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HIERARCHIES FOR COMPUTER-INTEGRATED MANUFACTURING:

A FUNCTIONAL DESCRIPTION

by

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ABSTRACT

In the recent past, several hiearchies have been proposed as candidate models for the integration of decision and control functions within a Compeuter-Integrated-Manufacturing environment. A common theme in the definition of these models is to construct an analog to managerial hierarchies that are currently employed in many corporate settings. This paper will adopt an alternate approach. Rather than defining a hierarchy, this paper will discuss the manufacturing functions that a CIM hierarchy must address. Whenever possible, mathematical formulations for the functions will be given with consideration for the stochastic environment in which they will function. The conclusion outlines several concerns arising in the definition of a generic CIM hierarchy and associated research topics that must be addressed.

1.0 INTRODUCTION

Throughout history, the organization has played a vital role in the success of large manufacturing companies by providing a means for addressing the strategic goals of the company. Designing an organization to address those goals involves [GAL77]: 1) defining the tasks to be performed; 2) dividing those tasks into layers of subtasks for assignment to individuals; 3) developing a managerial structure to coordinate those subtasks; and 4) determining methods for processing the information to make the decisions associated with 1, 2 and 3.

Task decomposition allows individuals to become highly skilled at a small number of tasks. While this improves both the quality and quantity of their work and leads to greater output from the same number of people, it also increases the interdependence among workers and the need to coordinate their output. Traditionally, hierarchical managerial structures (Figure 1) have been used to ensure such coordination. Each position within that hierarchy is obliged to follow the commands of a single superior. In addition, each position is expected to issue commands to its subordinates. In this way, no position is left uncoordinated.

Within a given hierarchy, the number of layers and the responsibilities of the managers at each layer depend on the size and complexity of the company. In some cases, all decisions are made at the top, and managers simply implement them at their own level. In other cases, each manager is expected to make certain decisions, based on input from his superior, and exert the control necessary to have subordinates execute his decisions. Each strategy has implications on the amount and type of information processing required to make and carry out decisions. Both can be successful [GAL77] in meeting a company's needs.

Recent attempts to design and build Computer Integrated Manufacturing (CIM) systems have been based on similar concepts of organization. That is, tasks are decomposed, "logically" grouped, and then assigned to one or more computers and/or pieces of automated equipment. Several decision-making and control hierarchies have been proposed [JON85] to manage and coordinate the activities within these CIM systems, and in nearly every instance, a functional decomposition has been used to define the levels within a given hierarchy. That is, the basis for choosing a specific hierarchical design and task

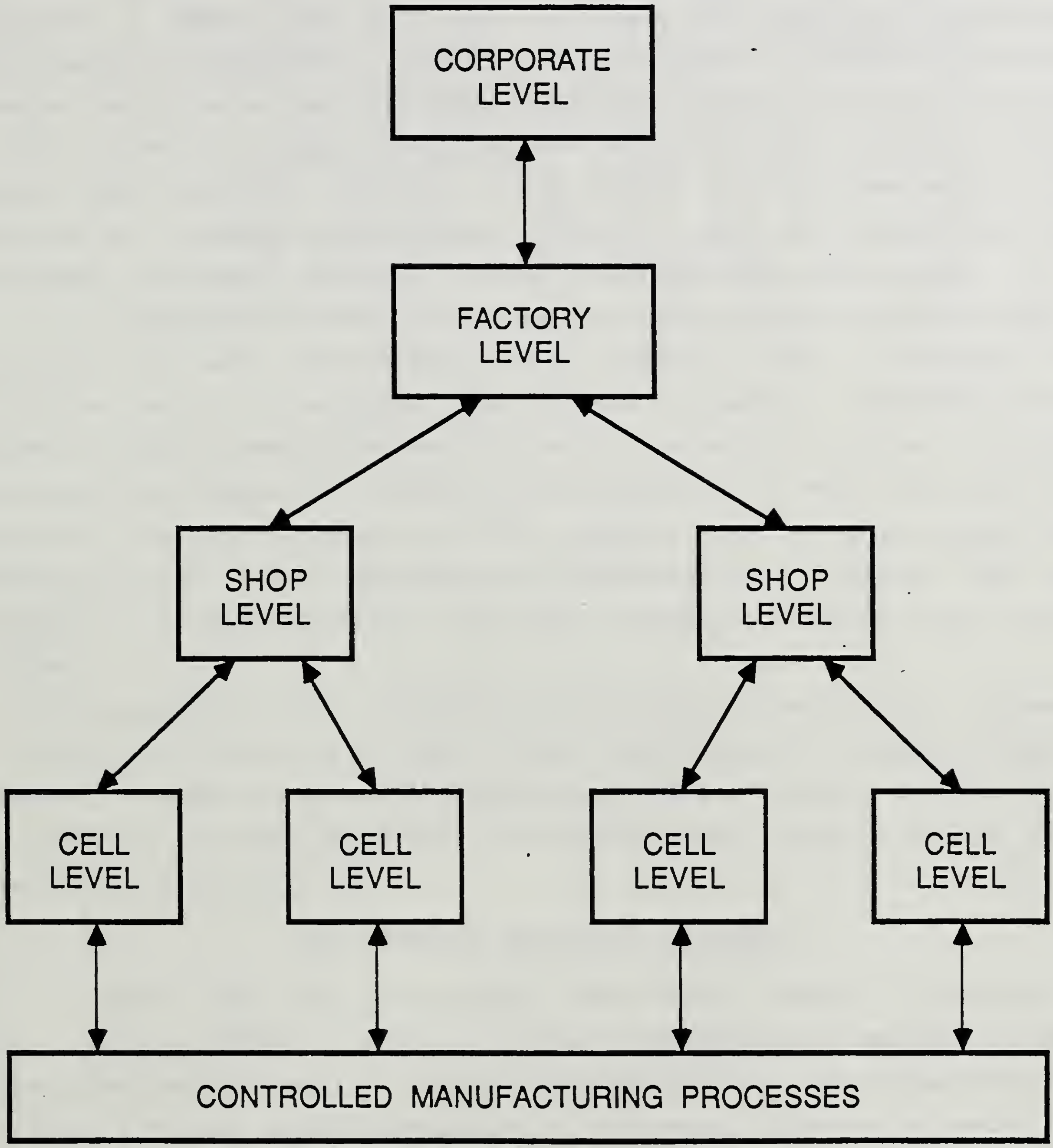

FIGURE 1 -- MANAGERIAL ORGANIZATION FOR CIM ENVIRONMENT

decomposition for a new CIM system is usually the existing organizational structure within the same company.

Two questions arise. First, is it necessary, or even desirable, to implement a design for CIM that is based on existing, people-based organizational structures? Second, is it possible to develop quantitative measures which can be used to compare different management structures for CIM? To date, answers to these questions have not been found. While we do not answer these questions directly, we do attack a more fundamental issue: defining the "overall manufacturing problem." Once this problem has been formulated, meaningful attempts to answer these questions can be made.

It is impossible to develop an exact, detailed problem definition which is applicable to all manufacturing firms, because goals, strategies, and activities can vary tremendously from one firm to another. Therefore, we have chosen to present general mathematical models for several decision and control functions which impact the design and implementation of every CIM system (See Figure 2). The list of functions is not complete, since we have excluded those problems related to data management and communications. However, this paper represents, to our knowledge, the first attempt to define this "overall problem."

The organization of the remainder of the paper is as follows. In section 2, we describe models for a single process while section 3 presents models to capture the interactions among individual processes. Section 4 contains models of production planning decisions. We also include a summary section and an extensive bibliography.

2.0 MODELING INDIVIDUAL PROCESSES

We assume that the manufacturing shop floor contains N processes P_n $(n=1,\ldots,N)$ as depicted in Figure 3. These processes can be machining centers, inspections centers, material handling devices, etc. We also assume that these processes are used in the fabrication of M distinct products ρ_m $(m=1,\ldots,M)$. Modeling these processes is based on the concept of state transition functions.

2.1 State Transition Functions

The behavior of process P_n while producing product ρ_m can be modeled by the state transition function $g_{nm}[x_{nm}(t),u_{nm}(t),t]$ where $x_{nm}(t)$ is the state of the process P_n and $u_{nm}(t)$ is the controlling input into the process P_n at time t. Using a sequence of discrete sampling times $\{t_0,t_1,t_2,\ldots\}$ where

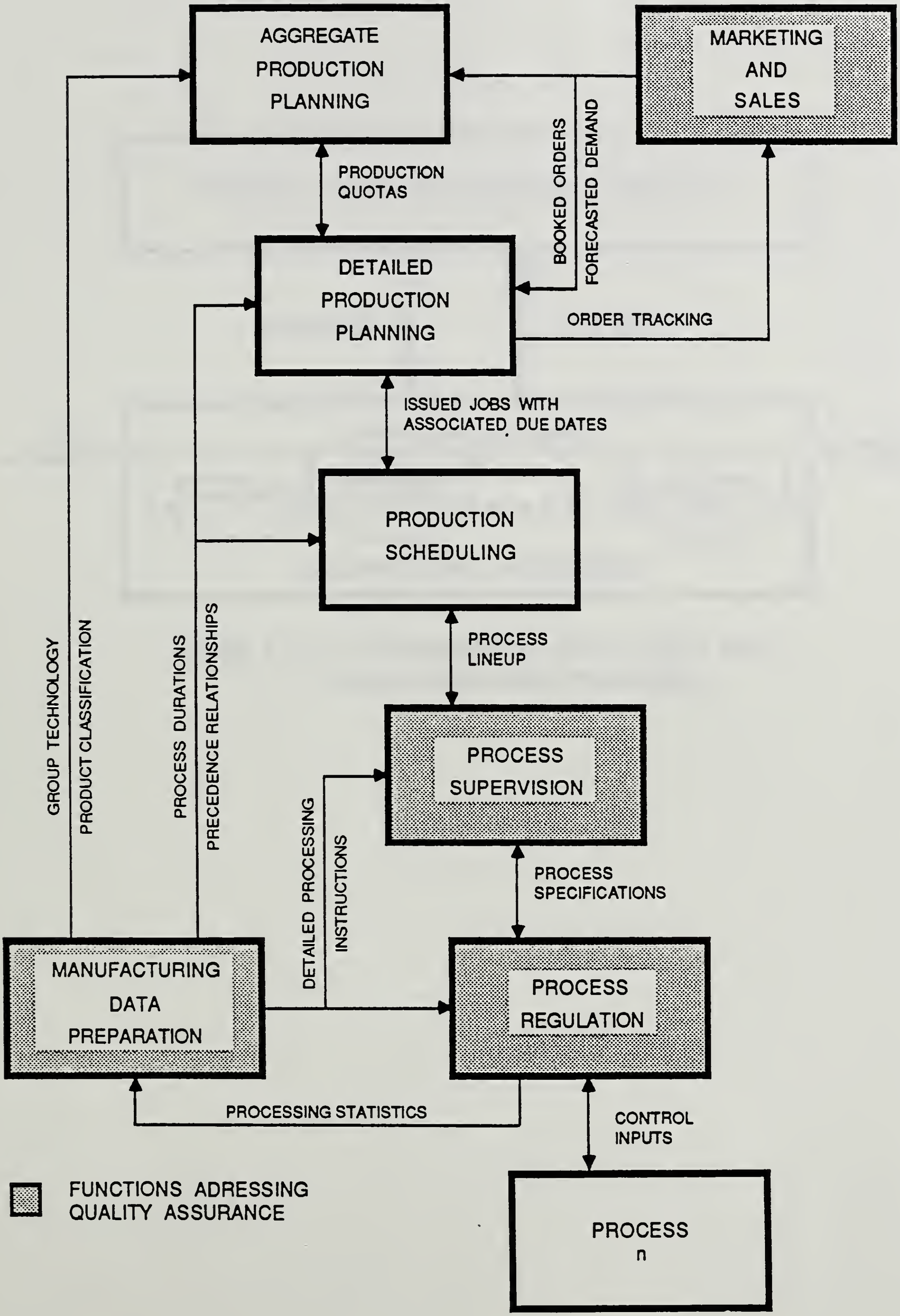

FIGURE 2-- MANUFACTURING FUNCTIONS COMPRISING CIM ENVIRONMENT

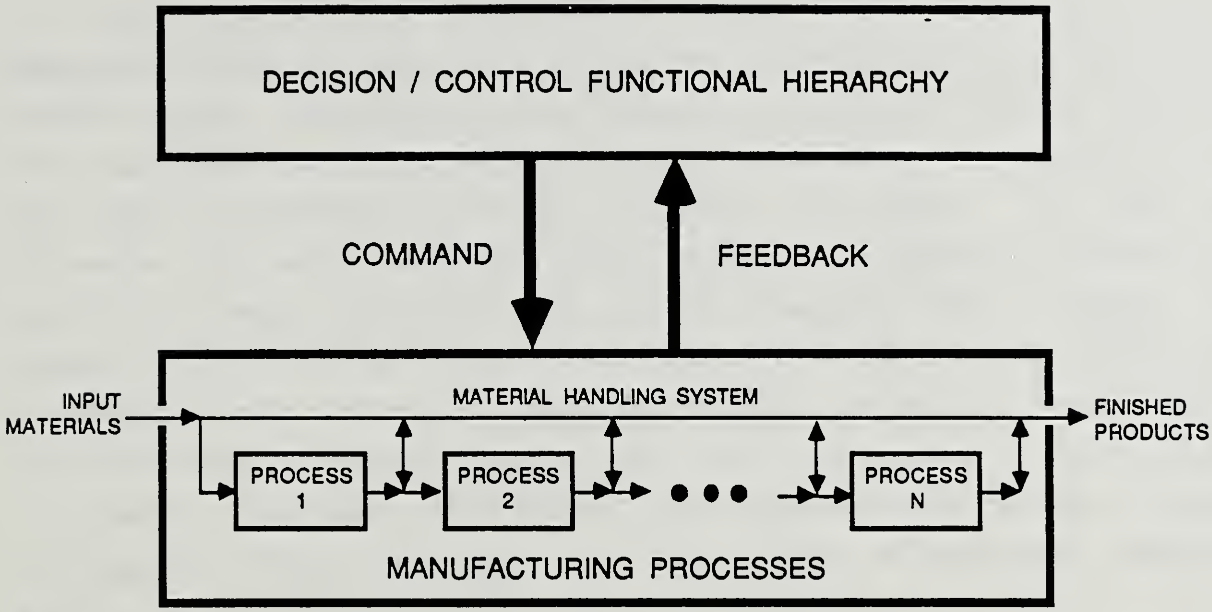

FIGURE 3 -- THE CONFIGURATION OF THE DCFH WITH THE MANUFACTURING PROCESSES

$$t_k = t_0 + k\,\Delta t \text{ for } k = 0,1,2, \ldots \tag{1}$$

we can define the evolution of $x_{nm}(t_k)$ via the recursive relation

$$x_{nm}(t_{k+1}) = g_{nm}[x_{nm}(t_k), u_{nm}(t_k), t_k] \tag{2}$$

There are several properties of $g_{nm}[\cdot]$ that ultimately govern the complexity associated with determining the controls $u_{nm}(t_k)$ and predicting the states $x_{nm}(t_k)$. The first is the functional dependence on time, which implies that the functional form of $g_{nm}[\cdot]$ can vary over time. The second is the fact that this variability is often stochastic in nature. In metal removal processes, the amount of input energy needed to maintain a constant cutting force can change drastically as the tool becomes worn. Another familiar example is the rolling of hot steel slabs, where the rolling process produces permanent plastic deformation upon the rollers. In both of these examples, it is impossible to predict $g_{nm}[\cdot]$ or the behavior of P_n with certainty. Consequently this means that the best that one can hope to do is to specify the prob$(g_{nm}[\cdot] \in G_{nm})$ where G_{nm} is a known subset of potential functions for $g_{nm}[\cdot]$.

Another important limitation in modeling manufacturing processes today is the fact that $x_{nm}(t_k)$ is seldom observed directly. Despite the abundant research in this area, on-line process monitoring and control techniques are still not available for many processes. Until this happens, we will continue to measure the output of the process rather than the process itself. This output, $y_{nm}(t_k)$, can be defined by

$$y_{nm}(t_k) = h_{nm}[x_{nm}(t_k), u_{nm}(t_k), t_k] \tag{3}$$

Since the calibration of a measuring device may change randomly over time, the same potential problems arise in estimating $h_{nm}[\cdot]$ as in the estimation of $g_{nm}[\cdot]$ in (1). Furthermore, although $h_{nm}[\cdot]$ is expressed as a function of time, it is rarely possible to measure all the processing outputs in real-time. As an example, consider a turning operation. In this case, measurements such as turning speed and the location of the tool holder can be made in real-time. However, as the tool wears the depth of the cut changes. Therefore, measurements such as the precise depth of the cut or the resulting surface roughness can not be made in real-time, and must await for the completion or the interruption of the process for a precise measurement. Let T_{nm} and t_0 denote the anticipated duration and initiation time for the processing task; $t_{nm} = t_0 + T_{nm}$ be the anticipated completion time; and $y_{nm}(t_{nm})$ the final measured output. Then the modeler may only have a rough estimate of the following

$$y_{nm}(t_{nm}) = h_{nm}[g_{nm}[x_{nm}(t^*), u_{nm}(t^*), t^*] \qquad (4)$$

where t^* is the last sampling time prior to t_{nm}. Letting Y_{nm} represent a set of acceptable outputs--usually a set of predefined tolerances--the best information the modeler can hope to supply is the prob $\{y_{nm}(t_{nm}) \in Y_{nm} \mid x_{nm}(t^*)$ and $u_{nm}(t^*)\}$.

It seems clear that using these functional relationships to monitor and control manufacturing processes will not be possible in the near future. The task of estimating prob$\{g_{nm}[\cdot] \in G_{nm}\}$, prob$\{h_{nm}[\cdot] \in H_{nm}\}$, and prob $\{y_{nm}(t_{nm}) \in Y_{nm} \mid x_{nm}(t^*)$ and $u_{nm}(t^*)\}$ will also be difficult. In most cases, these estimates must be based on the experiences gained from past implementations of each particular product. This, of course, leads to significant problems in estimating $g_{nm}[\cdot]$ and $h_{nm}[\cdot]$ for new products.

2.2 Process Control

To account for uncertainties in the evolution of a process, a self-tuning controller can be used [AST77,AST84]. As depicted in Figure 4, a self-tuning controller has two basic elements: a system identifier and a controller. The system identifier uses the current values of $u_{nm}[\cdot]$ and $y_{nm}[\cdot]$, to develop approximations for the $g_{nm}[\cdot]$ and $h_{nm}[\cdot]$, denoted $g'_{nm}[\cdot]$ and $h'_{nm}[\cdot]$ respectively. These approximations are then used by the controller to generate the next control input. Specifically, the controller computes the difference between the actual output $y_{nm}(t_k)$ and the desired output $y^d_{nm}(t_k)$. This error is used in conjunction with the optimal control law $U^*[y_{nm}(t_k), t_k]$ imposed by the Process Coordinator (PC) (see below), to determine the next control input for the process. Thus, the process controller continuously attempts to minimize deviations from the desired output trajectory specified by the PC. To be effective in this role, the controller's response time must be on the order of Δt.

For deterministic systems in which $g_{nm}[\cdot]$ is known with certainty, the system identification element is not needed. For processes where no formulation of the state transition function exists, the controller block would not exist. In this case, the system identification element would attempt to evaluate available system characteristics and would, in turn, subsequently define the initial process settings or control parameters. After initiation,

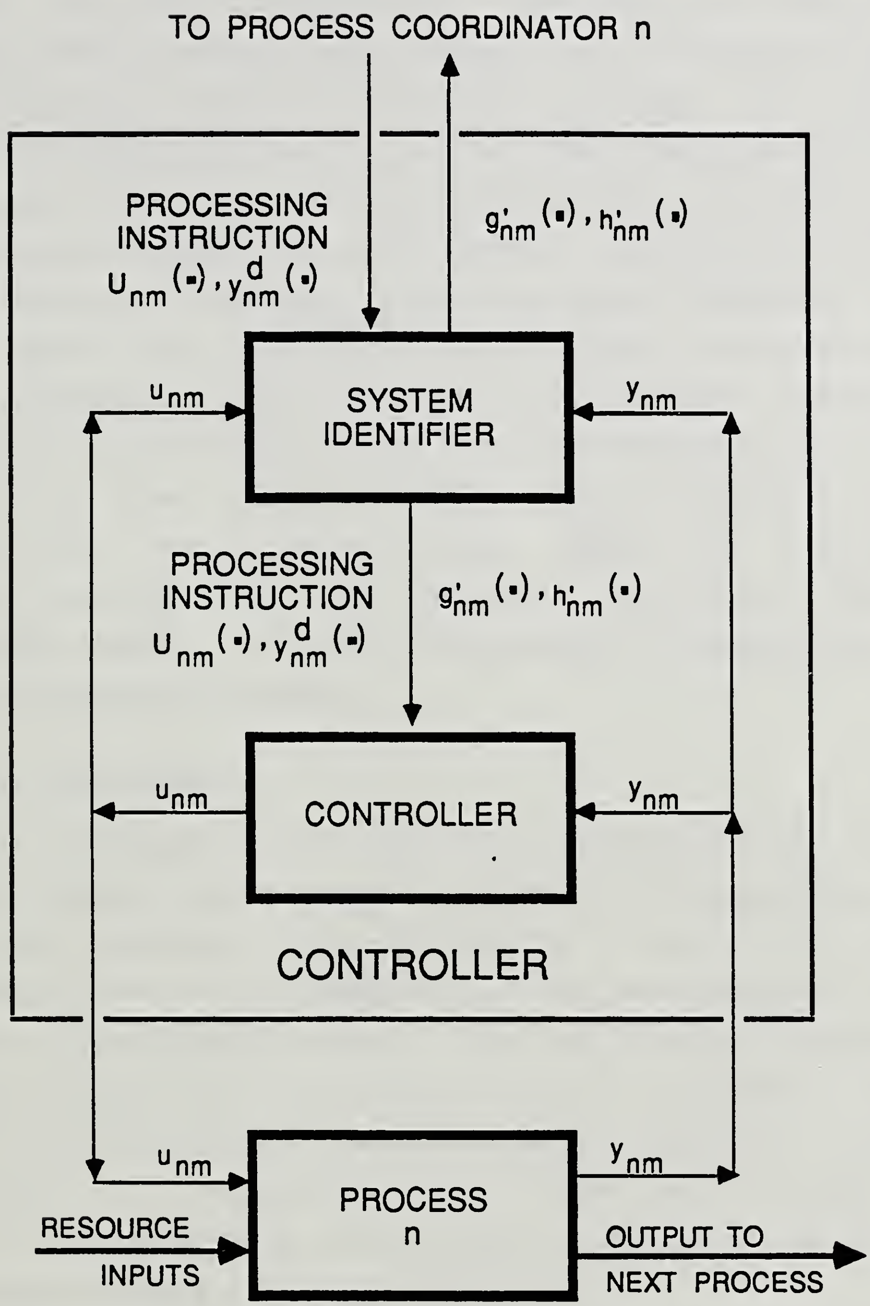

FIGURE 4 -- SELF-TUNING CONTROLLER FOR PROCESS P_n

the process would evolve in open loop fashion. As an example, consider the Basic Oxygen Furnace process in steel-making. Here the charge of molten iron, scrap steel, and alloy additives are introduced into the process. After approximately thirty minutes the finished steel is produced with little or no control intervention during the processing duration. As a consequence, there is only a 70% probability that the correct steel chemistry will be achieved.

Although limitations on process modeling exist, the self-tuning controller is being adopted in industrial environments. Astrom et al. [AST84] provide an excellent overview of the topic as well as several examples. Watanabe [WAT86] recently reported the development of a similar controller for a milling process. Papapanagiotou et al. [PAP84] has performed work demonstrating the applicability of self-tuning controllers to controlling the rollers in a hot strip mill for steel making. Blattner et al. [BLA86] have developed a formulation for controlling the blast furnace in steel-making. Their formulation includes not only parameter estimation within the system identification element, but also a simulation to predict the system response under various control strategies.

2.3 Process Coordination

Process Coordination (PC) determines the desired output trajectory $y^d_{nm}(t)$ for a given process and the optimal control law $U^*[y_{nm}(t_k),t_k]$ to be used in achieving that trajectory. Although this law is written as a function of time, it is typically set at the beginning of the processing and remains constant until some major problem arises. The PC detects potential problems by monitoring feedback from the process and its controller. Whenever the PC determines that a new control law and/or output trajectory is needed during the implementation of a processing task, it must also estimate the resulting probability that the process will be able to implement that law correctly, and thus, sucessfuly complete the processing task.

To understand the relationship between the PC and the process controller, consider the tool wear example from Section 2.1. First, the PC specifies an initial optimal control law, $U^*[y(t_k),t_0]$, which identifies the exact tool, speed, feed, cutter paths, and cutting time to be used in the process. This data is then used in negotiation with the production scheduler (PS) to determine start and finish times. But, as the process evolves in time, unanticiapated changes in the feed, speed, or cutting time may be required to account for tool wear or other changes in the processing environment. These changes, which are a function of the integrated measurements of $y_{nm}(t_k)$ and $x_{nm}(t_k)$, are dictated by the process controller's success in implementing the desired trajectory $y^d_{nm}(t)$. These changes are typically minor with respect to their consequences upon processing durations. If the tool breaks, major modifications could follow. First, the PC must determine if the job can be salvaged. If yes, then the PC must specify a new optimal control law with the associated probabilities for successfully implementing the task. These decisions would be based on the last measured value of $y_{nm}(t_k)$, the desired output $y^d_{nm}(t)$, and the current production schedule which also must be updated. It can be concluded that the focus of the PC is the total implementation of the processing whereas the process controller is focusing the immediate restoration of the desired output trajectory. We will now give two potential formulations for the determination of the optimal control law.

2.3.1 Off-line Determination of the Control Law. Process planning must determine the constraints upon the admissible set of functions for the optimal control law that will be used in completing JOB_j. These specifications prescribe the exact processes, precedence constraints, tools, and materials as well as limits upon operating speeds, feeds, and proposed durations. These specifications typically generate three types of constraints. The first set of constraints is the feasible (or admissable) set of control laws which is limited by the available materials and processing technologies. Second, there are capacity constraints on processes and tool life. Third, there may be a constraint on the minimum acceptable probability that the employed processing will produce a product that satisfies all the design specifications. Decision objectives could include minimizing processing cost, minimizing total processing time, and in some cases, maximizing the probability of successfully implementing the processing task.

Most process planning literature has focused upon this off-line, deterministic determination of the optimal control law. This is an acceptable approach provided the derived control laws are conservative in nature. For example, the cutting speeds must be selected without knowing the condition of the tool to be used. Furthermore, off-line process planning does not take into consideration the consequences of its decision on the production flow. This means that there is little interaction between off-line process planning and production scheduling. As an alternative, we advocate the consideration of the following on-line determination.

2.3.2 On-line Determination of the Control Law. As the process evolves in time, it may be necessary or beneficial to change the predetermined optimal control law generated by process planning. This problem is fundamentally different from the one described above for two reasons. First, current processing history does exist and estimates for $g_{nm}[\cdot]$ and $h_{nm}[\cdot]$ can be made. Consequently, an updated control law should incorporate this known information. Let $T\{g_{nm}[\cdot],h_{nm}[\cdot]\}$ represent the admissible class of functions for the optimal control law $U^*[y_{nm}(t_k),t_k]$. This set would be determined in the off-line analysis while the real-time analysis would be constrained to select $U^*[y_{nm}(t_k),t_k] \in T\{g_{nm}[\cdot],h_{nm}[\cdot]\}$. Secondly, a scheduled finished time, L_{jn}, has been established by the PS who can predict the consequences in the overall production flow if changes in L_{jn} must be made. To that end, we shall presume that the PS has a collection of objective functions $f^{\ell}(L_{jn})$ for $\ell=1,\ldots,L$ with an overall utility function $W[f^1(L_{jn}),\ldots,f^L(L_{jn})]$ expressing the tradeoffs among the objectives.[1] To permit the PC to coordinate its decision with that of the PS, we will assume that there are L′ compatible objectives for the PC, $\theta^{\ell}_{jn}[x_{nm}(t_k),u_{nm}(t_k)]$ for $\ell=1,\ldots,L'$, and a utility function, $\omega_{jn}\{\theta^1_{jn}[\cdot],\ldots,\theta^L_{jn}[\cdot]\}$ to quantify the tradeoffs among those objectives. A formal statement of the real-time optimal control problem can now be given.

$$\text{minimize} \quad \omega_{jn}\{\theta^{1}_{jn}[\cdot],\ldots,\theta^{L'}_{jn}[\cdot]\} \tag{5}$$

subject to for $t_{k'}=t_k,\ldots,t_k + T_{nm}$

$$x_{nm}(t_{k'+1}) = g_{nm}[x_{nm}(t_{k'}),u_{nm}(t_{k'}),t_{k'}] \tag{6}$$

$$y_{nm}(t_{k'}) = h_{nm}[x_{nm}(t_{k'}),u_{nm}(t_{k'}),t_{k'}] \tag{7}$$

$$u_{nm}(t_{k'}) = U_{nm}[y_{nm}(t_{k'}),t_{k'}] \tag{8}$$

$$U_{nm}[y_{nm}(t_{k'}),t_{k'}] \in T\{g_{nm}[\cdot],h_{nm}[\cdot]\} \tag{9}$$

$$\text{prob}\{y_{nm}(t_{k'}) \in Y_{nm}\} \geq pr^{min}_{nm} \tag{10}$$

$$t_k + T_{nm} \leq L_{jn} \tag{11}$$

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[1] The PS's objective functions $f^{\ell}(\cdot)$ for $\ell=1,\ldots,L$ are actually functions of several variables beyond the singular variable L_{jn}. However, during the real-time determination of the optimal control law, L_{jn} is the only variable upon which the PC has explicit control.

2.3.3 Deterministic vs. Stochastic. The preceding formulation assumes that the $g_{nm}[\cdot]$ and the $h_{nm}[\cdot]$ are known with certainty. Since this is not generally true, the derived solution will only approximate the true optimum. To overcome these inadequacies, equations (5) through (11) must be replaced by a collection of simulations. If the estimated values $g'_{nm}[\cdot]$ and $h'_{nm}[\cdot]$ are given, then the conditional probabilities $prob\{g_{nm}[\cdot] | g'_{nm}[\cdot]\}$ and $prob\{h_{nm}[\cdot] | h'_{nm}[\cdot]\}$ must be specified. Using Monte Carlo simulation, we can then generate the optimal solution to equations (5) through (11) for each sampled $g_{nm}[\cdot]$ and $h_{nm}[\cdot]$. For each simulated trial, the optimal $U^*_{nm}[y_{nm}(t_{k'}), t_{k'}]$ would thus be sampled. Through repeated simulated trials, an empirical probability density for the optimal $U^*_{nm}[y_{nm}(t_{k'}), t_{k'}]$ would emerge. Subsequent analysis would extract the actual $U^*_{nm}[y_{nm}(t_{k'}), t_{k'}]$ which appears to be the most robust optimal control law.

3.0 MODELING INTER-PROCESS INTERACTIONS

3.1 Combining Process Models

Thus far, the discussion has focused upon a single process. The state of the entire shop floor system at t_k is represented by the composite state vector $\{x_{1m_1}(t_k) \times \ldots \times x_{Nm_N}(t_k)\}$ where each individual process' state transitions are governed by $g_{nm}[\cdot]$ if process P_n is manufacturing product ρ_m. Similarly, the output from this collection of processes is given by the composite output vector $\{y_{1m_1}(t_k) \times \ldots \times y_{Nm_N}(t_k)\}$.

We note that as soon as process P_n completes one product and begins another, these representations are no longer valid. For each process we define a universal set of transition functions

$$\underline{S}_n = \{G_{n1}[\cdot], \ldots, G_{nM}[\cdot], \phi\} \qquad (12)$$

where ϕ is the idle state and $G_{ij}[\cdot]$ is the collection of potential transition functions from which $g_{ij}[\cdot]$ is chosen. If E_{jn} and L_{jn} represent the anticipated start and finish times for process P_n to work on JOB_j, then they also indicate the times where the transition function for the manufacturing system will change. These times are specified by production scheduling.

3.2 Production Scheduling

The primary problem related to inter-process coordination is production scheduling (PS). A formal statement of the (PS) problem is as follows: Assume that JOB_j $(j=1,\ldots,J)$ have been issued to the PS with associated due dates D_j $(j=1,\ldots,J)$ and that JOB_j requires the production of a specific product ρ_m $(m=1,\ldots,M)$. Further assume that the processes P_n $(n=1,\ldots,N)$ are available, and that $TASK_{kjn}$ $(k=1,\ldots,K)$ are the tasks of JOB_j to be performed on P_n. Then, if we define

$$E_{kjn} \ (k=1,\ldots K;\ j=1,\ldots,J;\ n=1,\ldots,N)$$

as the earliest start time for P_n upon $TASK_{jkn}$ from JOB_j and

$$L_{kjn} \ (k=1,\ldots,K;\ j=1,\ldots,J;\ n=1,\ldots,N)$$

as the latest finish time for P_n upon $TASK_{kjn}$ from JOB_j, the production scheduling problem is to optimize the utility function

$$W[f^1(E_{111},\ldots,E_{KJN};L_{111},\ldots,L_{KJN}),\ldots,f^L(\cdot)]$$

(subject to due date, material handling, resource availability, precedence constraints, and alternate routings) where $f^\ell(\cdot)$ for $\ell=1,\ldots,L$ are the criteria to be considered in the optimization. These criteria typically include minimizing tardiness, maximizing production throughput, and maximizing process utilization.

The PS is incapable of addressing the complete production scheduling problem by himself. That is, in considering the actual duration of the process P_n upon the JOB_j, the PS typically does not have complete knowledge about the current state transition function for each process. Hence, the exact production scheduling problem can not be completely specified. Instead, the PS must make its decisions based on an estimate for the duration d_{jn} $(=L_{jn}-E_{jn})$. Then, as discussed in 2.3, through negotiation the PC will subsequently develop the optimal control law which permits the process P_n to complete JOB_j by the mutually determined completion time L_{jn}. The basis of this negotiation between the PS and the subordinate PC's represents an elaborate decompositon of the production scheduling problem whose iterative solution mechanism represents a research topic beyond the scope of this paper. When the schedule is implemented, deviations from that plan may require changes to L_{jn}, or complete rescheduling. This represnts a control function for the PS that is similar to that of the process controller in implementing a desired processing trajectory.

The integration of this control function with the solution of the production scheduling problem again will not be addressed in this paper. For an excellent survey on the topic of mathematical representation of the objectives and constraints for the production scheduling problem, the reader should consult [RAM85,GRA82].

3.3 Production Flow

For each product ρ_m there exists a set of precedence relationships stating the order in which processes will be applied in the fabrication of the product which are typically defined by process planning. Consequently, there exists a process transfer function which determines the successor process to process P_n for product ρ_m. This function is given by

$$n' = T_m(n) \tag{13}$$

and can be used to describe the overall production flow for the manufacturing system. Based upon the relations of predecessor to successor processes emerging from equation (12) several production flow configurations can be defined.

3.3.1 Job Shop. A job shop configuration is characterized by the fact that there appears to be no preferred path among the processes. In the most general case, the range of successors for process P_n is again the universal set

$$\underline{N} = \{\phi, 1, \ldots, N\} \tag{14}$$

where here ϕ is the null process representing the completion of process for the product. Thus, for the general job shop configuration, we can state that

$$\{T_1(n) \cup T_2(n) \cup \cdots \cup T_M(n)\} = \underline{N} \tag{15}$$

3.3.2 Flow Shop. At the other extreme, the pure flow shop, which is most closely realized in assembly operations, has a only single production path through the processes. This property allows the processes to be numbered in a manner such that for any m = 1,...,M

$$T_m(n) = n+1 \quad \text{and} \quad T_m(N) = \phi \tag{16}$$

Typically, for the same number of processes, the material handling problem (and consequently the production scheduling problem) is much more complex for the pure job shop than for the pure flow shop.

3.3.3 Hybrid. The pure flow shop and job shop are configurations that are seldom actually realized in real manufacturing environments. Typically, a hybrid configuration emerges. One common hybrid is the multiple path flow shop. Here the processes can again be numbered such that

$$T_m(n) = \{n' \cup \phi\} \quad \text{for any } m = 1,\ldots,M \tag{17}$$

where $n' > n$. In this configuration, if a process is required, it must always be used after a fixed subset of preceding processes. However, not all processes need to be employed in the manufacture of a given product ρ_m.

3.3.4 Flexible Manufacturing Systems. Flexible manufacturing systems are striving toward another hybrid configuration which could be termed a "preferred path job shop". A group technology (HAM85) approach is used to configure work cells. This significantly reduces the set of potential successors to a given process P_n. In fact, the goal is to partition the entire set of processes into disjoint subsets with little or no interaction. This, in turn, impacts the material handling constraints, which simplifies the production scheduling problem. To date, however, these goals have not been achieved.

4. MODELS FOR PRODUCTION PLANNING

A manufacturing system is always driven by two stochastic inputs: materials from vendors and demands from customers. However, the impact that these inputs have may differ from one system to another. For example, the classic job shop rarely stocks large quantities of finished goods. It usually responds to the customer order as it is placed. Assembly line systems, on the other hand, may produce a given product at a specified mean production rate to meet past and future demands. This implies the possibility of a large inventory holding. The manufacuturing system responds to the inputs by generating a stochastic output, namely finished goods. One major objective of the manufacturing system then is to minimize the difference between the input demand and the output of finished products. Another common objective is to maximize the present value of the derived profit stream over a given planning horizon.

In the preceding sections, we have proposed models which can be used to estimate the contribution of processing decisions to these objectives. We now present some production planning models which address the optimization of these objectives.

4.1 Production Planning Strategies

Today, two complementary production planning strategies are often discussed: push and pull.

4.1.1 Push. The first type of production planning strategy is the Material Requirement Planning (MRP) [BUZ68,ORL75,HAL83]. MRP attempts to "push" each order through the system just before its due date occurs. The resulting schedule begins with this due date and works backward to determine the times by which each required process must begin and end. This technique also considers the capacity and availability constraints of each process in the manufacturing system as well as the material handling requirements. Subsequent to the determination of the initiation times for each process, orders for input materials must be issued to ensure their availability when the processes are initiated. In short, MRP seeks to minimize all input, output, and work-in-process buffers simultaneously. Push strategies could also be defined by considering other objective functions.

4.1.2 Pull. The second type of production strategy, which has found more application in the flow shop environment, is the pull for which the Kanban or the Just-in-Time (JIT) approach is one potential implementation [SUG77,FIN86]. This approach begins by defining an ideal state for the manufacturing processes and then releases orders to them so that the ideal state is maintained. For example, one Kanban approach would be to limit the number of orders that have been processed by a given process, but have not yet completed processing at the successor process. In the flow shop environment, this Kanban implementation is particularly useful since it allows a given process to function at maximum capacity whenever bottlenecks do not exist at subsequent processes, but inhibits production when excessive orders are building up in the system. Consequently, an inherent benefit of the Kanban approach is to stabilize the response characteristics of the overall system.

4.1.3 Remarks. The designation of push versus pull strategy is unfortunate as it appears to imply that one or the other can be applied. The fact is that both strategies can be implemented simultaneously. As noted above the MRP is but one optimizing approach that attempts to minimize the inventories present in the system. This optimization can be performed subject to the constraints of a pull approach which simply limits the states that processes can assume with the hope that the response of the overall manufacturing system will be stabilized.

4.2 The Aggregate Production Planner

Aggregate Production Planning (APP) attempts to generate production quotas for individual products (or groups of products) to be manufactured over an extended planning horizon. In addition, the APP must specify target inventory levels for all buffers. These decisions are made subject to capacity constraints and both the real and forecasted demand for finished goods.

4.2.1 Problem Formulation. As discussed, above the APP's decision can be based upon individual products or an aggregate product grouping. However, to minimize the introduction of additional notation, the formulation for that APP's decision will be given in terms of the basic products ρ_m (m=1,...,M). Assuming that T planning periods will be considered, the primary decision input into the APP are the actual and forecasted demands for each basic product type in each planning period τ, denoted by $d_m(\tau)$ for m=1,...,M and τ=t+1,...,t+T. Let $a(\tau)_{nm}$ represent the production capacity for process P_n consumed in the production of one unit of product ρ_m in period τ while $c_n(\tau)$ will represent the availability of process P_n in period τ (τ=t+1,...,t+T). Finally, letting $\rho_m(\tau)$ represent the planned production of product ρ_m in period τ, the basic production capacity constraint is given as

$$\sum_{m=1}^{N} a_{nm}(\tau)\ \rho_m(\tau) \ \leq\ c_n(\tau) \quad \text{for } n=1,\ldots,N \text{ and } \tau=t+1,\ldots,t+T. \qquad (18)$$

Note this formulation assumes that the production quota $\rho_m(t)$ for the current period t has already been submitted to the DPP for implementation. Also in the more general case, we might desire to differentiate between regular and overtime production capacity.

The next set of constraints will consider the material balance pertaining to inventory. Let $I_m(\tau)$ be the level of planned inventory for product ρ_m in planning period τ while $B_m(\tau)$ represents any backorder for product ρ_m that results in production planning period τ. The resulting inventory constraints have the form

$$\rho_m(\tau) + I_m(\tau-1) - B_m(\tau-1) - I_m(\tau) + B_m(\tau) = 0$$

$$\text{for } m=1,\ldots,M \text{ and } \tau=t+1,\ldots,t+T \qquad (19)$$

The planner may additionally desire to impose production smoothing limiting the fluctuations in $\rho_m(\tau)$ from period to period as well as inventory smoothing constraints which limit the fluctuations in inventory. An additional set of constraints, which must be considered but are difficult to include due to their product specificity, are the constraints dealing with the availability of input materials for each product type.

The APP will typically have a collection of objective functions to be optimized. Let

$$\Phi^{\ell}[\rho_1(t+1),\ldots,\rho_M(t+T),I_1(t+1),\ldots,I_M(t+T),B_1(t+1),\ldots,B_M(t+T)]$$

for $\ell=1,\ldots,L$ represent a collection of L objectives to be considered in the planning problem which are to be optimized subject to the above constraints. To represent the compromise to be considered among the objectives, it will further be assumed that the utility function $\Omega[\Phi^1(\cdot),\ldots,\Phi^L(\cdot)]$ has been defined. The above problem represents a chance-constrained optimization. That is, the demands $d_m(\tau)$ for $m=1,\ldots,M$ and $\tau=t+1,\ldots,t+T$; the productivity efficiencies $a_{nm}(\tau)$ for $n=1,\ldots,N$ and $m=1,\ldots,M$; and the process availabilities $c_n(\tau)$ for $n=1,\ldots,N$ and $\tau=t+1,\ldots,t+T$ are never known with certainty.

4.2.2 <u>Potential Problems</u>. The production planning decision must be strategic in nature, considering all possible contingencies and stochastic aspects of the problem. Charnes and Cooper [CHA69,CHA83] have investigated the chance-constrained optimization problem. Several shortcomings exist in the adoption of this approach. First, the inclusion of chance-constrained elements significantly complicates the structure of the problem. For example, linear constraints become nonlinear when the probabilistic definition of the constraint is made. Second, the decision optimizes only the expected values, foregoing an extensive analysis of contingencies that could arise if the expected planning scenario did not occur. Finally, the approach currently considers a single objective only.

Davis and West [DAV87] recently merged the approaches of Monte Carlo simulation and mathematical programming to develop a method for strategic project scheduling. They used Monte Carlo simulation to generate and solve one thousand potential linear programs. Subsequently, an empirical probability density function for the optimal solution was developed which could be employed to analyze potential contingencies that could arise. Although their approach was computationally expensive, the comparison of the method to other stochastic decision-making approaches provided potential avenues for simplifying the approach. Nevertheless, the need for analyzings potential contingencies was clearly demonstrated. To date, the authors are unaware of any reported investigations of chance-constrained, multi-criteria optimization approaches.

4.2.3 Feedback and Updates. Although the APP plans for the production periods t+1 through t+T only the product quotas $\rho_m(t+1)$ for m=1,...,M are implemented. During the next planning period, feedback indicating the actual production from the previous period and a new $\rho_m(t+1)$ will be generated. Thus, the APP must respond to the deviations between actual and planned production quotas. Furthermore, the APP must continually update its planning as forecasted demand becomes realized with actual booked orders. Again, however, the time scale upon which this updating must proceed is on the order of a week or more. Finally, the APP must continually learn through the acquisition of real production data that arises from it previous planning.

4.3 The Detailed Production Planner

The detailed production planner (DPP) considers the specified production quotas over a shorter horizon, and issues a request that specific products be produced along with their associated due dates for finished production. Before the request for a given product is issued, the DPP ensures that all essential inputs for the product will be available when required during production and that the essential processes to manufacture the product will be available. The DPP also executes all the inventory policies established by achieving the preplanned target inventory levels. Bitran et al. [BIT81,BIT82,BIT84] have provided an aggregation/disaggregation formulation for the interaction between the APP and the DPP. Their formulation provides for a static decision-making framework with no uncertainty. Axsater and Jonsson [AXS79,AXS81,AXS83] have adopted a similar approach. Graves [GRA82B] has treated the problem as a two-point boundary value problem and have presented a dynamic formulation of the problem. The two-point formulation represents a special case of the optimal tracking problem, and their formulation again lacks the consideration of the uncertainties that exist. Recently, Gershwin [GER87] has defined a hierarchical structure which employs control theory methodology to define optimal production rates which will implement the selected production goals.

The approach recognizes the stochastic nature of the production system, and develops its strategies based upon expected system performance.

4.3.1 Determining the Job List. When receiving the product quotas, $\rho_m(t)$ for m=1,....M, for a given product (or group of products) in the current planning period t, the DPP will first review the booked orders to specify which JOB_j for specific products ρ_m should be issued. However, before the actual JOB_j is generated, the DPP first assures that all the essential material inputs are available. As input materials are removed from inventory, the stocks would be replenished by issuing orders to vendor as prescribed by current inventory policies. (The reader is referred to Orlicky [ORL75] for a discussion of several inventory models.) The availability of the required processes is an additional factor. The DPP does not explicitly consider material handling requirements, but it nevertheless must consider both the anticipated processing time at the individual process P_n as well as the travel times between subsequent processes. The latter consideration explicitly requires the inclusion of the precedence relationships for the specified product ρ_m and implicitly contains the consequences of material handling. The above decision cannot consider the JOB_j individually, but must consider the consequences of production flow and process availability arising from the complete ensemble of $\{JOB_1,...,JOB_J\}$. Since the stochastic elements exist within the manufacturing environment, a deterministic specification of these consequences is impossible, and a statistical specification will be required.

4.3.2 Due Dates. The customer's requested delivery date, R_j, for JOB_j becomes one of the important considerations in generating the assigned due date D_j. In specifying the optimal due dates for the ensemble $\{D_1,...,D_J\}$, typically multiple criteria must again be considered. To optimally track the output of the manufacturing system against the customer demand, the desired objective in its simplest form may be to

$$\text{Minimize} \quad F^{\ell}(D_1,...,D_J) = \sum_{j=1}^{J} C_j^I \;(D_j - R_j) \tag{17}$$

where

$$D_j \leq R_j \quad \text{for} \quad j = 1,...,J \tag{18}$$

and C_j^I is the per unit time inventory cost. Obviously the due date performance constraint, equation (18), may not be feasible and the optimal tracking objective must be enhanced to account for both the costs and losses due to back ordering. Other objectives might include maximizing process utilization, maximizing production throughput, and optimizing production smoothing. In conclusion, a collection of objectives $F^{\ell}(D_1,\ldots,D_J)$ for $\ell = 1,\ldots,L$ will exist to be considered. Their existence implies that there must exist an overall utility $W[F^1(D_1,\ldots,D_J),\ldots,F^L(D_1,\ldots,D_J)]$ to be optimized. After the "best" compromise due date ensemble $\{D_1^*,\ldots,D_J^*\}$ is selected then the perturbation costs associated with each $F^{\ell}(D_1^*,\ldots,D_J^*)$ for $\ell = 1,\ldots,L$ must be defined to allow the production scheduler (PS) to define both a commensurable set of objective functions, $f^{\ell}(E_{11},L_{11},\ldots,E_{JN},L_{JN})$ for $\ell = 1,\ldots,L$ and an utility function $u[f^1(\cdot),\ldots,f^L(\cdot)]$ which has already been addressed above. Furthermore, the perturbation costs for the DPP must also be commensurate with similar costs pertaining to perturbation costs associated with the APP's objective functions, $\Phi^{\ell}(\cdot)$ for $\ell=1,\ldots,L$ and the utility function $\Omega[\Phi^1(\cdot),\ldots,\Phi^L(\cdot)]$.

4.3.3 Feedback and Updates. The DPP must correct for deviations between its planned due dates, and the feedback information D_j' supplied by the production scheduler. Futhermore, as the JOB_j is completed it must be removed from the list and new jobs appended. The size of the actual buffer of pending jobs should be kept small. Specifically, the jobs ideally should be released to the PS just before it is to be released to the shop floor.

5. SUMMARY AND FUTURE WORK

This paper discusses mathematical models for several decision and control functions which impact the design and implementation of a CIM system. Because of the limits of current technology, many of these models cannot be used directly to solve their corresponding manufacturing problems. They do, however, provide a baseline to guide future manufacturing-related research and development in several areas: operations research, artificial intelligence, on-line process controls, and sensor technology. In addition, these models form the foundation for serious investigation of the problems involved in integrating various manufacturing functions into a viable organizational structure for CIM.

We plan to continue this model development in several other areas: data-management and communications, on-line versus off-line process planning, and design for manufacturability. We hope to use these models to develop metrics which can then answer the questions posed at the beginning of the paper.

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In the recent past, several hiearchies have been proposed as candidate models for the integration of decision and control functions within a Computer-Integrated Manufacturing environment. A common theme in the definition of these models is to construct an analog to managerial hierarchies that are currently employed in many corporate settings. This paper will adopt an alternate approach. Rather than defining a hierarchy, this paper will discuss the manufacturing functions that a CIM hierarchy must address. Whenever possible, mathematical formulations for the functions will be given with consideration for the stochastic environment in which they will function. The conclusion outlines several concerns arising in the definition of a generic CIM hierarchy and associated research topics that must be addressed.

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