, data processing, computation associated with the control action, and implementation.

8) We may illustrate the temporal hierarchy by identification of layers of control action in the operation of a heat exchanger network (as part of a larger chemical process system). We consider the purpose of the network: (i) to satisfy various temperature constraints on the process streams as required by the associated process units, (ii) to conserve thermal energy by optimal interchange of heat among the process streams. This leads to a possible partitioning of the decision vector into subsets as follows (partial listing):

m_1: Direct control of flowrates to the exchangers to satisfy specified temperature constraints and to satisfy specified load allocation.

m_2: Determine optimal flow distribution to maximize thermal efficiency of network.

m_3: Update parameters of optimizing control algorithm; modify temperature constraints according to revised needs of the system induced by the production schdule.

m_4: Scheduling of shutdowns for cleaning, etc.; update parameters of heat transfer models.

m_5: Structural changes of the system, replacement of units, etc. as reflected in long range plans.

With each subset, we may identify the relevant disturbances, externally imposed constraints, and the design criteria for defining the control actions.

CONCLUSIONS

The systems approach to control of CRS must consider the broad spectrum of decision-making functions that range from process control at one end to production scheduling and planning at the other. Basic to the approach are the multilevel and multilayer control hierarchies which provide the conceptual frame-work for (i) decomposing the complex problem of optimizing overall plant performance into a set of simpler subproblems, (ii) effective utilization of information in updating models and control actions, (iii) integrating the various decision-making and control functions that interact to determine overall plant performance.

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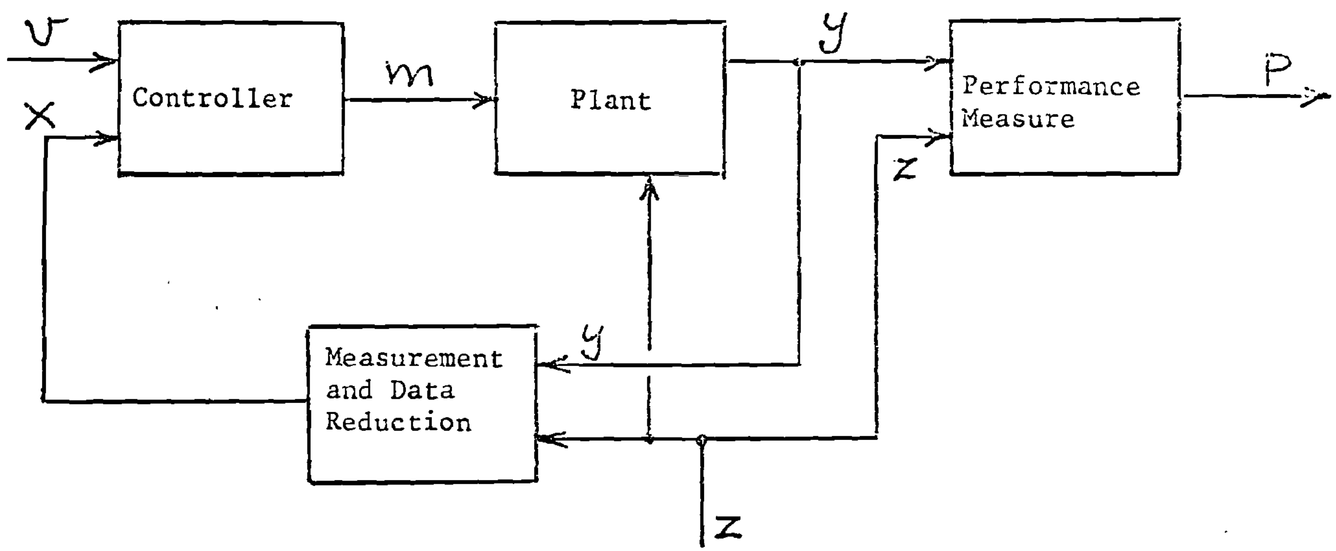

Figure 1. Block Diagram of Basic System

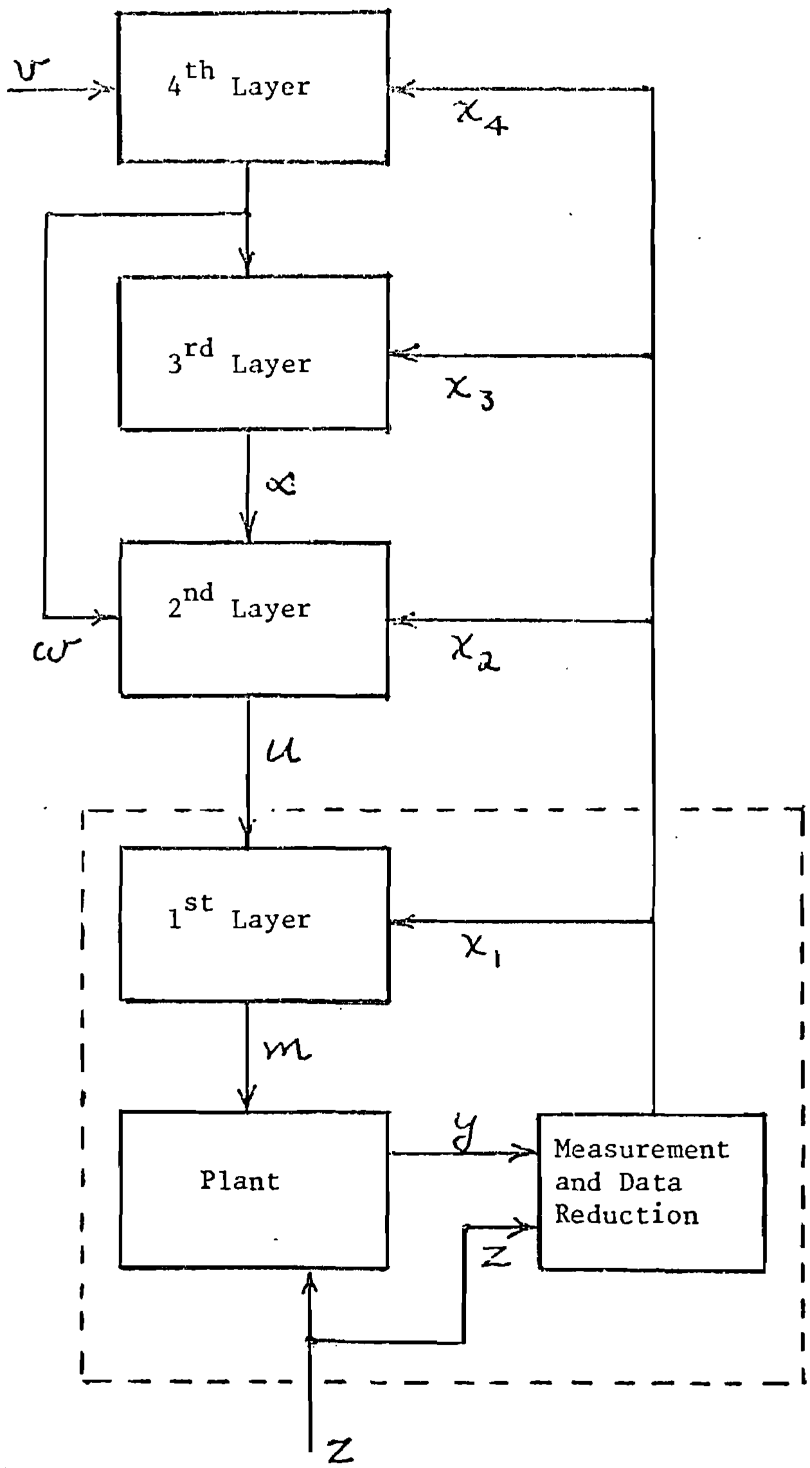

Figure 2. Functional Multilayer Hierarchy

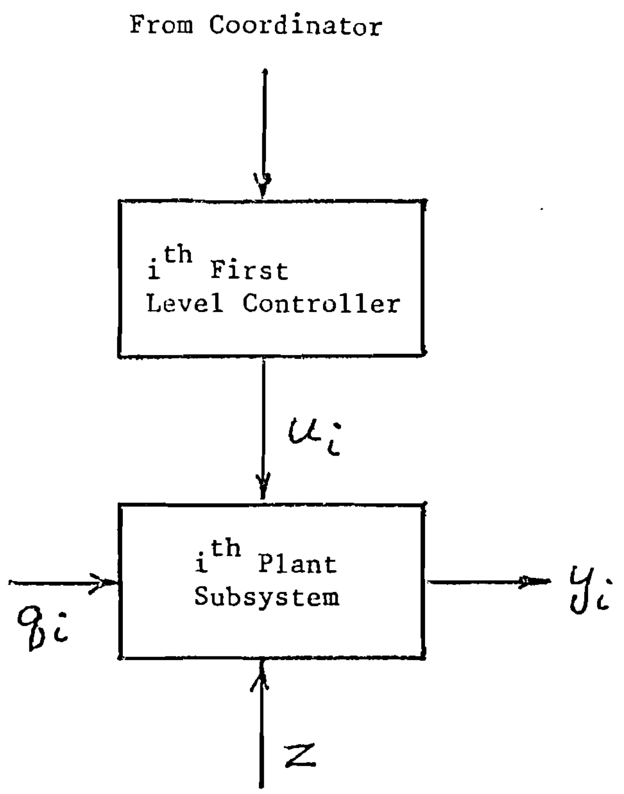

Figure 3. Subsystem of Multilevel Decomposition

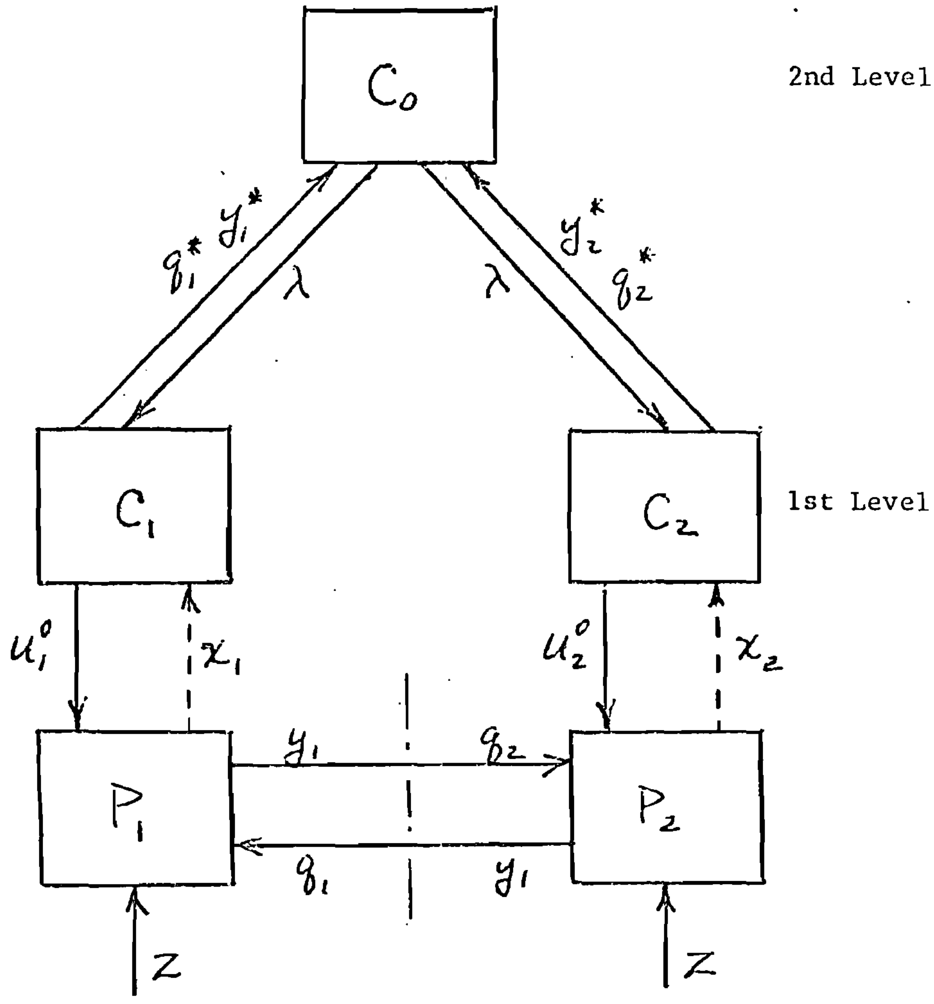

Figure 4. Two Level Structure Illustrating Model Coordination

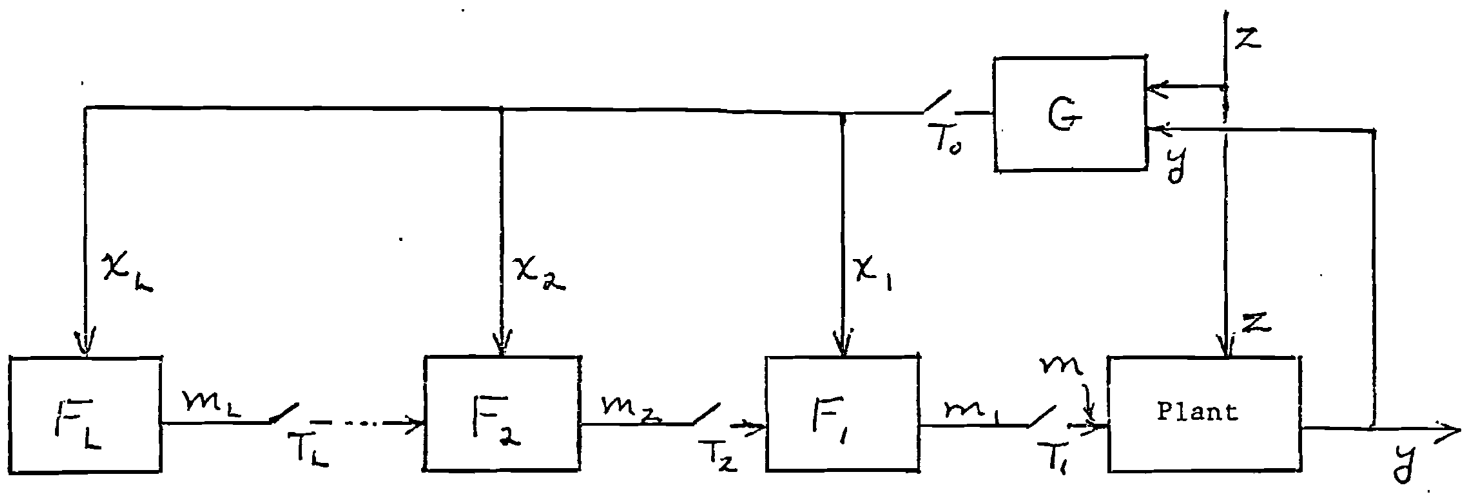

Figure 5. Temporal Multilayer Hierarchy