Enterprise Modeling and Simulation: Complex Dynamic Behavior of a Simple Model of Manufacturing

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Simulating a structurally simple model of a manufacturing enterprise revealed complex dynamic behavior. Enterprise modeling and simulation provided estimates of end-of-life inventory and order delivery performance based on interactions of forecast quality, quoted product availability, material procurement and safety stock policies, vendor lead times, product life cycle, and part commonality. An unexpected result was that end-of-life inventory can exist even under ideal environmental conditions. Prospective applications of these methods include estimating the effects of incremental improvements, verifying impacts of process changes, and generating enterprise behavior information.

by M. Shahid Mujtaba†

Can we understand the potential impacts of process changes? Can we quantify the expected amount of improvements and benefits? Can we anticipate the effects of environmental changes? Can we predict the effects and side-effects of making changes? And can we do all these before taking action and making major resource commitments?

We suggest that the answer is yes to all these questions, and the means is enterprise modeling and simulation.

The purpose of this paper is to show how enterprise modeling and simulation research activities at HP Laboratories can be applied to predict system behavior and gain insights using sound engineering and scientific principles and techniques before implementing the new solution at the level of the business enterprise.

In this paper, we first discuss modeling and simulation technology in broad terms to provide background and context. We then describe one model, the Simple Model, in detail, and present the insights gained from running simulations on that model and analyzing and displaying the results. An unexpected insight was that end-of-life inventory existed at the end of the product life cycle even though the method for computing safety stocks should theoretically have resulted in none when customers ordered exactly according to forecast. Other interesting insights were that high inventory levels can occur when actual orders come in too high or too low with respect to forecasts. In other words, forecast quality has a major impact on some of the metrics under consideration. We then describe the current state of enterprise modeling and simulation, future research directions, and possible application areas, including process reengineering on page 8. In the appendixes we include more detailed explanations and sufficient technical details of the model to permit the results to be duplicated by other researchers. A glossary of terms and a summary of the values for different experiments are provided for quick reference on pages 7 and 17. The evolution of enterprise modeling and simulation activities at HP Laboratories and the place of the Simple Model in those activities provides a historical context and is described on page 12.

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Modeling and Simulation

Extensive literature exists on the simulation modeling process, for example Chapter 1 of Law and Kelton,[1] Chapter 1 of Pritsker,[2] Chapter 6 of McHaney,[3] and Law and McComas.[4] The general consensus is that the purposes of the simulation modeling process are to define a problem clearly and to develop a model as a tool to understand and solve that problem.

"Modeling and simulation have become endeavors central to all disciplines of engineering and science. They are used in the analysis of physical systems where they help us gain a better understanding of the functioning of our physical world. They are also important to the design of new engineering systems where they enable us to predict the behavior of a system before it is actually built. Modeling and simulation are the only techniques available that allow us to analyze arbitrarily nonlinear systems accurately and under varying experimental conditions."[5]

"The facility or process of interest is usually called a *system*, and in order to study it scientifically we often have to make a set of assumptions about how it works. These assumptions, which usually take the form of mathematical or logical relationships, constitute a *model* that is used to try to gain some understanding of how the corresponding system behaves."[1]

Thus, a model is a conceptual abstraction of an existing or proposed real system that captures the characteristics of interest of the system. Modeling is the process of building the abstraction (model).

"If the relationships that compose the model are simple enough, it may be possible to use mathematical methods (such as algebra, calculus, or probability theory) to obtain exact information on questions of interest; this is called an analytic solution. However, most real-world systems are too complex to allow realistic models to be evaluated analytically, and these models must be studied by means of simulation."[1]

"Simulation is the use of a model to develop conclusions that provide insight on the behavior of any real world elements. Computer simulation uses the same concept but requires that the model be created through programming on a computer."[3]

In general, modeling and simulation are useful when system prototyping is too costly or time-consuming, seriously disruptive, or simply impossible. They are useful for exploring proposed system changes by providing performance estimates of a proposed system or of an existing system under some projected set of operating conditions. A simulation model or set of models can provide an experimental testbed on which to try out new ideas or concepts, since it is cheaper to experiment in the laboratory than on the real system.

Our premise is that these techniques applied to enterprise processes could help predict the behavior of the organization more quantitatively than repeated assertion or the application of mental models.

Enterprise Modeling and Simulation

We define enterprise modeling as the process of building abstractions or models of three primary functional components of an enterprise: manufacturing, marketing, and R&D (research and development) for the purpose of gaining insight into the interactions between these functions and the interaction of the enterprise with other enterprises. The complexity of the enterprise and the large number of people who have ownership of different parts makes it difficult for a single individual to grasp a detailed understanding of all the components. There is a limit to the level of complexity and the means to share and communicate it with others that can be carried in the head of a single individual.

Many process changes and decisions are based on implicit mental models in the heads of decision makers or advocates. Mental models[6] are deeply ingrained assumptions, generalizations, or even pictures or images that influence how we understand the world and how we take action. Very often, we are not consciously aware of our mental models or the effects they have on our behavior.[6] Generally mental models assume that there are a small number of factors in cause and effect relationships. The problem with mental models is the difficulty of communicating them, checking their consistency, and combining the mental models of different people. It is very difficult to estimate the effects of interacting factors and to combine mental models into a larger-scale composite model that incorporates the insights, knowledge, and understanding of many individuals.

One means of merging different viewpoints is the use of Hierarchical Process Modeling,[7,8] which provides an explicit, graphical representation of the process with which individuals can agree or disagree. Experience in applying Hierarchical Process Modeling[9] to the building of enterprise models suggests that the result is a repository for knowledge of the processes we are studying. During its creation, team members develop a common understanding of the dynamics of model behavior through interaction with one another and with the model. The result is an explicit model that reconciles differing points of view and a reusable model that serves as a foundation on which to build future models.

There is an awareness that a model can be used to embody knowledge of a system rather than be used as a tool.[10] For example, Funke[11] states that at the Boeing Company, simulation has provided "a forum for the collection of process operating rules and assumptions in one medium as a basis to develop the model" of a process or system.

Other ongoing works on the application of models to embody knowledge at the enterprise level of manufacturing operations include TOVE[12] and CIM-OSA.[13,14] Pardasani and Chan[15] describe the expansion of an infrastructure for creating simulation models based on the ISO reference model for shop floor production standards to create enterprise models.

In applying the process of enterprise modeling and simulation we need to engage in activities of modeling in the large (with "model as knowledge") where the major issues of interest are communication and documentation, team coordination, modularity and large model development, and multimodel organization, instead of modeling in the small (with "model as tool") where the issues of interest are top-down design, informal and formal program specifications, simplification and elaboration, and validation and verification.[10]

In modeling the manufacturing enterprise, the primary area of focus is the manufacturing function, which includes, in addition to the traditional production and shop floor functions, the production and material planning, material management, and order processing functions. In traditional modeling and simulation applied to the manufacturing domain, computer simulations have been applied to the production floor or machine shop level to study machine utilization and production and material flows and buffers. These methods together with traditional operations research methods have helped reduce inventory on the production floor and cut build times to a level where these are small compared to the other parts of the system. Enterprise modeling and simulation expand the scope so that traditional modeling and simulation are components in the enterprise modeling and simulation system.

Enterprise modeling and simulation indicate the impact of proposed improvement efforts at the enterprise level before the changes are made. The "simulation" in enterprise modeling and simulation is the process of running the model in a computer to understand the behaviors over time under different operating conditions and circumstances. It will help us identify leverage points and indicate where we can expect to get the most impact for a given investment or change.[16]

According to Senge,[6] "The real leverage in most management situations lies in understanding dynamic complexity, not detail complexity." He suggests that most systems analyses focus on detail complexity (that is, a large number of variables), not dynamic complexity ("situations where cause and effect are subtle, and where the effects over time of interventions are not obvious"). We suggest that enterprise modeling and simulation help in understanding dynamic complexity, and in addition provide the framework for slowly expanding the detail complexity.

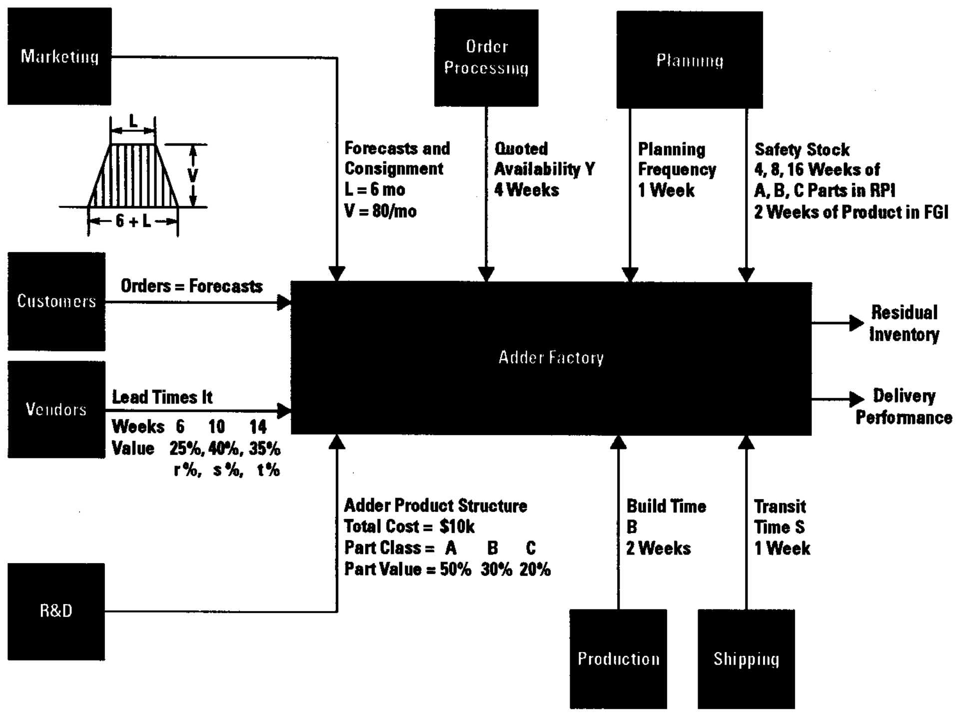

Fig. 1. Diagram of the Simple Model for the nominal case experiment.

Modeling and simulation at the enterprise level are showing increasing levels of activity. For example, a recent article in Fortune magazine[17] discusses business-oriented economics that focuses on what economists call "the firm" and the rest of us call "the company" as the unit of analysis. (Traditional microeconomics, by contrast, is concerned with markets and prices. It looks at the economy or at an industry, but rarely peeks inside the individual enterprise.) Fortune cites the example of Merck's finance team, which built a completed model and subjected it to Monte Carlo simulation analysis.

The Simple Model

The Simple Model (shown with capital letters because of its importance in this paper), was one in a series of models developed at HP Laboratories (see page 12). The Simple Model was named because of its structural simplicity, but as subsequent descriptions will show, it exhibits dynamic behavior that is complex and not intuitively obvious until it is explained. Expressed in terms used by Senge,[6] the Simple Model is a tool for understanding dynamic complexity using a model with very low detail complexity.

The Simple Model was commissioned to abstract a real manufacturing facility with greatly simplified assumptions, such as a single product with a one-level bill of materials and a trapezoidal order demand pattern. The purpose of the model was to explore the relationship between different factors and metrics used in manufacturing. Although the model can generate data on many different metrics, this paper will focus on two main metrics: (1) inventory levels and write-off at the end of the product life cycle and (2) customer satisfaction metrics. We will first describe the structure and assumptions of the Simple Model and then show the results of running the model under different conditions.

Conceptual Description

Fig. 1 shows conceptually the Simple Model of a factory producing a product called Adder.† Marketing specifies a trapezoidal order forecast profile for customer orders, and the number of consignment units (defined as demonstration units used in the sales offices). R&D specifies the Adder product structure. Order processing quotes a product availability of four weeks. Production determines that the build time is two weeks, and shipping states that transit time for sending the product to the customer is one week. We assume that the production and shipping processes are under sufficient control that they do not vary from these constant numbers.

The problem assumes that the values of class A, B, and C parts in the Adder product make up 50, 30, and 20 percent, respectively, of the product material cost. In valuing the finished product, labor cost is small enough to be factored into the material cost, and the value of the product is the sum of values of its parts. In addition, we assume that the values of 6-week, 10-week, and 14-week lead time parts make up 25, 40, and 35 percent, respectively, of the product cost, that the vendors deliver the parts exactly on time, and that there are no rejects because of defective parts.

These characteristics are reflected in Table I, which shows the value of each part category. There are a large number of unit costs and part quantity combinations that satisfy the above constraints. The actual bill of materials used for the model is shown in Table II.

The length of the longest lead time among the parts is 14 weeks for parts A.3, B.3, and C.3. Allowing a build time of

† There was a little bit of whimsy in naming the product. The author selected the name from a fairy tale in which somebody ordered the biggest adder available, expecting it to be an adding machine. When the box was opened, out popped a snake. Snakes, of course, was an internal HP code name for a class of workstations.

Table I
Simple Model Adder Product Structure

(a) Product Structure by Part Value

Part	Value	Part	Value	Part	Value
A.1	$1250	B.1	$750	C.1	$500
A.2	$2000	B.2	$1200	C.2	$800
A.3	$1750	B.3	$1050	C.3	$700

(b) Part Value by Part Class Safety Stock

Class	Parts in Class	Value	% Value	Safety Stock
A	A.1,A.2,A.3	$5000	50%	4 weeks
B	B.1,B.2,B.3	$3000	30%	8 weeks
C	C.1,C.2,C.3	$2000	20%	16 weeks
	Total	$10,000	100%	

(c) Part Value by Lead Time

Lead Time	Parts	Value	% Value
6 weeks	A.1,B.1,C.1	$2500	25%
10 weeks	A.2,B.2,C.2	$4000	40%
14 weeks	A.3,B.3,C.3	$3500	35%
	Total	$10,000	100%

Table II
Adder Bill of Materials

Part	Quantity	Unit Cost	Value in Product
A.1	1	$1250	$1250
A.2	1	$2000	$2000
A.3	1	$1750	$1750
B.1	1	$750	$750
B.2	1	$1200	$1200
B.3	1	$1050	$1050
C.1	1	$500	$500
C.2	1	$800	$800
C.3	1	$700	$700

two weeks and transit time of one week means that the period from the time parts A.3, B.3, and C.3 are ordered in the manufacturing enterprise to the time that the product using those parts is received by the customer is 17 weeks. This means that the policy of waiting for customer orders before we order parts from our vendors will lead to an order-to-delivery time of at best 17 weeks.

To quote availability of four weeks requires us to order material and plan production before we receive customer orders. The best information we have on current and past customer behavior is actual orders, and the best information we have on future customer orders is the order forecast.

Given that we want quoted availability to be less than the sum of material delivery, production, and product delivery times, we need to plan ahead of time how much to build based on order forecasts. This decision on how much to build in future weeks is the responsibility of production planning, which each week computes the number of units to be started in future weeks.

Forecasts of future customer orders are estimates; customers may order more or less than forecasted. In the event that customers order less, we should have no problem meeting the demand if we build to meet the forecast. However, if customers order more, we might run out of product. To allow for this contingency production planning must specify that we need to build a few more units and carry them in a stock of finished goods inventory (FGI). The amount of extra product to be carried is the safety stock, and depends on many factors including the average expected order level, the expected fluctuations in orders, and how much we want to allow for contingencies. A high safety stock level will protect us from low forecasts, but requires a greater investment in inventory. One way of specifying inventory levels is to use a measure related to number of weeks of forecasted demand. In the case of this model, we assume that production planning specifies two weeks of 13-week leading average forecast as target FGI safety stock.

The discussions for FGI safety stock are also applicable for raw material. There must be enough raw material on hand when the time comes to build the product. To allow for excess demand from the production line because of high customer demand, and for late deliveries by vendors, we need to order some extra material. This extra amount is determined by material planning and is the target raw parts inventory (RPI) safety stock. The amount of RPI safety stock can be determined in different ways. One way is to use part classification.

In practice, part classification indicates the relative importance of a part and hence the attention it receives. Since class A parts are reviewed more frequently, a smaller quantity is carried than for the B or C parts. In our model, part class determines the amount of material safety stock to be carried in weeks, and all parts are reviewed weekly by material planning. For A, B, and C parts the target RPI safety stock is 4, 8, and 16 weeks, respectively, of the 13-week leading average forecast. The 13-week leading average forecast and the FGI and RPI target safety stocks are discussed in greater detail under "Target Safety Stock," below.

Fig. 2 shows the trapezoidal product order forecast supplied by marketing. The demand during each week of a four-week month is constant. The demand builds up over three months,

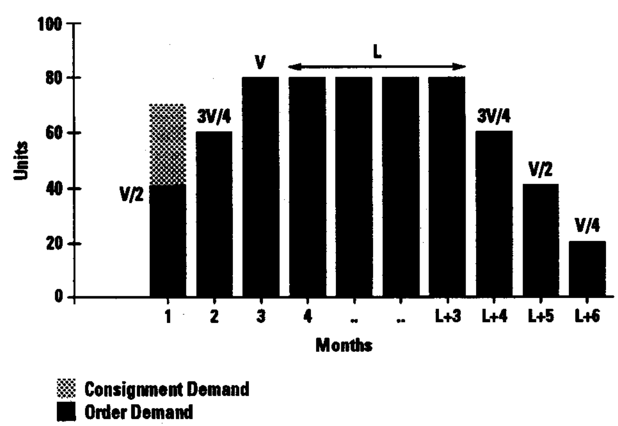

Fig. 2. Adder order forecast and consignment demands in units.

remains constant for L months, and then reduces to zero over three months, so the total product life is L+6 months. In the first month, some units are required for consignment purposes. The mature monthly demand V is 80 units, and the total amount of inventory for consignment is set at 1.5 weeks of projected mature demand, or 30 units. In our experiments we used a baseline value of 6 months for L. This order forecast results in a lifetime total of 780 units, or a total forecasted production cost flowthrough (PCFT, see Glossary, page 7) of $7.8 million, exclusive of the 30 consignment units.

Of the many performance metrics for the system during the product life cycle, the three main ones of interest are the end-of-life inventory, which needs to be disposed of or written off, the shipment and delivery performance, and the inventory during the product life cycle.

Detailed Description

The fundamental description of the Simple Model of the enterprise and the primary flows and dynamic components that interact with it over time are shown in Fig. 3.

Entities External to the Enterprise. Customers send orders to the manufacturing enterprise. In the simulation each order for a single unit is sent individually to the manufacturing enterprise. The orders go into the backlog of the manufacturing enterprise, and at some point a shipment fulfilling each order is delivered to the customer. Customers have the expectation that the time between ordering and receipt of delivery is the quoted availability, but are willing to wait indefinitely for orders.

The manufacturing enterprise sends orders for each part to the respective vendor, shown collectively in Fig. 3 as vendors. The shipment of physical parts arrives at some time in the future determined by the lead time for the part. Ideally the

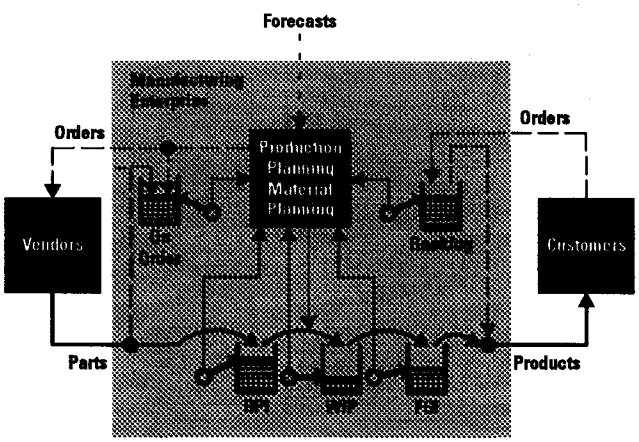

Fig. 3. Material, order, and information flows of the Simple Model simulation. The heavy solid lines represent the flow of physical material, the long-dash lines represent the flow of information related to individual orders, and the short-dash line represents the flow of periodic order forecasts. The containers represent the accumulation of physical material or orders, the pointers represent levels of the quantities in the containers, and the light solid lines from the containers represent this status information being transmitted to the planning function. The light solid line from the planning function represents a control signal flow that regulates the amount of material flowing from RPI to WIP and ultimately to FGI.

time between the issuance of an order and receipt of the material (parts) should be the lead time quoted by the vendor, and for all the runs in this paper, this will be the case.

Functions Internal to the Enterprise but External to Manufacturing. Periodically, *marketing* provides forecasts of customer orders in future periods. Each forecast is a list of the quantity of products that are estimated to be ordered in subsequent periods. In practice, forecasts are updated periodically and estimates for the same month in the future can vary from month to month. In the model, the forecast is used to compute the shipment plan, and to compute the 13-week leading average forecast for computing FGI and RPI safety stocks. *R&D* (not shown in Fig. 3) provides a bill of materials (BOM) that defines the product structure. Since the BOM does not change during the simulation, we do not show the R&D function.

Processes Internal to the Manufacturing Function. This section should be read in conjunction with Figs. 1, 2, and 3.

Order processing accepts orders and keeps track of all outstanding orders received from customers, and keeps a running total of the quantity of products required in the backlog. In addition, it prioritizes the orders by the ranking criterion, which in this model happens to be first-in, first-out (FIFO), into a ship list. The backlog level is provided to the production planning function. The prioritized list of orders and the quantity that needs to be shipped in the current period are provided to shipping.

Shipping fills and ships the orders on the ship list that order processing provides. From the point of view of the manufacturing enterprise, the duration between receipt of customer order and delivery of the shipment at the customer site should be the time period specified as the quoted availability. Filling an order is attempted no earlier than necessary to satisfy the quoted availability taking transit time into account. An order is filled and shipped only if at the time of the attempt the number of units in FGI is greater than zero. In other words, shipping's objective is to fill outstanding orders that need to be filled and not to try to maintain FGI at some level. This means that the actual order-to-delivery time for a particular order will depend on whether units are available to fill the order at the time the order is due to be shipped. If units are not available, the order will have a higher priority for being filled in the next period because of the FIFO rule used to establish the ship list.

Production planning computes the current shipment plan and build plan. It computes the current shipment plan from the current order forecasts and current order backlog to attempt to satisfy the quoted availability. It then computes the current build plan from the shipment plan, build time, current FGI, current WIP, and FGI safety stock.

To come up with a suitable build plan, production planning must know about the characteristics of the system it is trying to control, that is, it must have a model of the system that it uses for doing its computation. An important aspect of the computation is to take into account the number of units already in process rather than relying only on the number of units of product required. Such a model is generally a mathematical or analytical model, and the formulation is described in Appendix I. The build plan for the current period is used

Glossary of Terms and Abbreviations

Abbreviations

A/F. Actual-to-forecast ratio. This is the ratio of the actual orders received to the forecasted orders. Normally expressed as a percentage. A/F greater than 100% implies that actual orders came in higher than forecasts, that is, forecasts were low or demand was high. A/F less than 100% implies that actual orders came in lower than forecasts, that is, forecasts were high or demand was low.

BOM. Bill of materials. A description of the components that go into an assembly and their respective quantities.

- Single-level BOM. The components are raw materials fabricated or manufactured elsewhere (i.e., purchased parts).
- Multiple-level BOM. The components are other assemblies and purchased parts.

EOL. End of life (end of product life cycle).

FGI. Finished goods inventory.

RPI. Raw parts inventory. Raw material in stores waiting to be processed.

WIP. Work in process. Raw material on the production line being assembled into the final product.

PCFT. Production cost flowthrough. Dollar value of production passing through the manufacturing enterprise. Because of the assumptions underlying the Simple Model, in this paper PCFT is synonymous with shipments from the manufacturing enterprise.

Terms

Backlog. Products ordered by customers but not yet shipped.

Build Time. The time required for completion of the product when all the parts are available.

Committed Inventory. The total inventory to which the manufacturing enterprise is currently committed. It is the sum of the on-order material and the on-hand inventory.

Consignment Inventory. Inventory in the sales offices and for demonstration purposes.

End-of-Life Inventory. The amount of inventory left over at the end of the product life cycle, that is, when no more orders are backlogged or outstanding for the product. EOL inventory includes leftover unused RPI, unshipped units in FGI, and consignment inventory. In general, material and products left over at the end of the product life cycle are not useful for anything else and must be written off.

Forecast Quality. Qualitative description of the amount of deviation of actual customer orders from forecasted orders. The ratio A/F described above is one way to quantify forecast quality. Forecast quality is best for A/F = 100%, and gets worse as A/F moves away from 100%.

Lead Time. The time between placement of an order to the vendors and receipt of the material.

On-Hand Inventory. All physical inventory that is owned by the enterprise. It is the sum of RPI, WIP, and FGI.

On-Order Inventory. Same as on-order material.

On-Order Material. The total amount of material for which orders are currently open and which will eventually be received from vendors. It increases each time a new order is issued and sent to the vendor, and decreases each time a shipment of parts is received from the vendor.

On-Time Delivery. Measures whether the order is delivered to the customer within the quoted availability. When described in units or dollars, it represents the units or dollar value of the deliveries that are delivered within the quoted delivery time. When described as a percentage it represents the percentage of on-time deliveries with respect to the total deliveries.

On-Time Shipments. Products that were shipped to customers within the quoted availability minus the transit time, that is, those shipped to arrive in time to satisfy the quoted availability.

Order Backlog. The total amount of outstanding orders from customers that have not yet been shipped. It increases each time a new order is received from customers, and decreases each time an order is shipped to customers.

Order-to-Delivery Time. The time period from order issue to order delivery at the customer site.

Order-to-Ship Time. Time period from order receipt to order shipment at the manufacturing enterprise.

Orders Delivered. Orders that have been delivered to customers.

Orders Shipped. Orders that have been shipped to customers.

Product Life Cycle. The general shape of the increase, leveling off, and decrease in order volume for the product. We assume here it is trapezoidal.

S and S-Plus. S is a language and interactive programming environment for data analysis and graphics developed at AT&T Bell Laboratories. S-Plus is a product version of S that is sold and supported by Statistical Sciences, Inc.

to trigger the start of the appropriate number of units in the current period.

Material planning uses the BOM to generate a material consumption plan for each part that can support the build plan. It then uses the material consumption plan, on-order material, RPI, RPI safety stock, and part lead times to determine the material ordering plan, that is, how much of each part to order in the current and future weeks. Details of the computation of the consumption and ordering plans are given in Appendix I.

Material ordering sends orders for the appropriate amount of each part in the current week to the vendors. As each order is sent, the on-order material for that part increases.

Raw material stores (not shown in the figures) receives and stores incoming material in RPI and provides material to production when requested. As it receives deliveries from vendors, it sends information about the shipment to on-order material which is reduced by the amount of the shipment received.

Production receives a build plan and requests as much material as required from raw material stores to build the number of units required. Only complete sets of parts are drawn from stores, that is, if one or more parts are not available in sufficient quantities, all parts are drawn partially. For example, if the build plan calls for 10 units to be built, and there are only 5 units of part A.3 and more than 10 units each of the other parts in RPI, only 5 units of of each part will be drawn and sent to WIP, and only 5 units can be started. The objective of raw material stores is to fill requests for material if possible, and not to maintain RPI at any particular level. The mathematical derivation of the number of units actually started subject to the available material is given in Appendix I.

Enterprise Modeling and Simulation Applications in Reengineering

Process reengineering as defined by Hammer and Champy in their book, *Reengineering the Corporation*,[1] is "the fundamental rethinking and radical redesign of business processes to achieve dramatic improvements in critical, contemporary measures of performance, such as cost, quality, service, and speed." It is being applied at an increasing rate by three kinds of companies: those in deep trouble, those not yet in trouble but whose management has the foresight to see trouble coming, and those in peak condition with no discernible difficulties whose management is ambitious and aggressive. These three categories cover a large number of companies. The impact is on processes with throughputs measured in the billions of dollars.

Reengineering is pervasive, controversial, and disruptive, and has different interpretations. CSC Index, whose chairman is Champy,[1] states that even though they pioneered the practice of reengineering, they are startled by how widespread the phenomenon has become. Their survey results[2] based on 497 large companies in the U.S.A. and another 124 in Europe show that 69% of the U.S. companies and 75% of European companies are already reengineering (average completed or active initiatives in excess of 3). More than half of the rest were planning to launch an initiative over the next 12 months or were discussing one.

Hammer and Champy[3] mention three kinds of techniques that reengineering teams can use to help them get ideas flowing: boldly apply one or more principles of reengineering, search out and destroy assumptions, and go looking for opportunities for the creative application of technology.

A sampling of the literature reveals that redesign is influenced by the past experience of the reengineering team and the recommendations of reengineering consultants. Ultimately, many redesign decisions are made on speculation based on implicit mental models, convincing arguments by vocal proponents for change, sheer optimism, blind faith, or desperation.

A major concern is the uncertainty of predicting outcomes. Radical redesign and new ideas bring the possibility of boundless gain or tremendous loss. While assumptions are being searched out and destroyed ruthlessly, it should not be forgotten that some assumptions are rooted in scientific principles which cannot be ignored with impunity no matter how highly enthusiastic or motivated the reengineering team.

Enterprise Modeling and Simulation

Some areas suggested by Hammer and Champy[4] for reengineering the corporation include product development from concept to prototype, sales from prospect to order, order fulfillment from order to payment, and service from inquiry to resolution.

The Simple Model described in the accompanying article is a start towards addressing order fulfillment. Modeling and simulating the other processes on the list require different kinds of knowledge acquisition. For example, product development requires more knowledge about the R&D function, sales requires more knowledge about the marketing function, and service has not been considered in the current model, where the focus is on manufacturing.

The following paragraphs describe areas where enterprise modeling and simulation and the enterprise modeling and simulation system may provide value in the reengineering effort.

Identifying Processes

Hammer and Champy[5] suggest that once processes are identified and mapped, deciding which ones require reengineering and the order in which they should be addressed is not a trivial part of the reengineering effort. Typically there are three criteria for making the selection: dysfunction, importance, and feasibility.

Enterprise modeling and simulation provide one way of gaining insight in these areas by generating performance metrics with and without the change under different circumstances. For example, the Simple Model showed the importance of different controllable and uncontrollable factors to the different system performance metrics such as EOL inventory and order-to-delivery cycle times.

After selecting a process for reengineering, an understanding of the current process is crucial. It is necessary to know what the existing process does, how well (or poorly) it performs, and the critical issues governing its performance from a high-level view. This understanding is the prerequisite to redesign. The key is understanding the process rather than completely analyzing it in agonizing detail.

Enterprise modeling and simulation offer at least two ways of obtaining this understanding and possibly showing the cause of the dysfunction. First, the very act of building a consensus model that different people can agree with sheds light on what might not be working. Second, simulating the model will confirm or reject the validity of what is suspected. For example, after building the Simple Model, it was possible to test it in a large number of possible operating conditions to provide understanding of the cause and effect relationships. The first major insight from simulating the model was that what appeared to be a reasonable way of computing safety stock that would go to zero as demand went down actually gave rise to end-of-life inventory even though the demand was forecasted accurately. Enterprise modeling and simulation provide a way of gauging the relative impact of different process changes as a step towards selecting the appropriate subprocess to reengineer, and of quantifying the amount of prospective improvement.

Enterprise modeling and simulation can show the prospective impact of infeasible changes. In simulating the proposed reengineering changes, even if they are infeasible, the results will indicate if there is any promise in further consideration of a particular direction. For example, it is clearly not feasible to have zero build

The required material is drawn from RPI and goes into WIP where it remains for the duration of the build period. After that, the completed units go into FGI.

Target Safety Stock. Inventory is the amount of physical material, and ideally the enterprise would like to maintain it at or close to zero in RPI and FGI, and only carry it in WIP when raw material is being converted into final product. In practice, to reduce the effects on production of late vendor deliveries and customer orders coming in higher than forecasts, safety stock needs to kept. In the Simple Model, where vendor delivery time uncertainty is not an issue, to allow for the contingency that customer orders may come in higher than forecast, production planning targets the FGI safety stock to be two weeks of 13-week leading average forecast, and material planning targets RPI safety stock for each part to be the quantity of that part required for the production of the number of weeks specified in Table I(b) of the 13-week leading average forecast.

The 13-week leading average forecast at the end of a particular week in the future is the sum of the order forecasts over the 13 weeks immediately following the particular week divided by 13. This average anticipates trends 13 weeks (one calendar quarter) into the future, increasing as order forecasts increase, and decreasing as order forecasts decrease. In particular, the 13-week average forecast is zero at the end of the product life cycle, which means that any target safety stock expressed in weeks of 13-week leading average will aim for a zero target safety stock level at the end of the life cycle.

Having specified target safety stock in preparation for demands higher than forecasted, what is the impact if customers order exactly according to forecast? The expectation is that actual FGI should be equal to targeted FGI safety stock level, and actual RPI for each part should be equal to targeted RPI safety stock level for that part.

time for products and zero transportation times for shipments in the real world, but setting those values to zero in the model indicates the theoretical maximum benefits of these actions, and the magnitude of the results provides a data point for decisions on how much investment to put on driving these two times to zero instead of on other opportunities.

Furthermore, by showing the time behavior of the changes, enterprise modeling and simulation can show when actions can be expected to take effect. Inertia is a property of most systems, reflected in the time taken to respond to external influences or changes. Most physical systems are predictable in this respect, but the time behavior for organizational systems such as the enterprise is less predictable simply because it is not understood as well. Enterprise modeling and simulation help to increase the predictability of system behavior given that we know something about the system's structure and the behavior of its components. While immediate improvement for reengineering is the desired goal, enterprise modeling and simulation can show the length and causes of delays in obtaining the desired result.

Exposing and Challenging Assumptions

Hammer and Champy suggest that we question assumptions.[6] Enterprise modeling and simulation require assumptions to be stated explicitly during the model building process to reconcile differences in points of views. Challenges and disagreements on the validity are with respect to clearly stated assumptions rather than differences in opinions resulting from differences in mental models of different individuals. For example, the production planning and material procurement processes used in the Simple Model are expressed mathematically in Appendix I. If these are accepted as rational methods of planning, then there is no question or debate on the values of the outputs for a given set of inputs. If processes expressed mathematically are not acceptable as rational methods of planning and an alternative method is proposed, then that alternative method can certainly be tried, and the results compared with the previous method. The debate and challenge for improvement becomes one of improving the logic of planning rather than one revolving around the meaning of words and labels or one on how the model should behave based on past experience or speculation.

The approach advocated by Hammer and Champy suggests that changes be made by understanding the problem and devising the solution. This is central to modeling and simulation in addressing problems in the realm of the enterprise. Enterprise modeling and simulation offer a way of testing and verifying that given the current knowledge, the results of the simulation do not exhibit any obvious flaws before the process is implemented.

Role of Technology

Hammer and Champy devote a whole chapter to discussing the essential enabling role of information technology, and assert that modern state-of-the-art information technology is part of any reengineering effort. They caution that the misuse of technology can block reengineering altogether by reinforcing old ways of thinking and old behavior patterns, and that equating technology with automation does not result in reengineering.

We suggest that the application of enterprise modeling and simulation is a creative application of a well-understood technology to the processes of the enterprise. The technology of modeling and simulation has been applied to fields such as product design and the design of physical systems, but is only now beginning to be applied creatively in analyzing the processes of the enterprise. What enables the creative application of modeling and simulation is the tremendous increase in computational power. In this respect, we would like to suggest another rule along the lines of the rules described in reference 1.

Old Rule: Decisions regarding process changes are based on mental models and analysis of historical data.
Disruptive Technology: Enterprise modeling and simulation.
New Rule: Decisions regarding process changes are based both on historical data and analysis of computer simulated behavior of explicit models with explicit assumptions that show the prospective consequences of different actions under a large number of operating circumstances.

Conclusion

Reengineering is a philosophy of renewal and rapid, discontinuous, and drastic change in the way corporate enterprises do their work, which brings with it uncertainty and fear of the unknown future. It is disruptive and controversial, and there is as yet no agreement that successes outnumber failures. During the implementation, "People focus on the pain of the present and the joy of the past. They forget about the pain of the past and the joy of the present."[7] However, given that it is occurring on such a wide scale, we suggest that application of enterprise modeling and simulation can increase the chances for success by (1) quantifying the potential benefits of the reengineered process in an explicit, defensible way, (2) illustrating the transition between the pain of the present and the joy of the future, and (3) showing the possible outcomes of current actions, thereby making the future more predictable and less surprising to those most affected by it.

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Simple Model Simulation

The Simple Model described above represents a simple process design for a manufacturing facility that is subject to simulation. On the surface, the design appears to be reasonable and adequate, and in fact is based on representative data and characteristics of the process. However, simulations will show some unexpected behavior, as well as the envelope of the possible behaviors.

The Simple Model was executed on an evolving system called the EMS system, which consists of two parts: the simulation engine part and the data analysis and display part. The simulation engine has continued to develop with each model that we have studied. It captures and abstracts processes in the enterprise. The simulation engine is an object-oriented, enhanced discrete event simulation software system.

The initial implementation of the simulation engine part of the EMS system was the Manufacturing Enterprise Simulator on the TI Explorer II.[9] The current implementation runs on HP 9000 Series 700 workstations at the Manufacturing Systems Technology Department of HP Laboratories. The implementation language is the Common Lisp Object System (CLOS).[18] The simulation engine has been implemented in CLOS provided by three different vendors: Franz, Inc.,[19] Lucid, Inc.,[20] and Harlequin, Ltd.[21] Models subsequent to the Simple Model (see page 12) were large enough to stress the limits of all three implementations. Graphical output was produced using S-Plus. Further details of the history and development of the EMS system are given in reference 9. The initial version of the Simple Model was implemented within a week based on the full order-to-ship model[22] (see page 12). It then took successive refinement and a tremendous amount of time to analyze the results.

For the reader familiar with discrete event simulation, details of the similarities and differences in concept between this implementation and conventional discrete event simulation are discussed in reference 9. In general, orders and shipments

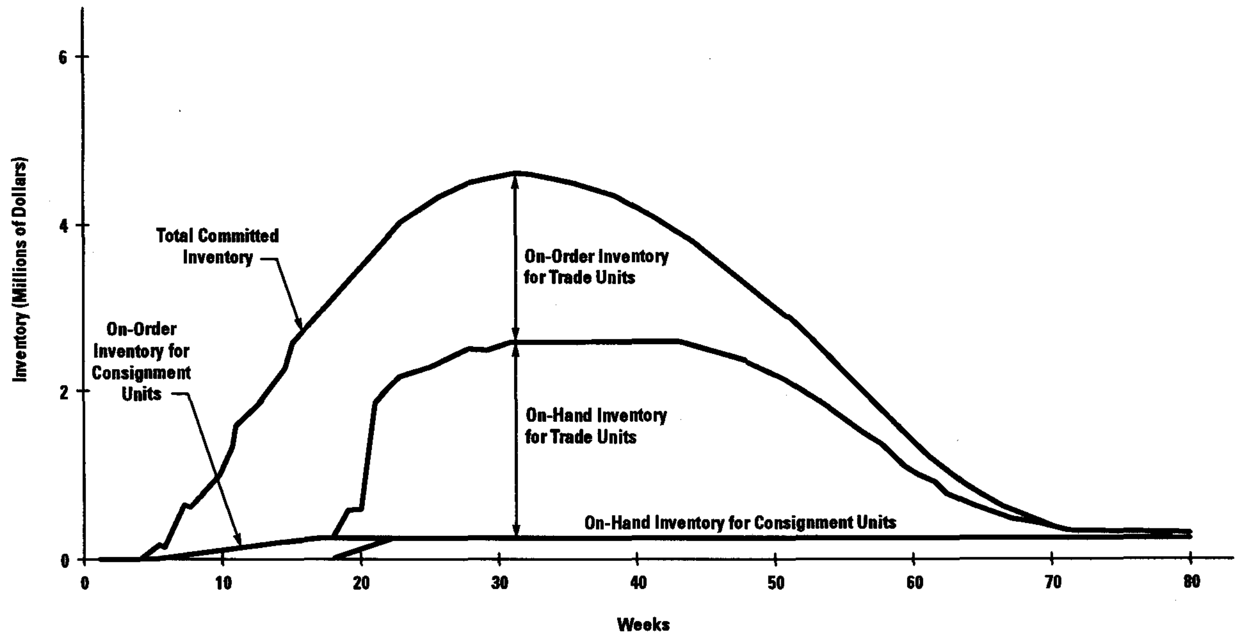

Fig. 4. Nominal case inventory components as functions of time. The experimental conditions are shown in Fig. 1.

are modeled as the entities of discrete event simulation. Backlog, on-order material, RPI, WIP, and FGI are modeled as queues. Customers and vendors are modeled as source-sink combinations of orders and material and vice versa. Production is modeled as an activity.

The production and material planning functions, which are essentially information processing and decision making functions, are implemented as mathematical models embedded in the simulation. The information generated by these planning functions determines when and how many units of product to start building and how many units of material to order. Thus, we can think of the Simple Model as an analytical mathematical model embedded in a discrete event simulation model. The analytical model (formulation given in Appendix I) dictates how the simulation model should behave in the same way as the planning functions dictate how operations should be handled in reality. The simulation model is the reflection of physical reality and reflects the behavior of the physical system that is told what to do.

There are two aspects of uncertainty: bias and variance. Most simulation models focus on variance and assume bias (offset) to be zero. While the EMS system supports the ability to simulate the model under stochastic conditions, in the runs described in this paper, variance is always zero and the emphasis of the analysis is on the situation in which bias can be nonzero.

Each run represents one combination of inputs and parameters of the system, and the traditional statistical analysis of means and confidence levels is not directly applicable for the analysis of these runs. While process variances are important considerations in a system, the motivation of this work was to identify the first-order effects of the various factors, considering the variances as second-order effects.

Details of the timing of the event sequence are shown in Appendix II.

Experimental Results

Experiment 0: The Nominal Case

The nominal case experiment assumes ideal conditions for testing the model. The purpose is to establish model baseline behavior and offer face validation by verifying that results are consistent with intuition and the observed behavior of the real system. Initial conditions for committed inventory and backlog are set to zero. A warmup period of five months (20 weeks) allows material to be ordered and received before customer orders arrive on week 21. The last customer orders arrive on week 68. Order forecasts are consistent with the trapezoidal profile already defined, and while they are generated weekly, they do not change from week to week. Week 21 corresponds to the first week of month 1, and week 68 corresponds to the last week of month L+6 in Fig. 2. Production begins during week 19 to ensure units in FGI at the end of week 21. The computation of FGI and RPI safety stock levels is assumed to apply only for weeks after week 20. Up to and including week 20, the required safety stock level is set to 0.

Time Response of On-Hand Inventory and On-Order Material. Fig. 4 shows inventory levels measured in dollar terms over time. The two bottom regions show the on-order material and on-hand inventory for consignment units. There is a gradual buildup of on-order material, which is rapidly transformed into on-hand inventory over four weeks, followed by a flattening out (since the consignment units are never shipped). The middle region shows on-hand inventory for trade or shippable units, which is the sum of RPI, WIP, and FGI. The upper region shows the on-order material commitment for trade units. The top surface of the graph shows how total material commitment changes over time.

Inventory Investment. Committed inventory at the end of week 20, before the first customer order arrives, is approximately

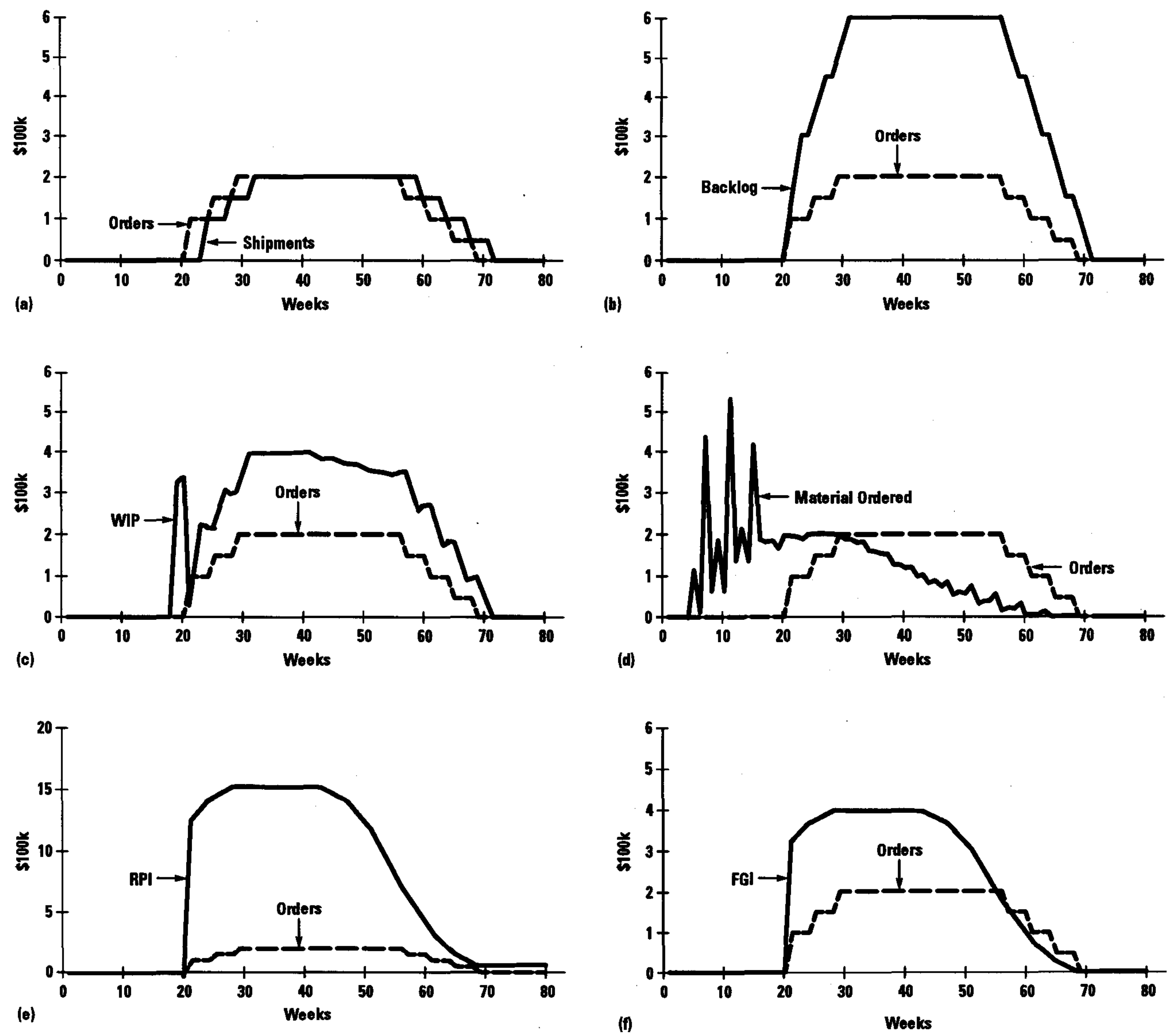

Fig. 5. Metrics as functions of time for the nominal case. (a) Shipments and orders. (b) Backlog and orders. (c) WIP and orders. (d) Material ordered and orders. (e) RPI and orders. (f) FGI and orders.

$3.5 million. If orders to vendors cannot be cancelled, this $3.5 million commitment must be disposed of if we decide to cancel the product before the first customer order arrives.

During the mature part of the life cycle of the product, the on-hand inventory is approximately $2.5 million and the total committed inventory is approximately $4.7 million. To support shipment levels of $200,000 a week requires $4.7 million of committed inventory (23.5 weeks of steady-state PCFT) and $2.32 million of on-hand inventory (11.6 weeks of steady-state PCFT), both of which include $300,000 of consignment units (1.5 weeks of steady-state PCFT). Details of the computations verifying these numbers in the simulation are given in Appendix IV-2. The maximum inventory exposure over the life cycle is $4.7 million.

The EOL consignment inventory of $300,000 reflects the amount of potential write-off because we did not dispose of the consignment units. The EOL nonconsignment inventory for trade units is reflected in the tail of the graph, and its value is approximately $64,000. If the material cannot be consumed any other way, there is an EOL write-off of $64,000 of nonconsignment inventory and $300,000 of consignment inventory for a PCFT of $7.8 million under ideal conditions of perfect forecast quality and on-time vendor delivery.

Time Response of Other Metrics. Fig. 5 shows other time series metrics in comparison to orders received. The shipment profile (Fig. 5a) is identical to the order profile but shifted in time by three weeks. This is because the four-week availability and one-week transit time require three weeks of order-to-ship time for on-time delivery.

Steady-state backlog (Fig. 5b) is $600,000, or three weeks of orders. Again, this is because the four-week availability and one-week transit time result in orders staying in backlog for three weeks, that is, the current backlog is the sum of the last three weeks of orders.

Enterprise Modeling and Simulation Research at HP Laboratories

Our work at HP Laboratories on enterprise modeling and simulation is an outgrowth of the factory modeling project, which began in early 1987. While we were working in the area of robotic automation for manufacturing, we began to appreciate the complexity of the geographically distributed, multientity marketing, manufacturing, and distribution operations necessary for HP to remain competitive. We also realized that there were very few tools available to help understand, design, and operate these complex systems.

Having been involved in product design with the evolving use of CAD and CAE tools, we thought that there was an opportunity of potentially tremendous magnitude for applying similar technologies to the design and operation of the factory and business systems used to market, manufacture, and distribute products. In an effort to capitalize on this opportunity, we began identifying the primary elements of a single factory and building our preliminary order-to-ship model that spanned all major activity from the receipt of an order to its shipment.

Preliminary Order-to-Ship Model

This early model was a vehicle to show the feasibility of applying simulation at a scope larger than a production line, where simulation was beginning to be applied. Developed and proposed for discussion purposes, it was a model to analyze why the order-to-ship time for some products stretched to weeks when the application of modern manufacturing techniques had reduced the build time to a matter of hours. More details on the reasons behind this work are given in references 1 and 2.

Full Order-to-Ship Model

By late 1988 the preliminary model was ready for testing in a real-world context. Data and operational information were provided by a real manufacturing division to help enhance our early model. This process helped to validate the preliminary order-to-ship model and led to the development of the full order-to-ship model.[3] The primary factors considered were order forecast quality, production capacity constraints, supplier lead times, and order filling policies. The primary metrics of interest were order lateness, backlog, and inventory. The model included three distribution centers, one manufacturing entity, and a centralized sales and order entry system. It was configured for one-level bills of materials (BOM), multiline orders, and long life cycle products.

The results of the analysis done with the full order-to-ship model were encouraging; they showed things that were consistent with real-world experiences (e.g., high forecasts led to high inventory and low backlog). The results also provided a view of greater potential by helping to identify areas for future improvement (e.g., the dominant cause of product shortages is long lead time parts coupled with poor forecasts rather than the build time).

While the results of this model were modest, the building and running of this model enabled us to explore some important technologies (i.e., Hierarchical Process Modeling for knowledge acquisition, a discrete event simulation language, SLAM II,[4] and a knowledge-based environment, Knowledge Craft, for system representation and building simulations). Our efforts led to generalized enterprise-level modeling elements and an object-oriented simulator. We also identified some new obstacles (e.g., managing large amounts of simulation data, extracting information) to be overcome in attaining our goals. More details are given in reference 1.

For about a year, no further model development was done, but rather, much effort was put into consolidating what we had learned about the modeling and simulation issues. This effort led to the complete overhaul of our modeling and simulation code while migrating it to the Common Lisp Object System on HP workstations. The power and speed of our system took a quantum leap forward.

Simple Model

With our improved system ready, we were presented with another real-world opportunity to apply our techniques. The Simple Model was proposed as a means of pulling together the main activities, processes and circumstances involved in a manufacturing enterprise. The primary purpose was to understand end-of-life (EOL) inventory and order delivery performance issues. The combined impacts of several environmental factors and operational policies were considered in the

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Fig. 5c shows an initial spike in WIP preceding the start of orders by two weeks. This happens because the number of units started during week 19 is not only what is to be shipped two weeks later, but also the quantity that must be in FGI (approximately two weeks of orders) at the end of week 21. The WIP levels taper off downwards starting in week 44 towards the latter part of the life cycle because as the desired FGI safety stock level decreases, less production is required than is shipped because some units shipped from FGI do not have to be replenished.

Fig. 5d shows material orders. The three large spikes in material orders are caused by different lead times for parts to fill the targeted RPI safety stock at the beginning of the cycle. Each of the three small spikes corresponds to the different lead time parts for the initial WIP spike. Once the initial spikes are past, the material ordering volume is approximately the same height as the customer orders, except that it is shifted earlier in time, showing that once the system has reached mature demand, material inflow in the form of material ordered is balanced by the material outflow in the form of shipments. Material ordering starts ramping down beginning in week 28 just as the orders reach the maximum demand for this particular set of circumstances.

Fig. 5e shows RPI as a function of time. Notice that the vertical scale is different from the other graphs. The RPI level is 7.6 weeks of PCFT during the mature demand period and starts ramping down in week 44. Fig. 5f shows FGI as a function of time. The FGI safety stock during the mature demand week is two weeks of PCFT, which is the same as two weeks of steady-state orders. The FGI level starts ramping down in week 44.

Inventory Results. The results establish the baseline behavior of a system designed to take contingencies into account when those contingencies do not occur. Appendix IV provides further details for computing some of these results on a theoretical or common sense basis. Some interesting observations can be made. First, EOL inventory and write-off exist even though customers ordered exactly according to forecast and we expect safety stock to go to zero. Second, the level of inventory required to support this level of business can be quantified. Third, long lead time parts make up a greater percentage of the value of parts on order than their percentage in the product structure.

EOL inventory is important for short life cycle products because the inventory cannot be used for anything else and must be written off. In this case it is a result of the way of computing safety stock. It occurs if in the early part of the life cycle too much material is ordered because of high targeted FGI and RPI. For short life cycle products it can be a significant percentage of PCFT. EOL inventory is less of an issue for long life cycle products because the leftover inventory is generally a smaller percentage of total PCFT and excess inventory in early periods can be used at a later time.

analysis. The model, leveraging our earlier work, dealt with a one-level BOM, one factory, one product, and subsequently a family of successive products with common parts and overlapping life cycles.

Our analysis provided some interesting insights, such as certain material procurement and safety stock policies result in EOL inventory even for perfect order forecasts, and with low forecasts, increasing material lead times and planning frequency result in increased EOL inventory. More important, we began to realize that we were onto something that could really have a positive impact for HP. In fact, the business results led to the development of the planning calendar model with the Simple Model as its foundation. We also continued our technical enhancements by connecting the output to S-Plus[5,6] for data analysis and the creation of a Lotus® interface to display output.

Planning Calendar Model

The purpose of the planning calendar model[7,8,9] was to determine the effects of planning cycle times on inventory levels. It required extension of the Simple Model to include production planning and material planning cycle times. It approximated a two-level BOM and multiple assembly sites using a one-level BOM at one site. It used historical forecasts and orders. The primary factors were forecast quality, the length of the planning cycle, and the maximum lead times for parts. The primary metrics of interest were average inventory, delivery performance, and inventory levels at the start of production. The primary technical development was the application of S-Plus data analysis capabilities to the data.

With this model, material lead times had a dominant effect on inventory levels and committed inventory. Historically, forecasts were generally low, so for the historical data given, the planning cycle time used for the particular product had insignificant impact compared to material lead times. There was greater potential for reducing inventory by reducing lead times than by reducing planning time. Low forecasts increased backlogs.

Current Modeling Activities

We are currently finishing an analysis of a single-site manufacturing system where we were looking at how to improve the supplier response time. The challenges in this application include managing a multilevel bill-of-materials and understanding the consequences of long, variable test cycle times. We are also working with sector-level reengineering teams to help understand the consequences of proposed changes and explore alternatives.

Our enterprise modeling and simulation capabilities have evolved considerably from our preliminary order-to-ship model. However, there are still many more interesting challenges to address before we reach our goal of a computer-aided business process design and operation system.

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Enterprise Modeling and Simulation Project
HP Laboratories

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This nonzero EOL inventory is significant because our safety stock policy targets zero safety stock levels in FGI and RPI at the end of the life cycle. Having observed this phenomenon in the simulation, we were able to show mathematically why the EOL inventory is not zero. The formal derivation of this result is outside the scope of the current paper, but more detailed analysis of the data showed that it is the Class C parts that are left over. The Class C parts will be zero in the case when orders come in as forecasted for the conditions of experiment 0 only if the target RPI safety stock for Class C parts is less than or equal to the 13-week leading average forecast. Also, for the conditions of experiment 0, any part with target safety stock greater than 13 weeks of 13-week leading average forecast will end up with EOL material. The behavior of the amount of Class C EOL material as the number of weeks of target safety stock goes down is given in Appendix IV-3, and an informal explanation showing the reasoning behind the EOL material is given in Appendix IV-4.

The nonzero EOL is a function of the number of weeks of 13-week leading average forecast. Other techniques of computing safety stock, for example using a cumulative leading forecast rather than the 13-week leading average forecast, might lead to different results.

Smoothing WIP and Production. The initial spike in WIP shows how the policy of starting production in week 19 (and not before) gives rise to a spike in capacity demand at the beginning of the product cycle. It could be eliminated by incorporating production capacity constraints into production and material planning or by allowing FGI to build up before the first order comes in (i.e., before week 21). Both of these require production to start before week 19.

Experiment Set 1a:
Single Uncontrollable Factor Variation

In the nominal case, the customer order pattern was accurately forecast. We now consider the situation where the actual orders are different from the forecasts.

We assume that customers order according to a constant order forecast profile multiplied by some constant factor Actual/Forecast or A/F. A/F is the ratio of actual orders to forecast orders; its definition is shown in Fig. 6a. In practice, marketing would change the forecasts periodically. Since we were not modeling the forecasting process, we chose the simplifying assumption that although a new forecast is generated every week, it is identical to the forecast generated the previous week.† Here is an example of bias in the order forecast with no variance. The model interpretation is that although estimates were wrong in the past, we expect that future orders will be equal to the original forecast. This is

† This is not a limitation of the model. A user-specified forecast can be accepted by the model. Later models have incorporated historical forecasts. The reason for this assumption was to get a better understanding of the effect of forecast bias. Fluctuating forecast deviations make interpretation harder.

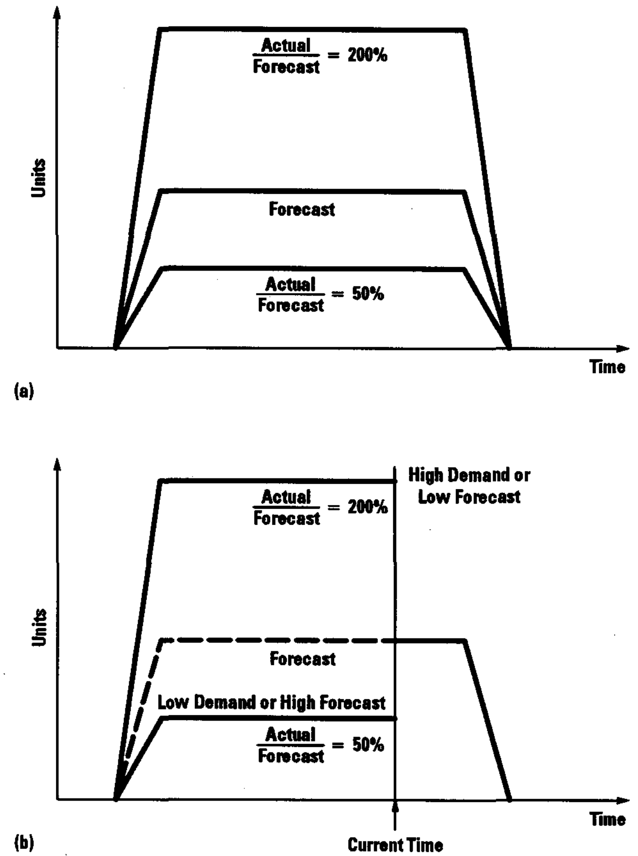


Fig. 6. Definition of A/F. (a) A/F ratio. (b) Actuals and forecasts at the current time.

reflected in Fig. 6b. Actuals came in as shown in the part of the graph to the left of the current time, while the part to the right of the current time line shows the current expectation of future orders.

Clearly, we would expect an effect when A/F is not 100%. If A/F is less than 100%, that is, if forecasts are high, FGI will start to build up, since production planning has directed a larger number of units to be built than are subsequently demanded. Production planning and material planning take this into account and plan to build less and order less material in the future, but the overall material level is higher than when A/F is equal to 100%. On the other hand, if A/F is greater than 100%, that is, forecasts are low, FGI will start to be eaten away because production planning has directed a smaller number of units to be built than are subsequently demanded. Subsequently, production planning and material planning take this into account and raise the production, but since they are always estimating low future demand, we would expect the inventory level in general to be lower than in the case where A/F is 100%. Surprisingly, this intuitive result does not hold, as will be seen later.

We ran the simulations with A/F ranging from 50% to 200% at equal intervals of 25%. In addition, we ran it at smaller intervals in the region of 95% to 125%.

EOL Write-off. A consequence of keeping forecasts identical for all runs is that the consignment profile does not change with respect to A/F. Fig. 7 shows EOL metrics as A/F ranges from 50% to 200%. Note that the changes in value are not constant across the horizontal axis. Fig. 7a shows that total EOL inventory increases as A/F decreases. Fig. 7b shows that the percentage impact is even worse, simply because the write-off is a higher percentage when PCFT, which is directly influenced by A/F, is lower. For low forecasts, that is, A/F greater than 100%, the EOL inventory decreases. For high forecasts, that is, A/F less than 100%, the EOL inventory increases. The lower the A/F, the higher the EOL inventory.

Fig. 7 leads to the obvious conclusion that inventory write-off can be reduced by the strategy of underforecasting orders. However, this is only one side of the story. The complete story is shown in Fig. 8.

Impacts on Time Series of A/F Changes. Fig. 8 shows the impact of A/F changes on different time series measures. *To avoid clutter we will not show inventory for consignment in subsequent time series.* FGI, WIP, RPI, on-order material, and on-hand inventory will refer to the material associated with trade units unless otherwise specified.

All of the graphs in each row of Fig. 8 exhibit identical behavior before week 21. This is to be expected, since before the first orders come in on week 21, the situation is the same for all cases. Only as different amounts of orders come in on or after week 21 is the situation different for different values of A/F.

Fig. 8a shows the order forecasts and actual orders for reference. The ratio of the values of the two lines at any time in the graph is equal to A/F.

Fig. 8b shows the backlog and actual orders time series on the same scale. Notice how the backlog increases spectacularly as A/F goes beyond 125%. Fig. 8c, which displays backlog in terms of mature demand, shows that for an A/F value of

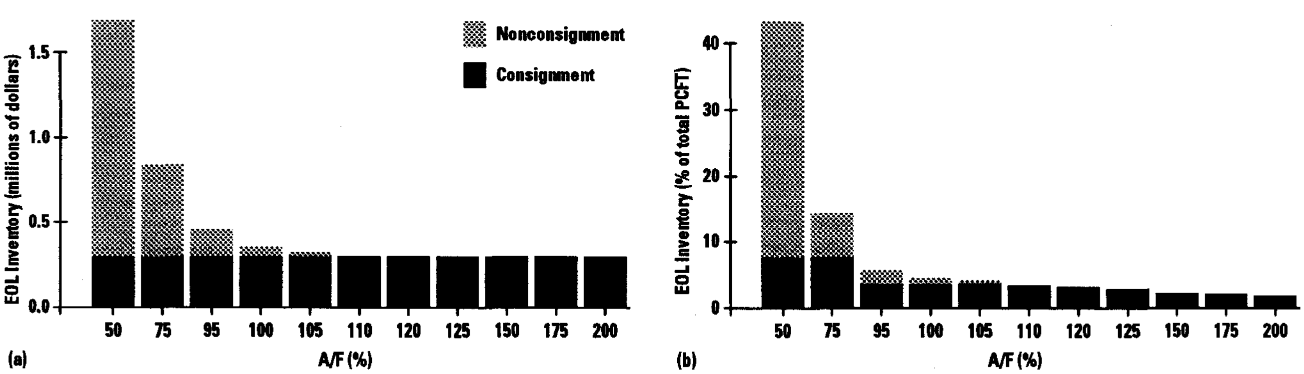


Fig. 7. EOL (end-of-life) inventory for experiment set 1a.

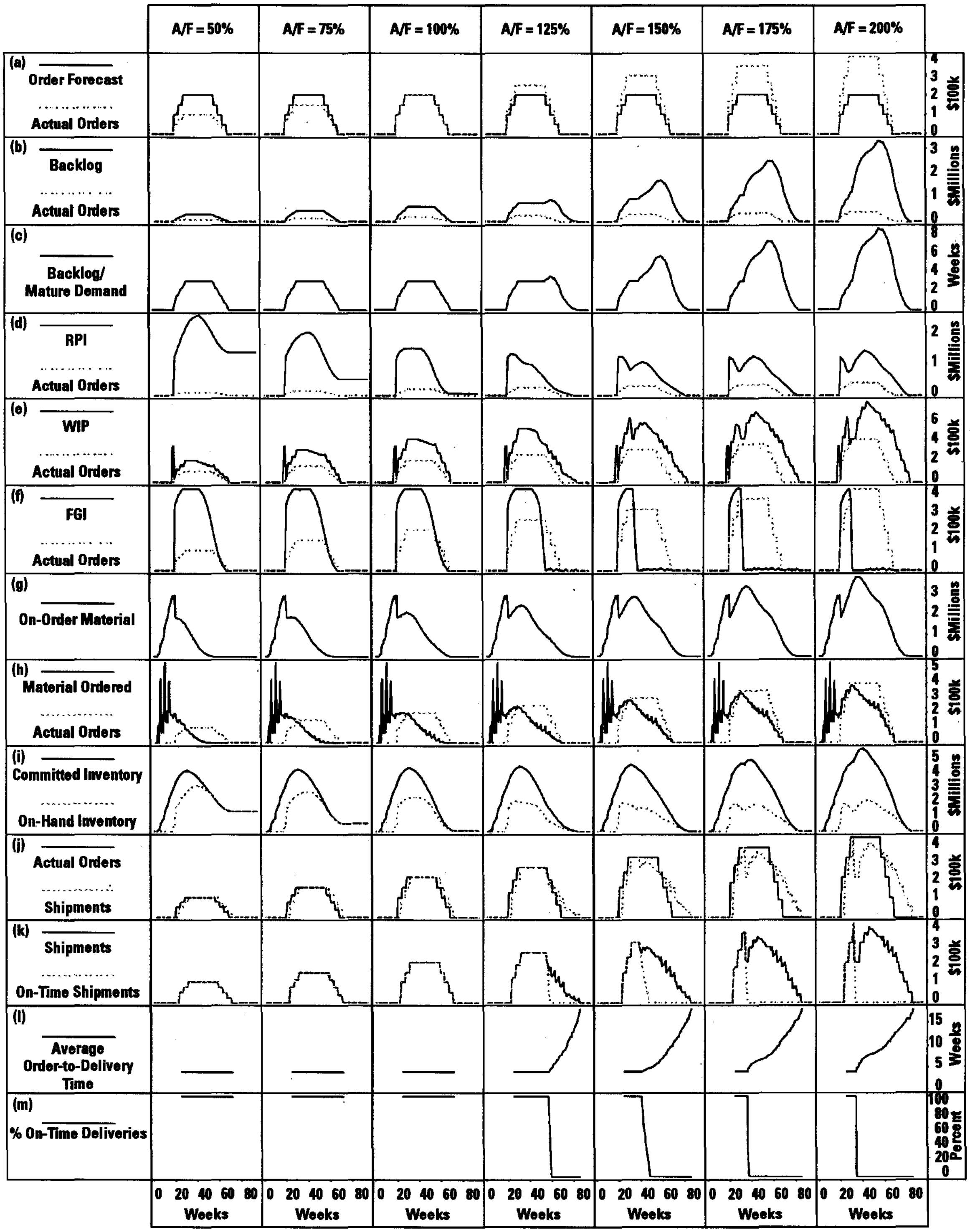


Fig. 8. Time series data for various values of A/F for experiment set 1a.

200% the backlog can be as much as eight weeks of mature demand. Backlog measured in terms of weekly mature demand is constant for low A/F. It increases for high A/F because products cannot be shipped as fast as orders come in.

Fig. 8d shows that the EOL RPI level falls as A/F increases. In addition, the general level of RPI as a function of time falls as A/F increases until A/F is greater than 150%, when the RPI level actually appears to rise as A/F increases. The reason is that because of shortages we order more of all material to build the shortfall in units. The short lead time parts show up first, but cannot be used because of a shortage of the long lead time parts with minimal safety stock. An analysis of the results shows that the critical part is A.3.

Fig. 8e shows that the WIP profile increases as A/F increases. This is expected, since WIP is directly related to the shipments flowing through the system, and the shipments are directly related to orders, which are directly related to A/F.

Remember that this is true only when the production capacity constraint is not reached. If production capacity is only a little greater than forecast, high demands would result in the level of WIP being capped at some limit but spread out over time.

Fig. 8f shows that the FGI level is identical for all values of A/F less than 100%. For A/F greater than 100%, the FGI gets eaten away slowly because the rate of replenishment of new units does not keep up with the shipments because of underforecasting. However, since FGI safety stock levels are based on two weeks of 13-week average forecast and the forecasts used are identical in all the experimental runs, the peak FGI tends to be the same.

Fig. 8g, on-order material, shows initial large spikes for material for RPI and FGI safety stock, followed by a drop after the material for safety stock has been delivered. Subsequently the profile shows an increasing level over time as A/F increases.

Fig. 8h, material ordered, shows the same spikes before week 21 that we have seen before. Again the material ordered versus time increases as A/F increases.

Fig. 8i shows that, in general, committed inventory after week 21 is higher for higher A/F and stretches out farther over time. For lower A/F the committed inventory is lower in the early part of the life cycle, but there is an increase in EOL inventory.

Fig. 8j shows that for A/F less than 100%, shipments follow the order stream nicely. High A/F (high demand) values cause the initial orders to be filled as specified, but subsequently shipments drop off and then catch up. The product shipment over time is smooth when A/F is less than or equal to 100%. When A/F is greater than 100%, during the early part of the life cycle the orders are filled as they come in. As the FGI safety stock is consumed, the shipments fall to the forecasted levels, and then subsequently tend to rise to the actual order levels.

The on-time shipment graphs in Fig. 8k show that initial orders are delivered on time in all cases. For A/F less than 100% (forecasts are high), all orders are delivered on time. For A/F greater than 100% (forecasts are low), initial orders are delivered on time, but subsequent orders are late. As A/F increases beyond 100%, both the percentage and the total dollar value of on-time shipments (and consequently deliveries), go down, and the late orders never catch up. On-time delivery graphs, which are not shown, would be identical to on-time shipment graphs shifted by one week.

As expected, because of the policy of shipping as late as possible, Fig. 8l shows that average order-to-delivery time never goes below four weeks, but increases with time up to 18 weeks as A/F increases to 200%. Fig. 8m, showing the percentage of on-time deliveries, is consistent with Figs. 8k and 8l in terms of on-time deliveries.

How Late Are Late Orders? How late are the late orders and how many orders are delivered on time (namely, within four weeks of being ordered)? These questions are answered in Fig. 9, which shows the dollar volume of deliveries and the order-to-delivery time. For A/F less than or equal to 100% (forecasts high or demand low), all orders are delivered on time. For A/F = 105%, most orders are delivered on time. For A/F = 150% and 200% (forecasts low), some orders are delivered on time, and a large fraction of orders are delivered late. Furthermore, for high A/F values, even though the total volume of shipments is higher, the amount of on-time shipments and deliveries actually goes down. Some orders are delivered as much as 14 weeks late, that is, 18 weeks after receipt of order. This 14 weeks is the upper limit of lateness for this particular model and data configuration. No matter how high A/F gets, orders will never be later than 14 weeks. The explanation for this is given in Appendix IV-5.

Interpretation of Results. In this model, forecasts were not updated on the basis of orders. In reality, when orders are very much under or over forecasts, there will be pressure to change the forecasts. If further information on the forecasting process is available, this can be incorporated into the model. Another study that could be done is to see what happens if we treat the initial orders as early indicators of the whole life cycle, that is, after some period of time, we revise the forecasts so that they more closely represent the volume of actual orders. On the other hand, if the life cycle is very short, it may turn out that revising the forecasts when the first orders come in may not have an impact on system response. We have established a nominal trapezoidal product life cycle, but this could be changed in various ways. It could be stretched out horizontally to increase the life cycle (as is done in subsequent experiments), or vertically, to show a higher level of product demand.

Customers need to receive the products within a reasonably short time, or they might cancel the order. For the model, we assume that customers are willing to wait patiently as long as it takes for the manufacturing facility to produce and ship the products, and that they will not cancel the order.

The purpose of this detailed discussion is to show how changing the one factor, A/F, can have different impacts on different metrics, and how this might affect different parties interested in the outcomes. A/F is partly under the control of customers, and partly under the control of marketing, assuming that greater effort will provide a better estimate of orders. It shows that if A/F is low, order processing and shipping would have excellent performance metrics in getting products out in a timely fashion, whereas material procurement would be in the situation of trying to explain why there is so much material in the plant, and marketing and the plant manager may have to explain why orders are below target. On the other hand, if A/F is high, customers

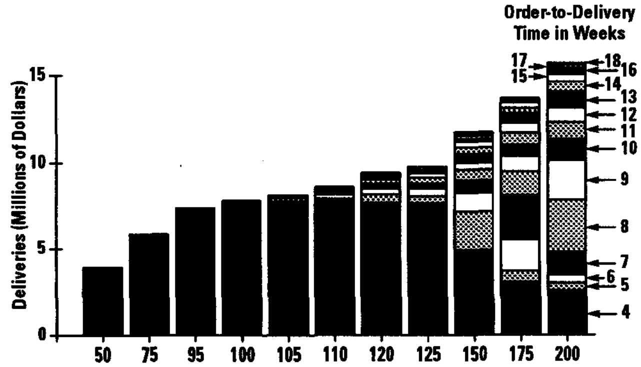


Fig. 9. Deliveries by order-to-delivery time in weeks for experiment 1a.

Table III
Range of Values of Factors for Different Experiment Sets

Factor Description	Parameter Name	Number of Different Values	Values
Actual/Forecast, %	A/F	11	A/F (%) = 50,75,95,*100*,105,110,120,125, 150,175,200
Part Safety Stocks Class A 4K weeks Class B 8K weeks Class C 16K weeks	K	5	K = 0.5,0.75,*1.0*,1.5,2.0
Life Cycle, L+6 months	L	5	L = 0,3,*6*,12,18
Availability, weeks	Y	5	Y = 1,2,*4*,8,12
Percentage value of 6, 10, and 14-week lead time parts in the product (r%,s%,t%)	lt	4	rrr = (100,0,0),rst = *(25,40,35)*, sss = (0,100,0), ttt = (0,0,100)

Experiment 0 (nominal case): Values shown in italics.

Experiment Set 1a (uncontrollable factor A/F varied): Values of A/F varied as shown. Values of other factors same as experiment 0.

Experiment Set 1b (A/F = 100%, controllable factors varied): Values of factors other than A/F varied as shown in turn. Values of other factors same as in Experiment 0.

Experiment Set 2 (dual-factor experiments): Values of factor A/F and one other factor varied in turn. Values of other factors same as in Experiment 0.

Experiment Set F (all factors varied): Values of all five factors varied as shown.

will be screaming for products, order processing and shipping will be trying to placate angry customers, production will be under pressure to put out products faster, and material procurement will have to explain the perpetual shortage of raw material A.3 while other material is piling up.

Experiment Set 1b: Controllable Factors Varied with 100% A/F

We next look at the effect of changing the factors over which the manufacturing enterprise has some control. In the single-factor experiments, the variation of each factor is summarized in Table III. Except for the set of runs where A/F varied as in experiment 1a, A/F was set at 100%.

Changes in safety stock levels can be characterized in many ways—for example, for each part individually. We chose to multiply the safety stock levels of experiment 0 by a constant multiplier K whose value ranged from 0.5 to 2.0. Life cycle lengths were changed by using values of L to result in life cycle lengths L+6 between 6 and 24 months.

Availability Y was varied from 1 week to 12 weeks (it cannot be less than 1 week because of the 1-week shipment transit time). Y = 1 requires off-the-shelf delivery and implies a total build-to-forecast strategy. As Y increases, the production strategy shifts from build-to-forecast to build-to-order. From prior considerations, an availability Y of 18 weeks will result in on-time delivery of every order regardless of forecast quality.

While there are different ways to characterize modification of part lead times—for example, changing it for each part—we chose to change part lead times by changing the percentage of parts with lead times of 6, 10, and 14 weeks to be 100% in turn.

EOL Results. The EOL inventory graphs for A/F = 100% are summarized in Fig. 10. EOL inventory increases as safety stock increases; the results are consistent with experiment 0. When K is 0.75, we carry 12 weeks of C parts and there is no EOL RPI. When K is 1, we carry 16 weeks of C parts and end up with EOL inventory of C parts. When K is greater than 1, EOL RPI increases. When K is 2, we carry 16 weeks of B parts and EOL RPI includes both B and C parts.

Fig. 10b shows that product life length has no impact on EOL inventory. This is to be expected in the model because increasing L stretches out the middle portion of the time series graphs, and the behavior towards the end of life tends to be the same in all cases when L increases (illustrated in a future graph, Fig. 11b). For short L, the effect of the rising demand in the beginning of the life cycle affects the behavior at the end of the life cycle. Fig. 10c shows that as availability Y is shortened, EOL inventory increases, that is, quoting shorter lead times to customers exposes us to more risk of EOL inventory. This is intuitively correct; the longer the quoted availability, the longer we can afford to wait before ordering material.

Part lead time has no impact on EOL inventory when A/F = 100% (Fig. 10d).

Other Results. Fig. 11 shows the inventory measures over time as different factors are varied. Delivery performance is not shown because for A/F = 100%, delivery is always 100% on time.

Fig. 11a shows the inventory measures over time as a function of raw material safety stock multiplier K. The heights of the three initial spikes for material orders increase as K increases, directly impact RPI and on-order material, and indirectly impact on-hand and committed inventories. In general, the higher the K, the higher the inventory levels, including EOL inventory, which is the tail of the committed inventory graph. The on-order material level before the start of production increases as K increases. Keeping all the other factors constant, there is no change in backlog or delivery performance, and these are not shown in Fig. 11a.

Fig. 11b shows the inventory measures over time for varying the product life cycle by changing L from 0 to 18 months. This is one of the less interesting graphs, shown here for

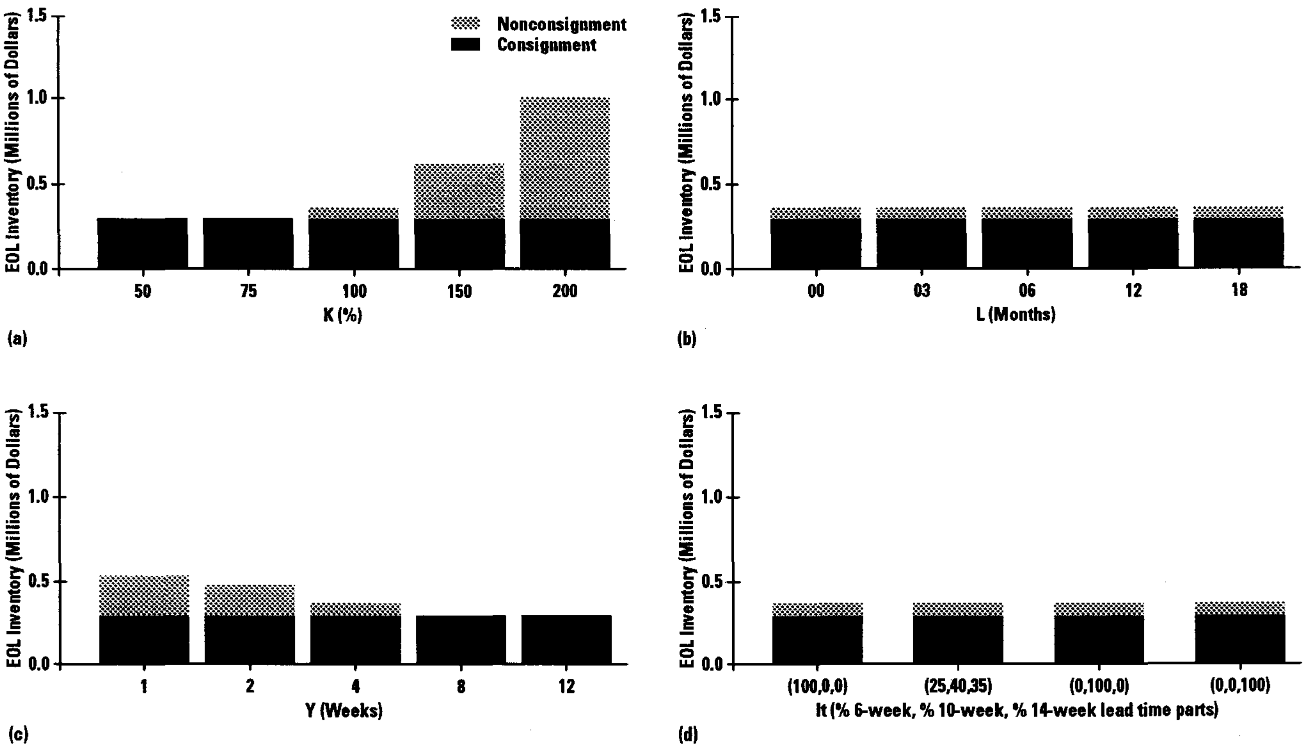


Fig. 10. EOL Inventory by single-factor changes with A/F = 100% for experiment set 1b. (a) Effect of material safety stock (5 runs). (b) Effect of product life (4 runs). (c) Effect of availability (5 runs). (d) Effect of lead time (4 runs).

completeness. EOL inventory is the same in all cases. However, because total PCFT increases, EOL inventory is a lower percentage of PCFT as L increases.

Fig. 11c shows the inventory levels over time for varying quoted availability Y. As Y increases, after the same three initial spikes, the amount of material ordered gets delayed, and the on-order material graphs get stretched to the right. The committed inventory graphs are also stretched into the future. The committed inventory is lower and the EOL inventory (tail of the committed inventory graph) tends to decrease. The delivery profiles are shifted out into the future and the backlog levels are higher.

Fig. 11d shows the time responses of the inventory metrics as part lead times vary. Notice the change in shape of the material ordered graphs. For lt = (25,40,35), there are three large and three small spikes, whereas for the other cases, there is one large spike and one small spike. As lead time increases, the material needs to be ordered earlier. On-order material increases as the lead time increases. On-hand inventory does not change. There is no impact on EOL inventory, order backlog, or on-hand inventory (RPI+WIP+FGI) as long as A/F remains constant at 100%.

Interpretation of Results. This set of results shows how each organization in the manufacturing enterprise can improve its performance metrics assuming that it relies on the forecasts given as being accurate and does not try to second-guess them. For example, if material procurement is under pressure to lower inventory levels, it would naturally try to reduce K. On the other hand, order processing and shipping would prefer to reduce Y to reduce having to deal with impatient customers.

Experiment Set 2: Dual-Factor Experiments

In this experiment set, we varied two factors in combination and attempted to observe the effects. However, instead of looking at all combinations, we looked at the impact of each of the other factors when A/F changed. This enabled us to see the effect of the controlled action in various situations of customer ordering behavior.

Results of Two-Factor Experiments. Fig. 12 summarizes the information on EOL and on-time deliveries as A/F and other factors are varied. Fig. 12a shows that as K increases, there is higher exposure to EOL inventory as A/F decreases. However, increasing K in general gives better delivery performance by shortening the average order-to-delivery time as A/F increases above 100%. Below an A/F value of 100%, K does not have an impact on the already excellent delivery performance shown by 0% late deliveries.

Fig. 12b shows that as L increases, the total shipments for a given A/F increase. For long L, the absolute volume of on-time deliveries initially increases as A/F increases. As A/F keeps on increasing past 100%, the absolute volume of on-time deliveries decreases. The average order-to-delivery time is not affected very much by L, and the EOL inventory is impacted insignificantly. The absolute amount of EOL inventory seems to depend little on L except when L is 0. For L = 0, the long lead time and high safety stock parts may actually cause most of the material for life cycle use to be ordered before the first customer order is received. The percentage of EOL writeoff decreases for a given A/F as L increases, reflecting the fact that the EOL writeoff is a smaller percentage of the total shipments as total shipments increase.

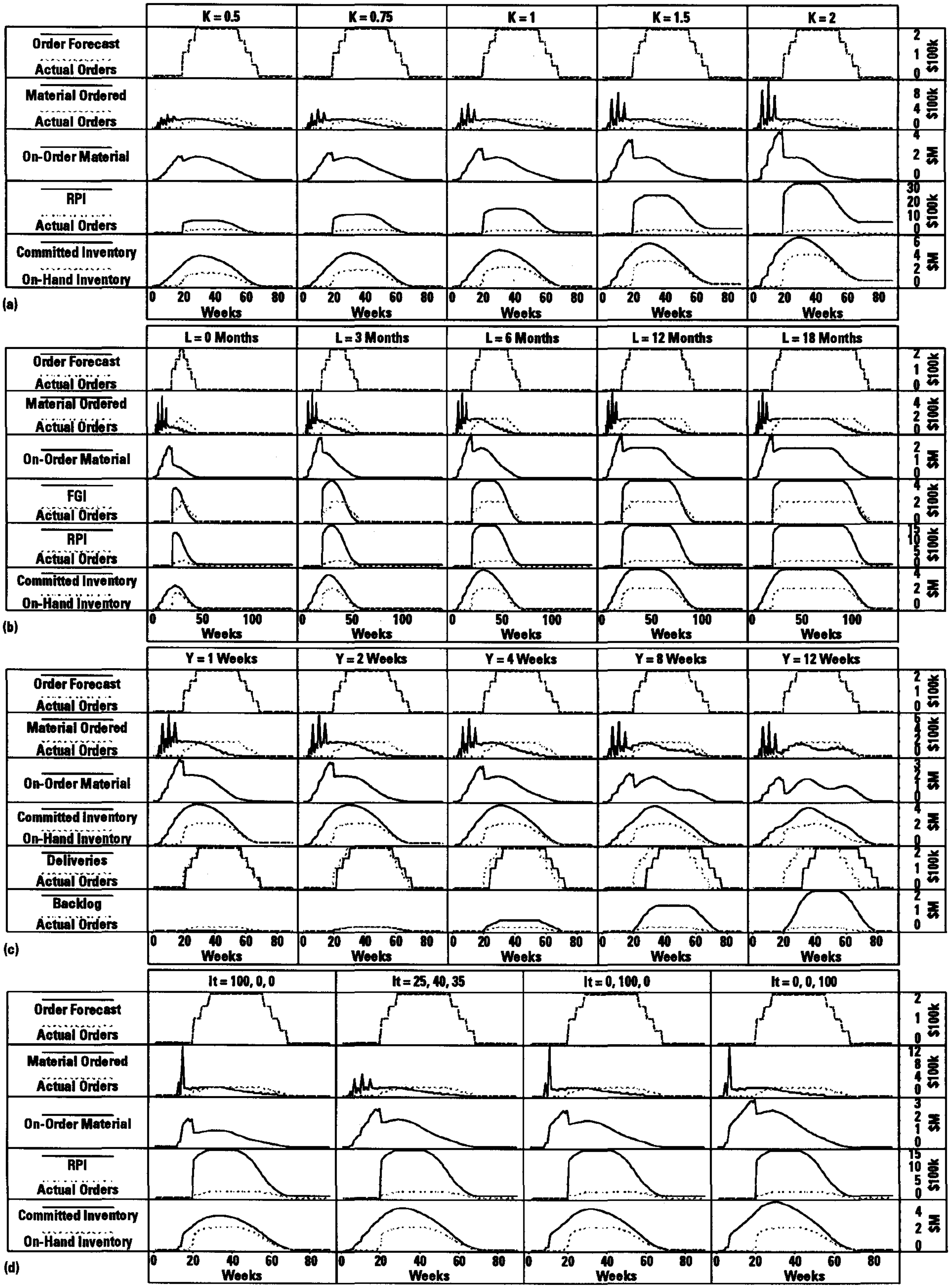


Fig. 11. Inventory measure time series for experiment set 1b: varying different factors with A/F = 100% (order forecast graph coincides with actual orders graph). (a) Varying safety stock levels (5 runs). (b) Varying life cycle (5 runs). (c) Varying availability (5 runs). (d) Varying lead time (4 runs).

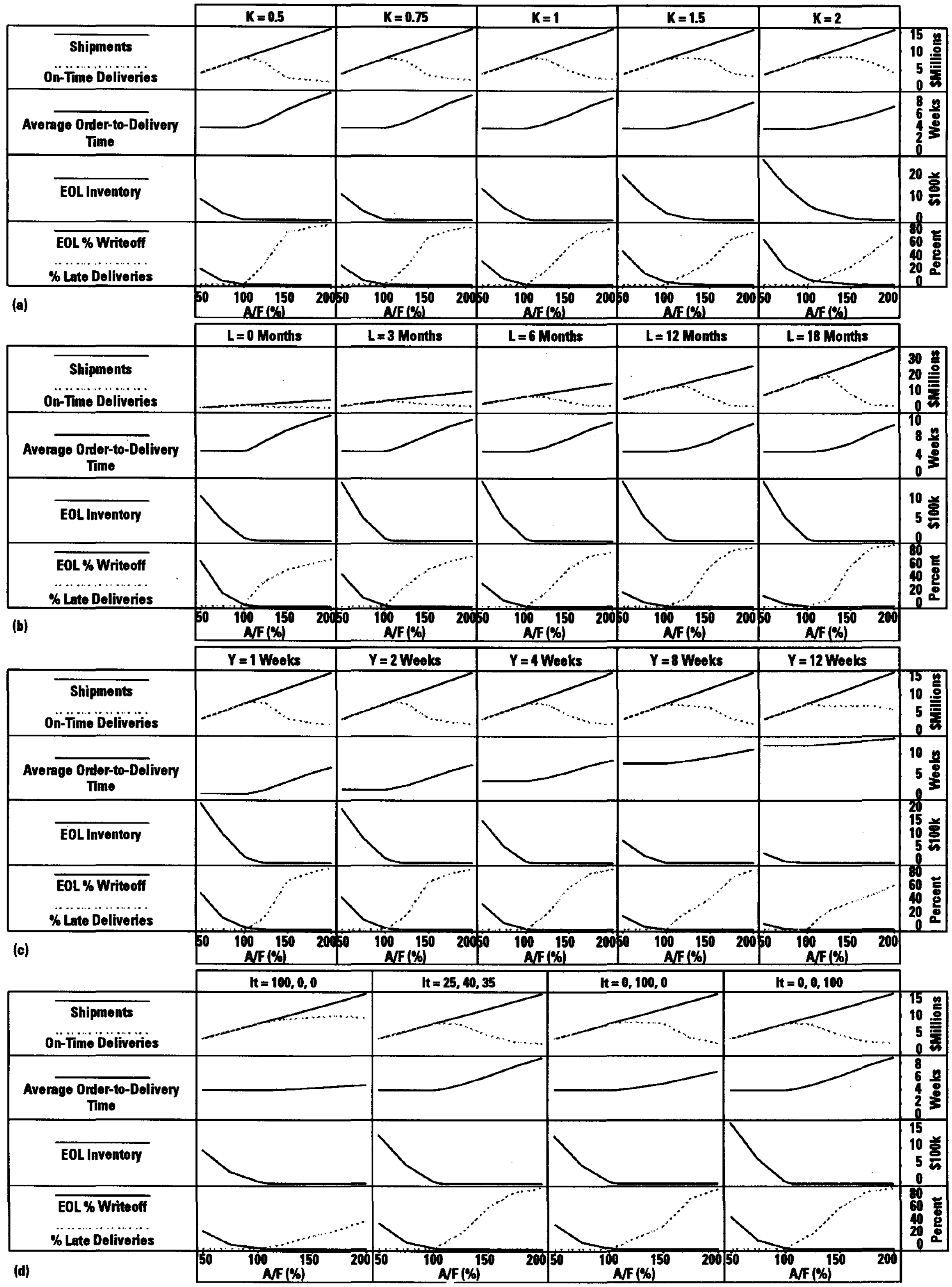


Fig. 12. EOL and shipment metrics as functions of A/F for experiment set 2 as each of the other factors is varied. (a) K varied. (b) L varied. (c) Y varied. (d) lt varied.

Fig. 12c shows that increasing Y is desirable for reducing the percentage of late deliveries and reducing EOL inventory, but that the average order-to-delivery time increases, resulting in customers waiting for long periods of time, which in practice might lead to possible order cancellations. When Y = 1, the worst average order-to-delivery time is lower than the best average order-to-delivery time when Y = 12 weeks. This is an example of a situation in which trying to reduce late deliveries by quoting a longer lead time actually leads to longer average delivery times and possibly lower customer satisfaction.

Fig. 12d shows that if all other things are kept constant, longer vendor lead time leads to poorer performance when A/F is greater than 100% and increased EOL exposure when A/F is less than 100%. For lt = (100,0,0), that is, lead time for all parts is 6 weeks, A/F has little impact on average order-to-delivery time over the given range. Furthermore, the percentage of late deliveries is generally lower than for the other values of lead time. If Y could be set to 12 weeks for the case lt = (100,0,0), no orders will ever be late, regardless of the value of A/F. Applying reasoning similar to that on page 4, the policy of waiting for customer orders to arrive before we order parts could lead to an order-to-delivery time of nine weeks, which is shorter than 12.

Observations. We have looked at the interactions of A/F with the other factors in our experiments and noticed the complexity of the interactions. The results of experiment set 2 show the impact of uncertain customer behavior on various organizations within the enterprise. In an uncertain world where A/F is outside our control, it would appear that increasing K and L, reducing lt, and increasing Y would increase on-time deliveries, which is desirable from the point of view of the manufacturing enterprise. However, increasing Y will tend to increase order-to-delivery times and backlog volumes, which could potentially lead to poorer customer satisfaction and high backlogs for order processing and shipping to deal with.

The other problem of taking these actions is that while delivery performance for the enterprise improves in general, different people and organizations are responsible for influencing and setting the values of K, Y, and lt and obtaining the reward of improved metrics. Increasing K results in better availability but increased write-off, especially if A/F is below 100%. One individual owns K, another individual owns Y, the vendors and R&D together determine lt, marketing owns L, and customers determine A/F. Any one of these can influence the other measures unilaterally, so it is necessary to coordinate the efforts of increasing some parameters and reducing others simultaneously. For example, material procurement could reduce K on the assumption that it will reduce RPI, committed inventory and EOL inventory, and this would be correct if A/F were 100%, but if A/F came in greater than 100%, the overall delivery performance would be poor. On the other hand, if R&D chose longer lead time parts because vendors demanded a premium price for short delivery times, EOL inventory would tend to be higher regardless of what value of K was chosen by material procurement. If quoted availability Y were reduced from 4 weeks to 1 week, inventory levels would tend to go up.

We could also consider the effects of the four other factors on one another, and that would give rise to another six combinations. These discussions are outside the scope of this paper.

Experiment Set F: All Factors Varied

In experiment 0, we looked at the results of one simulation run. In experiment 1, for each factor we looked at four to eleven runs. In experiment 2, we looked at 44 to 55 runs for each combination of A/F and the other factor. As we study the effects of multiple factors, the number of runs increases exponentially. Complexity increases not only in terms of number of simulation runs considered but also the way in which we analyze the data. A full factorial experiment, that is, one in which all the factors are varied in all combinations given here, requires the analysis of 5500 runs. While it is easy to specify different levels of factors, the analysis of the amount of data generated as a result of increasing the number of factors becomes intractable. For example, if all of the time series graphs of a single run were plotted on one sheet of paper each, we would have a pile of printouts eleven reams of paper thick. To do the analysis, we used a graphing technique supported in S-Plus called a design plot.†

Design Plots. Fig. 13 shows the design plots of the means of each of four different metrics at each of the levels of the five factors. The four metrics are EOL inventory, EOL inventory percentage, total on-time deliveries, and percent on-time deliveries. Each plot reflects one metric and summarizes the value of that metric for 5500 runs. The point labeled A is the mean of the EOL values of all experimental runs with A/F = 50% (mean of 500 values). A longer line indicates greater sensitivity of the metric to that factor over the range considered, all other things being equal. For example, A/F appears to have the strongest impact on EOL inventory, EOL percentage, and on-time shipments. On the other hand, the mature demand period L has a strong influence on the total dollar volume of on-time product deliveries.

An interesting point is that mean EOL and EOL percentage decrease steadily as A/F increases. On-time deliveries in dollars increases up to a point as A/F increases to 125%, but subsequently decreases (point B in Fig. 13c). The explanation is that the safety stock policy gives some protection for on-time delivery in dollars when A/F > 100%. On-time deliveries as a percentage remains at 100% for A/F ≤ 100% and subsequently decreases as A/F increases over 100% (point B′ in Fig. 13d).

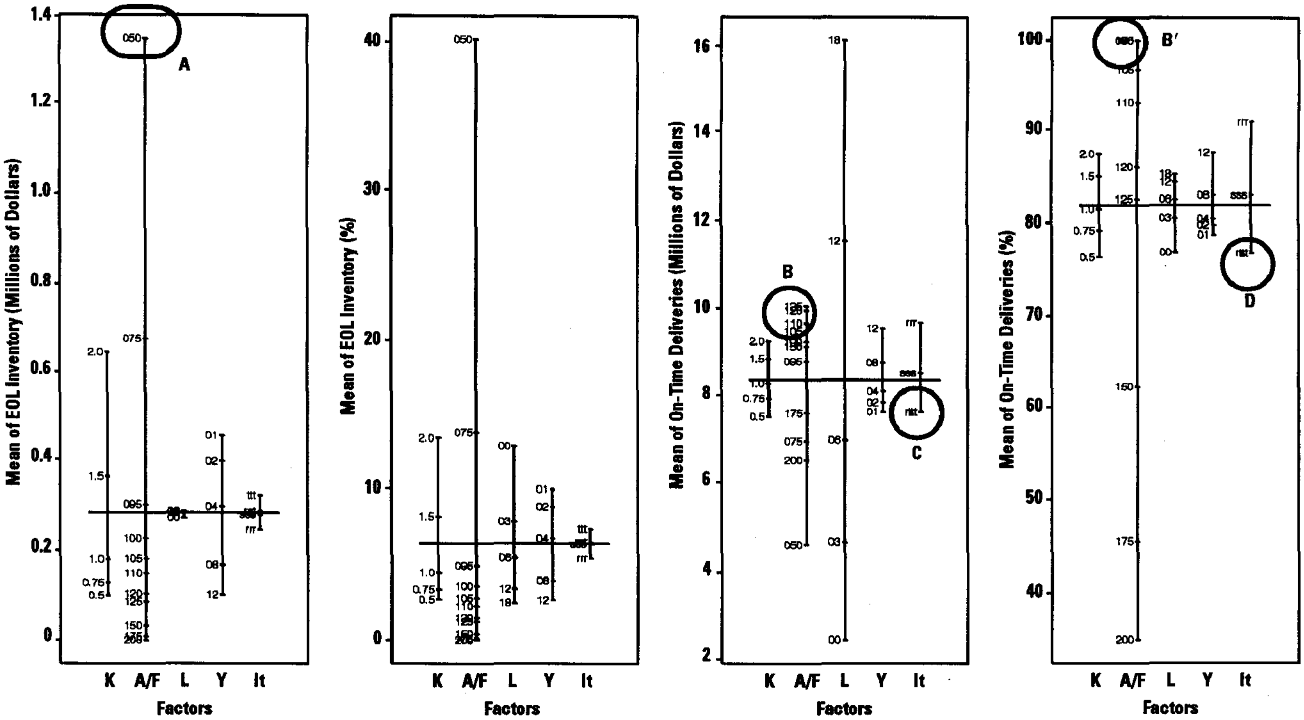
Another interesting behavior is that of the points marked C and D. The fact that the mean values of the metrics appear close together for the (25,40,35) case and the (0,0,100) case suggests that the length of the maximum lead time of parts in the bill of material has a very strong influence on on-time deliveries if all other factors are kept constant.

Further Analysis. We have barely scratched the surface of what is possible in analyzing the simulation data of this one-level bill of material, single-product situation. Further analysis and display of the variables is possible through scatter plots of pairs of variables and responses, and the use of factor plots which show greater detail. For example, further analysis could try fitting a statistical model using least sum of squares of residuals for the responses, separately and jointly. This was not done for this paper.

Experiment Set M: Multiple Product Life Cycles with Part Commonality

This set of experiments showed the impact of part commonality across multiple product life cycles. The product

† We call it a design plot because it is generated by the S-Plus function plot.design. There is no standard name of this plot. In the literature,[23] it is referred to as a "a plot of the mean response for each level of each factor."



Note: It = (% 6-week, % 10-week, % 14-week lead time parts).
rrr indicates It = (100,0,0)
sss indicates It = (0,100,0)
ttt indicates It = (0,0,100)
rst indicates It = (25,40,35).

Fig. 13. Design plots for experiment set F: all five factors varied (5500 runs).

cycles overlapped in time, that is, one started before the preceding one finished, and we looked at a series of scenarios that differed in the values of common parts in adjacent products. These were the assumptions:

- There were four products: Adder-1, Adder-2, Adder-3, and Adder-4.
- Part commonality occurred between adjacent products only.
- Demand increased 30% for each new product.
- The unit cost of each product was 85% of the unit cost of the previous product.
- Each product life cycle was 6 months, or L = 0. This means that the complete cycle for each product is 6 months, or 24 weeks.
- There was a one-month overlap between products, that is, the first month of demand of a new product begins in the last month of demand of the previous product. This implies a total lifetime of the product family of 21 months, or 84 weeks.
- Other factors and conditions remained as in the nominal case.

Fig. 14 shows a graphical representational of the part commonality between adjacent products for the different experiments. In particular, since part commonality for experiment M-0 is 0% across adjacent products, there are no shaded areas. A fuller discussion of part commonality is given in Appendix III.

Fig. 15 shows the forecasted and actual order patterns for the four products.

Fig. 16 shows the RPI levels for parts used in the different products in Experiment M-0 (no part commonality). Consignment inventories are not shown to avoid clutter in the graphs. The WIP, FGI, products ordered, PCFT and delivery profiles are identical for all runs in experiment set M. However, each of the runs has a different profile for RPI. Note the EOL inventory of each set of parts.

Fig. 17 shows the consignment and EOL inventory levels for each run. As expected, the consignment level increases by product because the forecasted and actual orders increase by product. The consignment value for a particular product is the same across experiments. The EOL inventory for Adder-4 is the same in all the experiments. There does not appear to be any correlation between part commonality and the EOL inventory. A correlation exists between part obsolescence for a product and the EOL inventory for that product.

Fig. 18 shows the part obsolescence across products for each of the experiments. Notice how the EOL for each product in Fig. 17 is proportional to the obsolete parts for each product in Fig. 18.

Traditionally, in considering part commonality, design principles suggest using as many parts as possible from the old product. However, the results above suggest that from the point of view of EOL inventory, the amount of leftover material at the end of each product is proportional to the percentage of the part value of the obsolete parts in the old product.

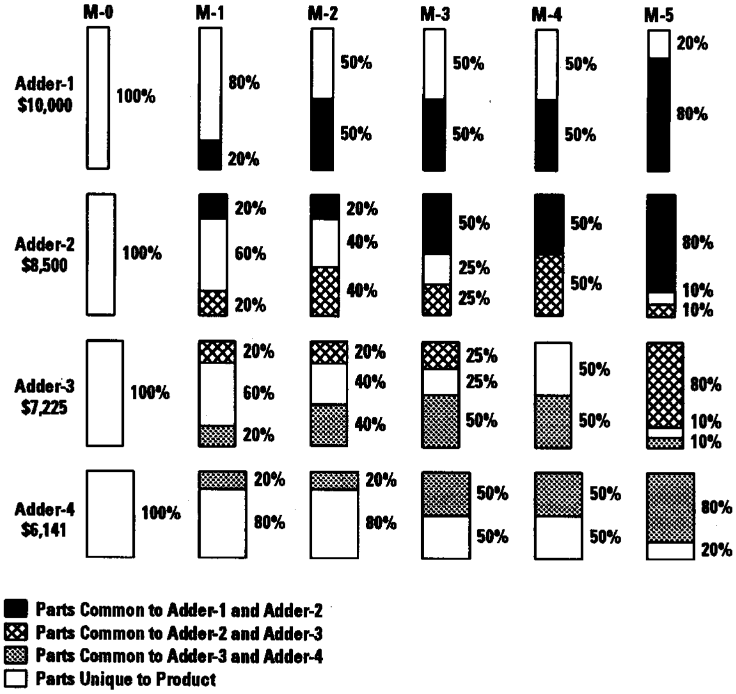


Fig. 14. Part commonality between products across experiment set M. Demand (width of bars) for each product is 30% higher than for the previous product. Unit cost (length of bars) is 85% of previous product cost.

It further suggests that the important consideration from the point of view of EOL inventory is that the percentage value of obsolete parts at the end of each product's life should be minimized.

Discussion

In this section we discuss specific results of the Simple Model, enhancements to the EMS system to do more detailed analysis, the role of the Simple Model in enterprise modeling and simulation, and optional ways of using enterprise modeling and simulation.

The major results can be summarized as follows:

- Rational material ordering and safety stock policies designed to reduce inventory to zero at the end of the product life cycle can give rise to leftover material if customers orders exactly according to forecast.
- System behavior and the impact on different metrics such as write-off, delivery times, and performance deliveries can be quantified with respect to the factors of forecast quality, safety stock levels, material lead times, product life cycles, and quoted availability individually as well as in combination.
- Forecast quality, which is influenced by the external environment, has a major effect on the metrics of interest. For example, high inventory levels may occur when actual orders come in too high or too low.
- The influence of part commonality on write-off can be quantified; this suggests an alternative way of looking at the practice of using common parts in a series of products.

What have we learned from the simulation runs on the Simple Model? We have derived a set of specific insights into system behavior under a variety of operating conditions using a methodology of generating behavior over time. We went through a large number of scenarios and showed how to gauge system behavior from the perspectives of different parties.

Interpreting the Results

The model results are sensitive to the underlying assumptions. Since we assumed the vendors always delivered on time in the simulation, the safety stocks in effect guarded only against demand uncertainties. We examined in detail the situation of order forecast bias with zero variance. This

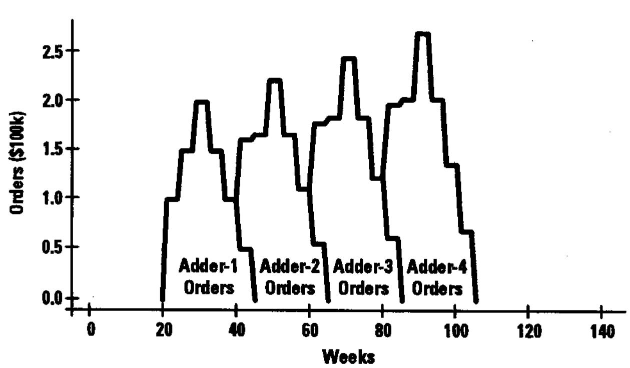


Fig. 15. Orders for different products for experiment set M.

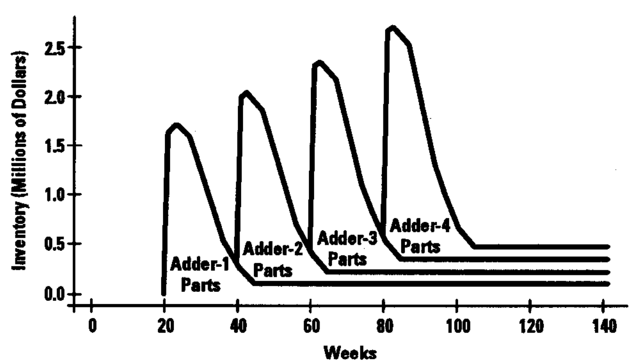


Fig. 16. RPI levels for the different parts as a function of time for experiment M-0 (no part commonality).

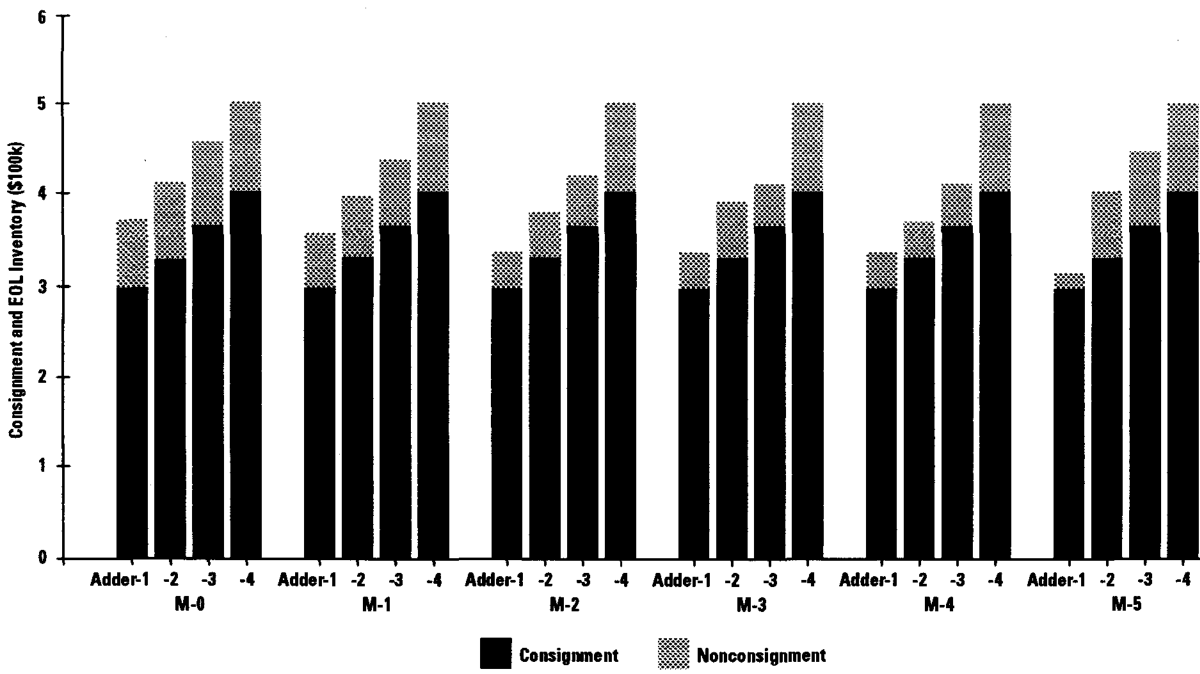


Fig. 17. Consignment and EOL inventory by product for different amounts of part commonality for experiment M-0.

is not an inherent limitation of the model, but reflects only the deterministic circumstances in which we ran the simulations. However, the results indicate that even if production and supplier lead times are completely predictable and suppliers deliver on schedule, interactions and delays within the system lead to long lead times being seen by the customers when there is underforecasting of customer orders. The manufacturing enterprise needs to take this into account and start looking elsewhere—merely making the production faster and more efficient is not sufficient.

The results so far have only scratched the surface of the analysis and interpretation possibilities. Other analysis could be done by varying ship times, FGI safety stock levels, production planning frequency, material ordering frequency, order filling policies, and uncertainty and time delays of information flow. This increases the number of runs and the quantity of data collected as well as the complexity of analysis, but would provide a richer set of relationships.

The Simple Model example may have left the reader with the impression that the current EMS system can deal with only simple or trivial cases. One goal of enterprise modeling and simulation research activities is to address successively more complex interactions and to model real-world intricacies more closely. In support of that goal, the following sections discuss subsequent and future enhancements to deal with other issues that have been raised.

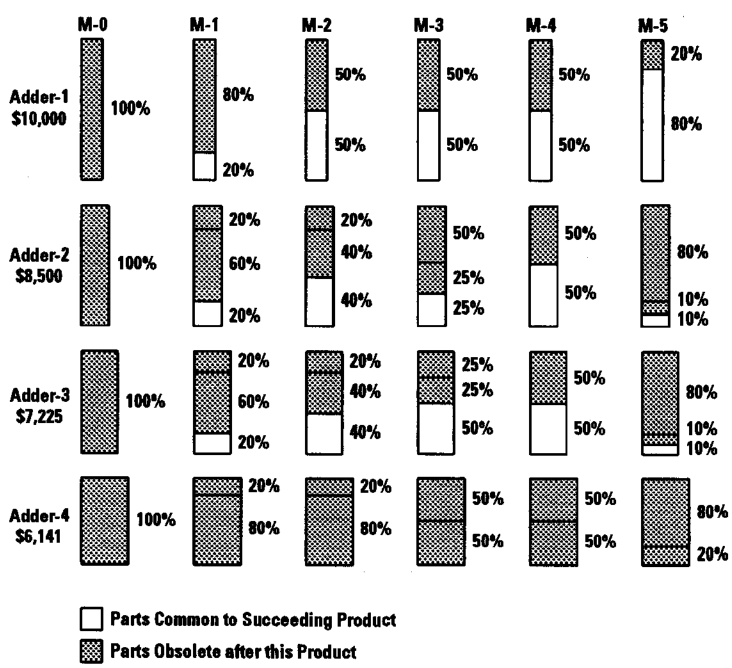


Fig. 18. Parts obsolescence between products across experiment set M.

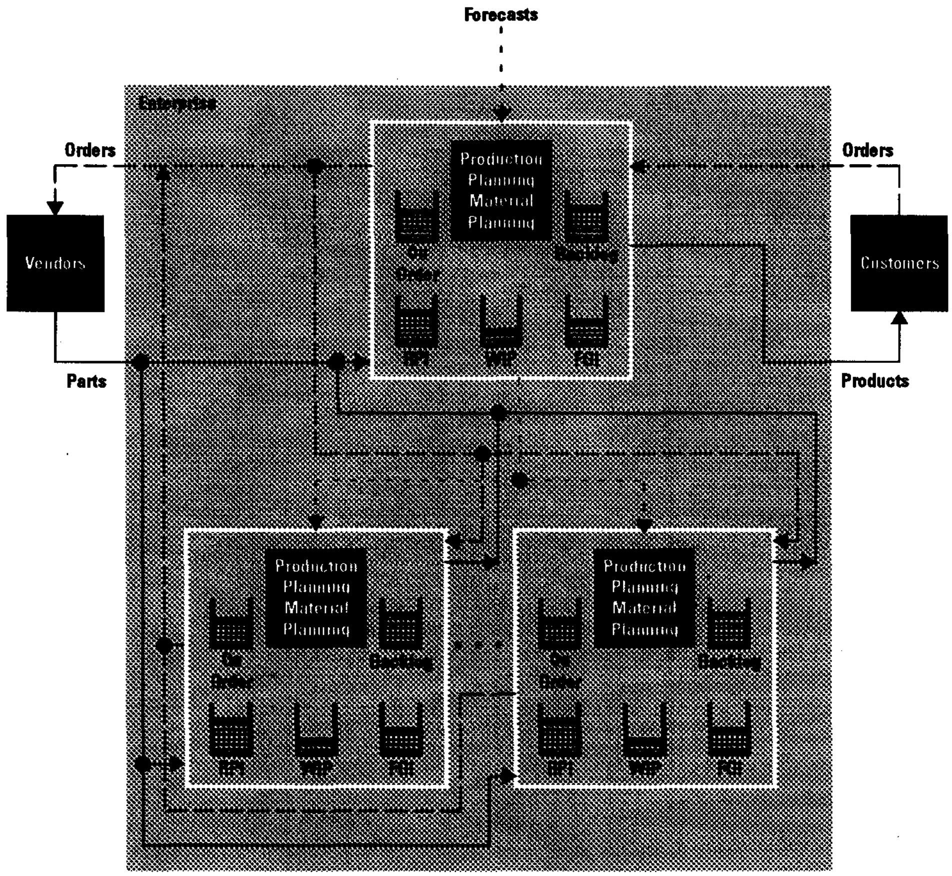


Fig. 19. Material and order flow diagram of a simple multientity distributed enterprise.

Uncertainty and Variability. In the experiments described, the Simple Model was run under deterministic circumstances. Demand values and process times were constant across a particular run for convenience of understanding, and we considered uncertainty in the form of forecast biases where demands were a fixed multiple of forecasts over the period of the forecasts. Other forms of uncertainty could include the actual life cycle being different from the forecasted life cycle. Uncertainly in process times could be handled by using two values for process times: the planned process time for planning purposes and the actual time for execution. This reflects the situation when actual process times are uncertain and different from the estimated times for the process. For example, the build time for planning purposes could be two weeks, but it could turn out that the actual build time was one or three weeks.

We did not deal with variances that might occur when the total demand is forecasted accurately but the week-to-week demand fluctuates widely. Furthermore, variances of process times (e.g., delivery times from vendors and assembly times), yields (e.g., defective units), and build times for individual units were not modeled.

Dealing with variances is fairly straightforward once they are characterized. It requires using random number generators and multiple runs starting with different random number seeds—the current practice of discrete event simulation. There are three primary costs associated with this: the increase in data collection to characterize the variances of different processes, the increase in computational effort, and the increase in analysis effort. Only the data for the model needs to be changed to reflect variances. The model structure itself requires no changes.

Distribution and Multisite/Multiorganizational Interaction. The product distribution function and interaction between multiple sites were not considered in the Simple Model. Multisite and multiorganization interactions have been implemented by enclosing cloned versions of a slightly enhanced manufacturing enterprise model as shown in Fig. 19. The enhancement requires the manufacturing facility to generate and transmit its projected material requirements in addition to material orders.

Capacity and Supply Limitations. In current practice, build plans and material plans are sometimes computed ignoring production capacity and vendor limitations. In some cases, these plans are adjusted to conform to production capacity and vendor supply constraints, such as a minimum order quantity or a maximum that can be ordered in a period. In other cases, these limitations are observed at plan execution, that is, at production, or when deliveries are not received from vendors when expected. There is no unique way of dealing with these limitations.

Implementing capacity limitations in the current Simple Model is straightforward during production. To deal with it during planning requires the inclusion of two classes of capacity constraints in the production planning algorithms: the capacity restrictions for an individual product, assembly, or subassembly as well as total capacity, and the rate at which production capacity can increase.

In reality, when prospective capacity limitations are detected, production and manufacturing line design and engineering considerations determine the rate of capacity expansion. When gross overcapacity is detected, consideration is given to reducing costs by reducing capacity. While currently the EMS system cannot model the strategic decisions of whether to expand capacity or forego extra orders, it can model the consequences of picking either of these actions.

Interaction of Multiple Products. The Simple Model assumed a single product with unconstrained production capacity. Consequently, a single unavailable part stops production of that product. Since this phenomenon also occurs with multiple products with no common parts, multiple products with no common parts can be analyzed by adding up the effects of the individual products separately. The reader familiar with linear systems will recognize this as the principle of superposition.

Adding up the results would also be valid for multiple products with common parts with no part shortages as in experiment set M. It would not be valid for multiple products with common parts, resources, and supply and production capacity limitations under scarcity conditions. When a part or resource is in short supply, decisions must be made on how to allocate the parts and resources based on some simple heuristic or optimal allocation scheme.

Multilevel Bills of Materials. The Simple Model dealt with a single-level BOM. Further expansions allow an arbitrary number of levels of BOM to be passed as data to the model. A seven-level BOM for a real product has been implemented and tested successfully. This capability to pass BOM as data allows us to make different runs with different product structures (as for example in experiment set M) without modifying the model structure.

Connection to a Mathematical Programming or Optimization Package. The Simple Model focused on applying simple algorithms for planning. The production planning and material procurement processes were initially implemented as the explicit closed-form solutions derived in Appendix I. It was realized subsequently that these algorithmic closed-form solutions were the solutions to the linear programming problem formulation. As more sophisticated planning decision techniques are proposed and studied, implementing the algorithmic solution for each new technique becomes impractical. An alternative approach is to formulate the planning process as an optimization problem and separate its solution from the formulation. This leads to concentrating on ways to better formulate the problem, leaving the solution to a separate process such as a mathematical programming package. This could provide a means of rapidly testing alternative strategies for production planning (e.g., global production planning across the entire enterprise versus local production planning at each site).

R&D, Marketing, and Cash Flow. Fig. 20 shows a proposed enterprise model at a broader scope for the next level of complexity. It generalizes Fig. 3 which focused mainly on manufacturing activities. Modeling the marketing function (and associated activities such as the forecasting process, pricing issues, and product obsolescence) could help show the impact of marketing decisions and activities on the overall system response as well as the impact of using current orders to project future forecasts. Modeling the R&D function could provide insights on impacts on time to market, with product development time taken into account in addition to build time. Modeling these functions can help us deal with situations that require coordination of marketing, R&D, and manufacturing activities and can help identify the existence of leverage points for process improvement. The blocks shown in the diagram represent functions, and each could describe multiple instances of that function. For example, the block labeled manufacturing could represent multiple manufacturing sites interacting with one another.

The primary flows in the Simple Model concentrated on information (e.g., orders, forecasts, plans, and status information), material, and control (e.g., triggers that cause activities like

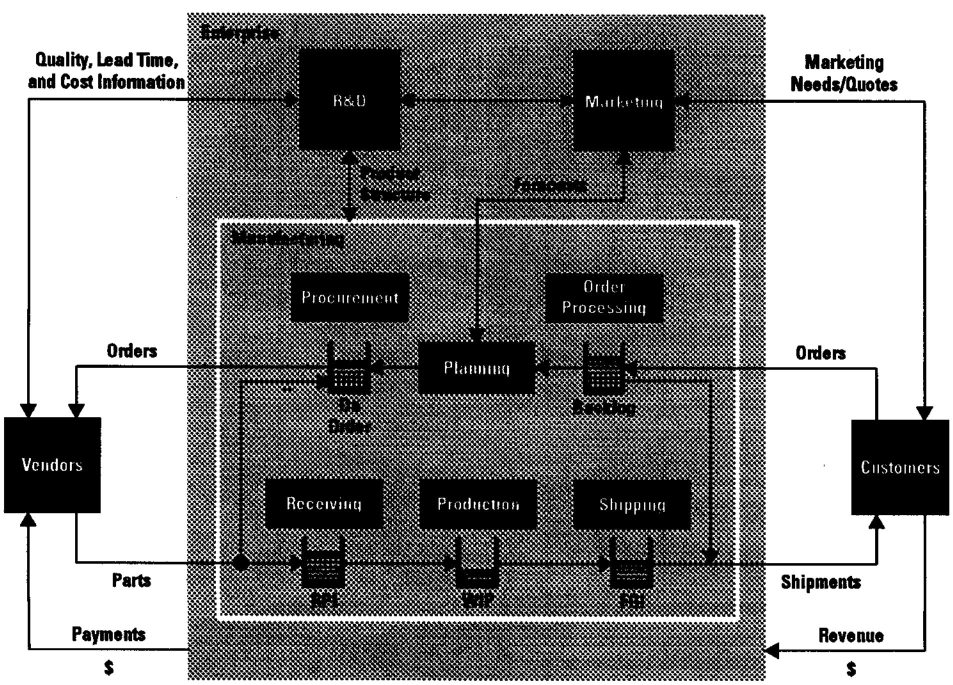


Fig. 20. Proposed enterprise modeling entities for expanded analysis.

production to start). Flows and inventory levels were converted to monetary units before being analyzed, but cash flows were not modeled explicitly.

Modeling cash flows for payments of parts, products, and process costs will provide a financial perspective. Showing projected cash flows and investments and the projected financial consequences of investment decisions will provide the stepping stones to doing discounted cash flow and net present value analysis. Modeling cash flows will also help generate pro forma financial statements to estimate revenue, cost, and income owing to different capital budgeting and allocation decisions, and provide a tool that could help address business issues. An example of such an issue is the transition from a high-margin business to a low-margin high-volume business.[24] The model may help by projecting cash requirements for investments and operations and providing estimates for return on assets during the transition.

Whither the Simple Model and the EMS System?

The Simple Model is not an end or final model; it is intermediate in a series of models that have contributed to the evolution of enterprise modeling and simulation (see page 12) and the development of the EMS system. Its simulation demonstrates the kinds of results that can be generated by enterprise modeling and simulation. Its value is in providing greater quantitative analysis where previously qualitative approaches have been adequate (see below). Its immediate subsequent application was the planning calendar model.[25,26,27]

The subsequent and future enhancements discussed make the Simple Model more complete. Some of the changes make the model larger, add detail complexity, and generate more precise results. Other changes broaden the scope of the model, and make it more representative of the other functions of the enterprise besides manufacturing; these changes require the addition of greater levels of abstraction, the ability to consolidate different points of view, and knowledge acquisition across the organization. All the changes are technically feasible and require different kinds of activities: the first set of changes requires greater emphasis on "modeling in the small," and the second set requires greater emphasis on "modeling in the large" (see discussion on page 3). Discussions based on the experience and views of some managers responsible for operations suggest that expanding the size by increasing the detail complexity, while providing greater predictability of the system, is difficult and requires a tremendous amount of investment to manage the complexity of the models and the generation and interpretation of the resulting data. Monroe[24] and Harmon[28] have individually recommended that there is greater value and potentially a far greater return on investment to be obtained by broadening the scope of future models to address and reflect business issues and concerns.

Regardless of the direction of model enhancement is the challenge of managing simulation data. The simulation runs for the experiments generated large amounts of data, and only aggregate data was collected and summarized. For instance, RPI levels for every part were generated for each week during the simulation, but the data collected was the aggregate dollar value of all the parts. The challenge became one not of collecting all data, but one of deciding ahead of time which data was interesting and not collecting that which was not; otherwise the storage requirements for storing all the generated data became significant. The data presented in the form of graphs and charts in this paper is only a small portion of the actual data collected and analyzed. A larger amount of collected data was discarded because it did not look interesting.

The sheer amount of detailed data that needs to be examined and interpreted tends to overwhelm the analyst. The analysis and interpretation of the data was very much a creative team effort requiring much discussion, and is not yet understood well enough to be automated. As we increase the number of factors, the behavior becomes more complex, and the amount of data tends to increase exponentially with the number of factors. When presented with the data in its raw form, decision makers and experts familiar with the problem issues but less familiar with modeling and simulation all have the same general reaction that it is too complex and difficult to understand. While this is a valid reaction, the reality is that the enterprise is a complex system of interacting information, material, resource, and control flows, and whether we like it or not, has complex behavior. Enterprise models as abstractions or idealizations for the real system merely reflect that complex behavior in the simulation. We can choose to ignore the complexity of the real system and use ad hoc qualitative methods to deal with the resulting behavior, or we can choose to face the complexity, understand it by selecting what we think are important factors that influence the behavior of the enterprise, and find opportunities for applying the understanding. Enterprise modeling and simulation represent one means of facing this complexity and providing an understanding of this behavior. As with most endeavors, we have found that the precursor to simplicity of expression is greater depth of understanding.

Increased technology in the hands of the modeling and simulation expert is not sufficient for providing the insight that will help make better decisions and highlight important results. Merely generating large numbers of insights and conclusions is insufficient. It requires the perspective of operations

The Simple Model: Sponsor's Perspective

As HP's Computer Systems Organization customers increasingly request delivery of complete systems with much shorter lead times, our design, manufacturing and delivery systems are being stretched beyond their performance limits.

Qualitative approaches to improvement have served us well in the past, but more quantitative analysis is needed to understand and improve the total system both from a customer and an HP perspective.

The Simple Model was conceived and developed in teamwork with HP Laboratories. We sponsored it to help learn and communicate the key drivers and characteristics of a manufacturing enterprise. The insight achieved could then be used in our order fulfillment initiative to design product, manufacturing, and delivery systems to match critical business requirements and position us to meet future customer needs effectively in the global marketplace.

Jerry Harmon
General Manager
HP Puerto Rico
Sponsor of Simple Model
for HP Computer Manufacturing

teams and decision makers to guide the direction of exploration and to emphasize the correct metrics to solve the current situation. In fact, Monroe[24] has suggested, and we in the enterprise modeling and simulation project concur, that techniques to digest and present large amounts of data rapidly and in a more easily understood fashion would be a beneficial next step and a fruitful area of research, and that joint work of a modeling expert with an operations team to further understand the issues of data reduction, interpretation, and presentation will help modeling and simulation take its rightful place as a useful tool in analyzing business decisions.

The Simple Model is a descriptive model that illustrates complex dynamic behavior of a manufacturing enterprise with low structural and detail complexity. As we have seen in this paper, its primary output is data and information on the state of the world, and it goes a great distance towards presenting observations. Unlike an optimization model, which is a prescriptive model whose solution recommends the best action under a given set of circumstances, the Simple Model does not suggest actions. It is up to the analyst or decision maker to come up with creative solutions to solve the problems highlighted by observations of the model behavior and then assess the results from a subsequent simulation run incorporating those solutions.

Prospective Applications

Let us now look at application areas for enterprise modeling and simulation. These include but are not limited to improving the performance of the current system (continuous improvement), studying the impact of reducing process times, and generating information for the enterprise, all of which are discussed below. A potentially far more powerful application is looking at new designs where the process itself is being changed (i.e., reengineering). Because of the strong current interest, large impact, and controversy surrounding reengineering, this subject is given its own discussion on page 8.

Incremental Improvements. Actions for continuous improvement can be suggested by running the nominal or baseline model and rerunning it with minor modification and changes in parameters or actions over which we have control. For example, it may not be possible to reduce all the part lead times down to six weeks, but we could certainly see the impact of reducing the value of 14-week parts in the product to determine the impact on the metrics of interest. We could look at the impact of reducing build times or FGI safety stock levels slightly to study the impact on the measures of interest. We could examine the impact of making two small changes at the same time. This application of enterprise modeling and simulation supports the process of continuous improvement by demonstrating the benefits of small changes.

Verifying Impact of Reducing Process Times. Davidow and Malone[29] talk about how short cycle times attenuate "the trumpet of doom," which is a plot of forecasting error versus time that implies that the further a person must forecast into the future, the greater the possibility of error. Rather than speculate on or guess on the impact of this trumpet of doom, enterprise modeling and simulation provide a way to quantify the effect of reducing system cycle times. This can be accomplished by making some estimates of the amount of uncertainties within the model.

Stalk and Hout[30] suggest mapping out explicitly the major causes of problems in processes such as new product development or in operations, and comparing actual versus standard cycle times. These maps provide qualitative relationships. To the extent that processes can be mapped explicitly and quantitatively, enterprise modeling and simulation can show how the system behavior changes for a given change in the process and can verify whether modifying the component processes has the desired overall global effect.

Generating Enterprise Behavior Information. Davidow and Malone[29] identify four categories of information of use to a corporation: content, form, behavior, and action. Content information is historical in nature and reflects the experience. Form information describes shape and composition and is usually more voluminous than content information. Behavior information often begins with form information and usually requires a massive amount of computer power to predict behavior through simulation. They suggest that the final triumph of the information revolution will be the use of action information—information that instantly converts to sophisticated action. Until recently, only the most elementary category, content, has been available to business in any systematic and manageable way, and obtaining or generating the other three categories has become economically feasible only in recent years. They go on to describe how behavior information generated by computer simulation is the new paradigm for product design ranging from molecular design through automotive design to airplane design. With such behavior information design disasters of the past might be averted, and potential and unforeseen future tragedy can be replaced with a successful and predictable conclusion. With the arrival of workstations in the 1980s, it became reasonable for the computer to create realistic models and put them through their paces rather than painstakingly building prototypes and testing them under a variety of operating conditions. High-speed simulators could be built that reproduced the actual electrical characteristics of devices in different configurations.

We suggest that enterprise modeling and simulation represent an assistive and enabling technology for the design and implementation of processes of the enterprise, and that the application of such techniques to the enterprise could potentially have greater impact than product design. Furthermore, these techniques have the characteristic of converting content and form information into behavior information on which action can be taken. While the enterprise modeling and simulation process currently does not suggest actions or alternatives, it describes the behavior of the system designed with alternate processes under different operational scenarios.

Conclusions

In this paper, we outlined activities in enterprise modeling and simulation at HP Laboratories and presented in detail the results of the simulation of a simple model of a manufacturing enterprise. We have also described possible areas where enterprise modeling and simulation might be applicable, and reiterate that enterprise modeling and simulation provide a way of quantifying the impacts of proposed changes before they are implemented.

The Simple Model captures the characteristics and behavior of a manufacturing entity at a fairly high level. It shows that in the best of circumstances (e.g., customers ordering exactly according to forecast), seemingly rational operational policies can lead to end-of-life inventory. The situation only gets more complex as greater uncertainty is introduced.

Experience with using the Simple Model suggests two directions for future research in enterprise modeling and simulation. The first is to expand the scope of the Simple Model to more completely represent the functions and organizations and their interactions in the enterprise. The second is to improve the process by which the data generated by the simulation models can be understood and summarized, and the resulting information presented in a form that permits decision makers to understand more completely and to act more rapidly and with greater assurance that the desired objectives will be achieved.

Acknowledgments

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Appendix I: Mathematics of Production and Material Planning for the Simple Model

I-1 The Planning Function

The planning function is actually an analytic model embedded within a discrete event simulation model. The fundamental principle on which the production and material planning algorithms are based is the conservation of mass, that is, consumption cannot be higher than the total supply available. The order in which the build plan computation is done is the reverse of the order in which subassemblies are built and products are shipped (i.e., from shipment to product build to part order). For ease of explanation, the current week is considered to be week 0. This derivation emphasizes clarity of explanation rather than rigorous detail.

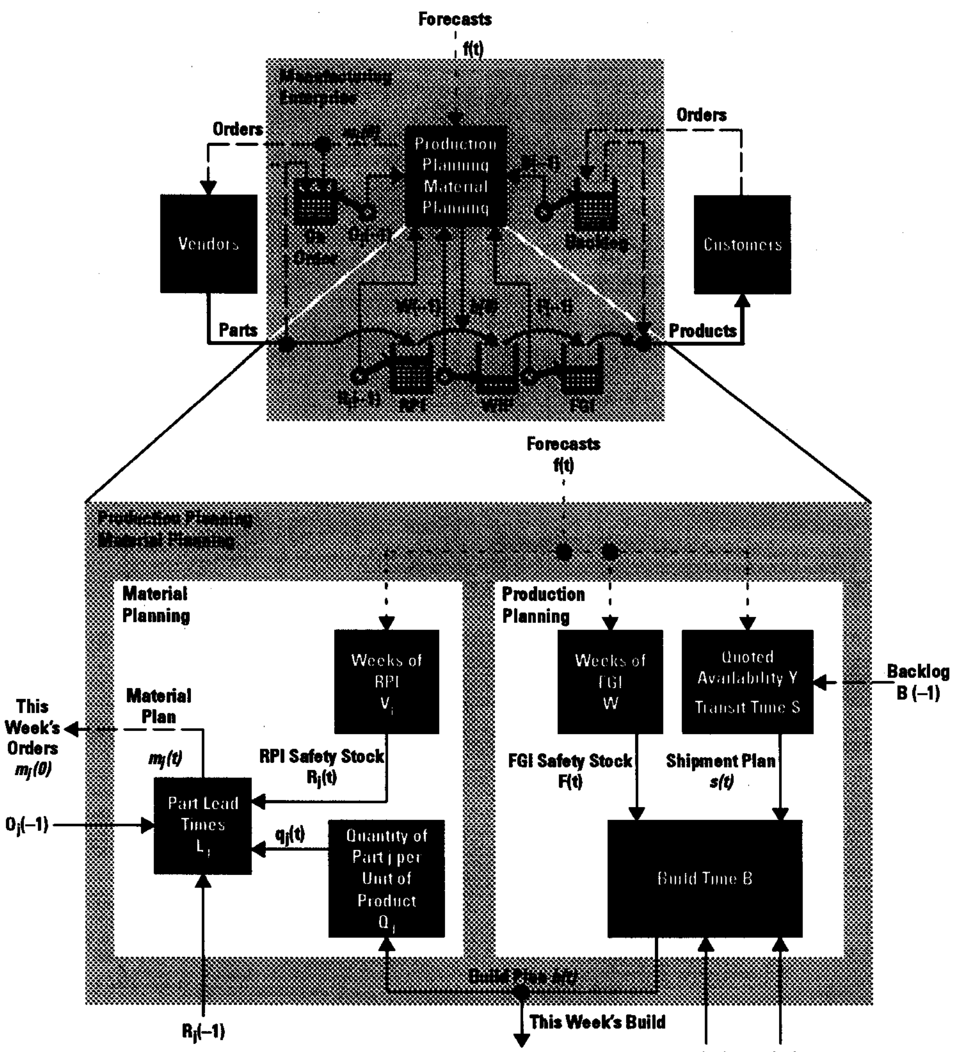
There are three sets of decision variables to be determined for each week: *s(t)*, the shipment plan, *b(t)*, the build plan, and $m_j(t)$, the material ordering plan. These are shown in italics.

Before we get into the mathematical formulation, let us first look at the process of computation. Fig. 1 illustrates how the production and material planning algorithms work in this model. The computational process is described in the following order:

- I-2 describes the notation shown in Fig. 1.
- I-3 describes the safety stock computation.
- I-4 describes the initial conditions for computation.
- I-5 describes the computation of the shipment plan.
- I-6 describes the computation of the build plan.
- I-7 describes computation of the number of units started this week.
- I-8 describes the computation of the material consumption and material ordering plans.
- I-9 describes the actual material ordered this week.
- I-10 describes the computation of the number of weeks for each of the plans.

I-2 Notation

- n, s, t = indexes for week number (current week = 0)
- f(t) = Current forecast of product orders for week t, t = 0, 1, ..., N_f
- F(t) = FGI at end of week t
- W(t) = WIP at end of week t
- B(t) = Backlog units at end of week t
- B(t,s) = Backlog units at end of week t having shipment dates in week s
- *s(t)* = Planned shipments during week t
- *b(t)* = Units planned to be started during week t
- B = Build time in number of weeks
- Y = Quoted availability in number of weeks
- S = Shipment or transit time
- j = Index relating to part
- Q_j = Quantity of part j per unit of product
- $q_j(t)$ = Planned consumption of part j during week t



Note: Subscript j indicates ∀j∈J.

Fig. 1. Notation and production/material planning. The shipment plan is computed from the backlog, forecasts, quoted availability, and transit time. The build plan is computed from the shipment plan, the build time, WIP, FGI, and FGI safety stock. The actual build is computed from the build plan and the material availability. The material consumption plan is computed from the build plan and the bill of materials. The material ordering plan is computed from RPI, RPI safety stock, the material consumption plan, on-order material, and lead time.

- $m_j(t)$ = Planned quantity of material j to be ordered during week t, t = 0, 1, ..., N_j, $j \in J$
- $R_j(t)$ = RPI of part j at the end of week t
- $r_j(t)$ = Units of part j received during week t
- $O_j(t)$ = Units of part j on order at the end of week t
- L_j = Vendor lead time for part j
- J = Set of parts that go into the product
- w = FGI safety stock in weeks of demand
- V_j = RPI safety stock of part j in weeks of demand
- N_s = Last week for computing shipment plan
- N_b = Last week for computing build plan
- N_f = Last week used for forecasts
- N_j = Last week for computing material order for part j.

Since the current week is 0, the values of these variables represent actual values for weeks before 0, and the values are computed, set, or derived for weeks 0 and later. In particular, the values of variables at the end of week –1 represent the current values of those variables, as described in I-4. All numerical quantities except time indexes are zero or positive.

I-3 Safety Stock Computation

Safety stock is expressed in number of weeks of 13-week leading average forecast. The 13-week leading average forecast at the end of week t is defined as:

$$\overline{f(t)} = \frac{1}{13}\sum_{i=1}^{13} f(t + i) \tag{1}$$

The target FGI safety stock at the end of week t is w weeks and the target RPI safety stock at the end of week t for part j is V_j weeks. The expressions for these quantities are:

$$F(t) = w\overline{f(t)} \tag{2}$$

$$R_j(t) = V_j Q_j \overline{f(t)} \tag{3}$$

I-4 Initial Conditions

- F(–1) = Actual FGI at the end of the previous week, that is, current FGI
- W(–1) = Actual WIP at the end of the previous week, that is, current WIP
- $O_j(-1)$ = Actual part j on order at the end of the previous week, that is, current on-order material
- $R_j(-1)$ = Actual RPI for part j at the end of the previous week, that is, current RPI for part j.
- B(–1) = Order backlog in units at the end of the previous week, that is, current backlog:

$$B(-1) = \sum_{s \in (\text{all shipment dates in current backlog})} B(-1, s) \tag{4}$$

- B(–1,s) = Component of current backlog with shipment date in week s.

I-5 Shipment Plan

The shipment plan indicates prospective shipments during the current and future weeks. It is computed on the assumption that customer orders are not shipped before they are due, but are shipped in time to satisfy the quoted availability requirements. This implies that for any week, the orders planned to be shipped are those that are already late (i.e., should have been shipped in an earlier week) and those that must be shipped to be delivered on time. Notice that in computing the shipping plan, we do not take into account the amount of inventory on hand or in process. This is representative of the way shipment plans are computed and then subsequently checked against reality.

Put another way, this can be expressed as planning to ship the minimum quantity in each week that will satisfy the quoted availability criteria. The problem can be formulated as shown in the set of equations below, which indicate that we are attempting to minimize shipments in the current week, current plus next week, current plus next 2 weeks, and so on such that the total shipments in those weeks is greater than the current existing backlog whose shipment date is already past or in those weeks, plus the forecasted orders whose desired shipment dates lie in those weeks.

Minimize $s(n)$, n = 0,1,...,N_s

$$\text{such that } \sum_{t=0}^{n} s(t) \geq \sum_{t \in (i \mid i \leq n)} B(-1, t) + \sum_{t=0}^{n-(Y-S)} f(t)$$

and $s(n) \geq 0$.

These equations define a series of (N_s + 1) linear programming problems. However, this formulation will always return a set of feasible solutions, and the optimal feasible solutions can be expressed in closed form as follows:

$$s(n) = \begin{cases} \sum_{s \in (i \mid i \leq 0)} B(-1, s) & \text{for } n = 0 \\ B(-1, n) & \text{for } 0 < n < Y - S \\ f(n - (Y - S)) & \text{for } n \geq Y - S. \end{cases} \tag{5}$$

The term (Y – S) is the difference between the quoted availability and the transit time (i.e., the order-to-ship time to achieve on-time delivery), and indicates the time in the future after which shipments depend solely on forecasts.

I-6 Build Plan

The build plan, which indicates how many units are to be started in the current week 0 and succeeding weeks, is based on the assumption that the FGI levels at the end of weeks 0,1,...,B–1 have already been determined by the current FGI, WIP, and shipments preceding week 0. It further assumes that we might be able to control FGI at the end of week B or later by deciding how many units we start this week and future weeks, that is, by controlling $b(0), b(1), \ldots, b(n)$. We want to keep the $b(n)$ as low as possible but greater than or equal to 0, such that the total planned build during weeks 0 through n must be greater than or equal to shipments during weeks 0 through B+n plus FGI at the end of week B+n minus current FGI and WIP. The complete formulation is as follows:

Minimize $b(n)$, n = 0,1,...,N_b

$$\text{such that } \sum_{t=0}^{n} b(t) \geq \sum_{t=0}^{B+n} s(t) + F(B + n) - F(-1) - W(-1)$$

and $b(n) \geq 0$.

Again, the above is a series of (N_b+1) linear programming problems, with optimal feasible solutions that are expressed in closed form as follows:

$$b(n) = \max\left\{0,\ F(B + n) + \sum_{t=0}^{B+n} s(t) - F(-1) - W(-1) - \sum_{t=0}^{n-1} b(t)\right\}, \tag{6}$$

for n = 0, 1, ..., N_b.

To summarize the above, the current build plan should look as follows:

Week:	0	1	2	...	n
Planned Build:	*b(0)*	*b(1)*	*b(2)*	...	*b(n)*.

I-7 Actual Units Started

The actual units started this week, b_0, will be $b(0)$ if there is sufficient material. If there is insufficient material the actual units started is the maximum possible with the available material, or:

Maximize b_0

such that $Q_j b_0 \leq R_j(-1) + r_j(0)$, $\forall j \in J$

and $0 \leq b_0 \leq b(0)$,

for which the closed form solution is:

$$b_0 = \min\left\{b(0), \min_{j \in J}\left(\frac{R_j(-1) + r_j(0)}{Q_j}\right)\right\}. \tag{7}$$

I-8 Material Requirement Analysis

If the lead time for a part j is L_j weeks, the RPI level for part j at the end of weeks $0,1, \ldots L_j-1$ has been determined by material on hand, material on order, and projected use. We could control RPI for part j at the end of week L_j or later by deciding how much of part j we order in this week and subsequent weeks. The estimated material consumption during a week is the quantity of the material for the build for that week, that is:

$$q_j(t) = Q_j b(t). \tag{8}$$

The material ordered during weeks 0 through n must be greater than or equal to the material consumed during weeks 0 through L_j+n plus the desired safety stock at the end of week L_j+n minus the current on-hand material and the current on-order material. This can be expressed mathematically as follows:

Minimize $m_j(n)$, $n = 0,1,\ldots,N_j$, $j \in J$

such that $\sum_{t=0}^{n} m_j(t) \geq \sum_{t=0}^{L_j+n} q_j(t) + R_j(L_j + n) - R_j(-1) - O_j(-1)$

and $m_j(n) \geq 0$.

After substituting equation 8, this becomes a series of linear programming formulations for which the closed form solution is:

$$m_j(n) = \max\left\{\begin{array}{l} 0 \\ \left(Q_j \sum_{t=0}^{L_j+n} b(t) + R_j(L_j + n) - R_j(-1) \right. \\ \left. \quad - O_j(-1) - \sum_{t=0}^{n-1} m_j(t) \right) \end{array}\right. \tag{9}$$

for $n = 0, 1, \ldots, N_j$, $j \in J$.

The current material ordering plan is shown by the following table.

	Week				
	0	**1**	**2**	...	**n**
Material 1	$m_1(0)$	$m_1(1)$	$m_1(2)$	...	$m_1(n)$
Material 2	$m_2(0)$	$m_2(1)$	$m_2(2)$	...	$m_2(n)$
...	...	...	...	...	...
Material j	$m_j(0)$	$m_j(1)$	$m_j(2)$	...	$m_j(n)$
...	...	...	...	...	...

I-9 Actual Material Ordered

Given the table above, the actual material ordered in this week must be $m_j(0)$, $\forall j \in J$.

I-10 Determination of the Required Number of Weeks

Since we want to compute the material procurement plan for material j for periods 0 through N_j, we need to make sure we have values of the forecasts, shipment plan, and build plan far enough in the future to allow us to do so. This section shows how many periods of those plans we need to compute.

In 10 through 16 below, "$m_j(n)$ requires x(n)" should be read as, "Computing $m_j(n)$ requires values of x(0), x(1), ..., x(n)." Thus 10 should be read as, "Computing $m_j(N_j)$ requires the values of $R_j(0)$, $R_j(1)$, ..., $R_j(L_j+N_j)$."

From 9,

$$m_j(N_j) \text{ requires } R_j(L_j + N_j) \tag{10}$$

$$\text{and } m_j(N_j) \text{ requires } b(L_j + N_j). \tag{11}$$

From 10, 3, and 1,

$$m_j(N_j) \text{ requires } f(L_j + N_j + 13). \tag{12}$$

From 11 and 6,

$$m_j(N_j) \text{ requires } F(B + L_j + N_j) \tag{13}$$

$$\text{and } m_j(N_j) \text{ requires } s(B + L_j + N_j). \tag{14}$$

From13, 2, and 1,

$$m_j(N_j) \text{ requires } f(B + L_j + N_j + 13). \tag{15}$$

From 14, 5, and 1,

$$m_j(N_j) \text{ requires } f(B + L_j + N_j - (Y - S)). \tag{16}$$

Computation of N_b. From 11,

$$N_b = \max_{j \in J}\{L_j + N_j\}. \tag{17}$$

Computation of N_s. From 14,

$$N_s = \max_{j \in J}\{B + L_j + N_j\}. \tag{18}$$

Computation of N_f. From 12, 15, and 16,

$$N_f = \max_{j \in J}\left\{\begin{array}{l} L_j + N_j + 13 \\ B + L_j + N_j + 13 \\ B + L_j + N_j - (Y - S) \end{array}\right. \tag{19}$$

Since $B \geq 0$, $(Y-S) \geq 0$, the middle expression dominates, and 19 reduces to:

$$N_f = \max_{j \in J}\{B + L_j + N_j + 13\}. \tag{20}$$

Appendix II: Weekly Event Sequence

In the following table, periodically scheduled events are shown in sequence.

Event Time	Event Frequency	Initiators	Event Description
Monday 1:00	Weekly	Customers	Generate and send orders; these orders are received by the Adder factory at 9:30:00 the same day.
Monday 8:00	Weekly	Factory	Completes computing FGI safety stock for future weeks. Completes computing shipment plan and build plans.
Monday 9:00	Weekly	Factory	Completes computing material requirements plan. Completes computing material procurements plan.
Monday 10:00	Weekly	Factory	Generates current week's material orders. Material orders arrive at the vendors instantaneously.
Monday 10:00:01	Weekly	Vendors	Finish filling and shipping orders due this week. Shipments arrive at the factory instantaneously.
Monday 10:30	Weekly	Factory	Begins current week's production. Completes production started two weeks ago.
Friday 16:30	Weekly	Factory	Completes filling and shipping orders for the week.
Friday 23:58	Weekly	Simulation Executive	Records values of all the state variables.

Appendix III: Details of Part Commonality Experiments

The following table shows the definitions used to describe part commonality. MC stands for material cost, with uppercase denoting dollar values and lowercase denoting percentage values. m represents the set of material.

	Set of Material	Value of Material	Percentage Value
Common to products i and i–1	$m_{i,i-1}$	$MC_{i,i-1}$	$mc_{i,i-1} = \frac{MC_{i,i-1}}{MC_i} \times 100$
Unique to product i	$m_{i,i}$	$MC_{i,i}$	$mc_{i,i} = \frac{MC_{i,i}}{MC_i} \times 100$
Common to products i and i+1	$m_{i,i+1}$	$MC_{i,i+1}$	$mc_{i,i+1} = \frac{MC_{i,i+1}}{MC_i} \times 100$

Commonality occurs only between adjacent products. This implies that a part can be used in at most two products.

Each of the $MC_{i,j}$ is further broken up into class A, B, and C parts with relative values 50, 30, and 20 percent. Each of these classes is made up of 6, 10, and 14 week lead times with relative values 25, 40, and 35 percent. (See Table I on page 5.)

At the end of the product i life cycle, obsolete inventory (if any) should come only from parts in sets $m_{i,i}$ and $m_{i,i-1}$. Any leftover parts from $m_{i,i+1}$ can be used in product i+1. This implies that $mc_{i,i-1}$ and $mc_{i,i}$ impact the obsolete inventory at the end of the product life cycle for product i.

The values shown in the following table should be derived from the real bill of materials. For our experiments, we reverse the process, that is, we generate a bill of materials from the table, which was generated heuristically from the experimental scenarios, with the following constraints on the values of mc:

- For each i and j, $mc_{i,j}$ must be greater than or equal to 0 and less than or equal to 100.
- For each i, the sum of $mc_{i,j}$ over all j must be 100.
- In each experiment, if any $mc_{i,i+1}$ is zero, then $mc_{i+1,i}$ must also be zero.

Description of Experimental Scenarios

Run M-0: no part commonality at all between adjacent products.

Run M-1: 20% part commonality between adjacent products. The parts common to products i and i+1 make up 20% of the part values of both products. This may happen by a reduction in either part quantity or part cost, but the reason is not reflected in the dollar value of leftover inventory or material.

Run M-2: 20% part commonality when moving to a new product. The parts common to products i–1 and i make up 20% of the part value of product i; the rest of the value of product i is split equally between the parts unique to product i and those common to products i and i+1. Since product Adder-1 has no prior product, the value is split equally between unique parts and parts common to Adder-1 and Adder-2. 20% of the value of Adder-2 is made up of parts common to Adder-1 and Adder-2; the remaining 80% is split equally between unique parts and parts common to Adder-2 and Adder-3. 20% of the value of product Adder-4 is made up of parts common to Adder-3 and Adder-4; the balance of the value is unique parts since there are no succeeding products.

Run M-3: 50% and 25% part commonality between alternate products. There is 50% part commonality between products Adder-1 and Adder-2 and between Adder-3 and Adder-4; there is 25% part commonality between Adder-2 and Adder-3.

Run M-4: 50% part commonality between adjacent products; no unique parts in Adder-2 and Adder-3; 50% unique parts in Adder-1 and Adder-4.

Run M-5: 80% part commonality between succeeding products.

Part Commonality Data (%) for Multiple Product Crossover

i	Product	Demand (units)	Product Cost ($)	Common Parts (%)	Experiment Run					
					M-0	M-1	M-2	M-3	M-4	M-5
1	Adder-1	V	10,000	$mc_{1,1}$	100	80	50	50	50	20
				$mc_{1,2}$	0	20	50	50	50	80
2	Adder-2	1.3V	0.85 × 10,000	$mc_{2,1}$	0	20	20	50	50	80
				$mc_{2,2}$	100	60	40	25	0	10
				$mc_{2,3}$	0	20	20	25	50	10
3	Adder-3	1.3 × 1.3V	0.85 × 0.85 × 10,000	$mc_{3,2}$	0	20	20	25	50	80
				$mc_{3,3}$	100	60	40	25	0	10
				$mc_{3,4}$	0	20	40	50	50	10
4	Adder-4	1.3 × 1.3 × 1.3V	0.85 × 0.85 × 0.85 × 10,000	$mc_{4,3}$	0	20	20	50	50	80
				$mc_{4,4}$	100	80	80	50	50	20

Appendix IV: Details of Explanations for Experiments 0 and 1a

IV-1 Estimated Financial Impact Based on Theoretical Considerations for Experiment 0

The impact of product Adder on the financial situation of the enterprise, as explained on page 11, is:

- Total PCFT = $7,800,000
- Mature volume = MV = mature PCFT = $800,000/month or $200,000/week
- Consignment inventory = $300,000.

IV-2 Mature Demand Week Considerations for Experiment 0

RPI Material to Support Mature Demand

		Class A	Class B	Class C	All Classes
①	Percentage of Part Value in Product	50%	30%	20%	100%
②	Weekly Use during Mature Demand ①×MV	$100k	$60k	$40k	$200k
③	RPI Safety Stock in Weeks	4	8	16	N/A
④	RPI in $: ③×MV	$400k	$480k	$640k	$1520k
⑤	RPI in Weeks of MV ④÷MV	2	2.4	3.2	7.6

On-Order Material to Support Mature Demand

①	Lead Time	6 weeks	10 weeks	14 weeks	All Parts
②	Percentage of Part Value in Product	25%	40%	35%	100%
③	Weekly Order during Mature Demand ②×MV	$50k	$80k	$70k	$200k
④	Amount on Order = Weekly Order × Lead Time: ③×①	$300k	$800k	$980k	$2080k
⑤	Percent Value of Part on Order: ④ ÷ $2080k	14.4%	38.5%	47.1%	100%
⑥	On-order Material in Weeks of MV ④÷MV	1.5	4.0	4.9	10.4

Total Inventory Metrics during Mature Demand

		Weeks of Mature Demand	Dollars
①	RPI	7.6	$1520k
②	WIP	2.0	$400k
③	FGI	2.0	$400k
④	On-Hand Inventory: ① + ② + ③	11.6	$2320k
⑤	On-Order Material	10.4	$2080k
⑥	Committed Inventory: ④ + ⑤	22.0	$4400k
⑦	Consignment Inventory	1.5	$300k
⑧	Total Committed Inventory: ⑥ + ⑦	23.5	$4700k

IV-3 End-of-Life Considerations for Experiment 0

Total PCFT = $7,800,000. Net profit = $78,000(i/100), where i is the profit as a percent of PCFT.

The following table summarizes the impact on the profitability of various margins i.

Write-Off as a Function of Profit on Shipped Units

①	Profit Margin i	5%	10%	20%	30%
②	Profit from Trade Units $7.8M × ①	$390k	$780k	$1560k	$2340k
③	Leftover Material	$64,615			
④	Leftover Material as % of Net Profit: ③ ÷ ②	16.57%	8.28%	4.14%	2.76%
⑤	Consignment	$300,000			
⑥	Consignment as % of Net Profit ⑤ ÷ ②	76.92%	38.46%	19.23%	12.82%
⑦	Total EOL Material as % of Net Profit: (③ + ⑤) ÷ ②	93.49%	46.75%	23.37%	15.58%

The following table shows the impact on Class C EOL material of reducing safety stock levels. These results were computed using means other than simulation.

Weeks of Class C Safety Stock	Class C EOL Material
16 weeks	$64,615
15 weeks	$35,385
14 weeks	$13,846
13 weeks	$0

IV-4 Why There Is Class C material Left Over for Experiment 0

The last period in which we expect to receive orders is week 68. The end of week 55 is 13 weeks before the end of the product life cycle. From the Adder order forecast in Fig. 2 on page 5 and the target RPI safety stock for class C material being 16 weeks of the 13-week leading average forecast (Table Ib on page 5), at the end of week 55 the amount of class C material in RPI should theoretically be 16/13 of the total demand to the end of life, or $(16/13) \times (1\frac{3}{4} \times V) = (28/13) \times V$ units, where V = 80.

In week 56, we need to start building the units for orders received in week 55. Ignoring the current FGI, the maximum new build from week 56 to the the end of life is equal to the demand from week 55 through the end of life, that is, 2V. Thus, at the end of week 55, there is more class C material on hand—enough to build (28/13) × V units—than needed for the demand to the the end of the product life cycle.

Remember that we did not consider units in FGI. If we want to reduce FGI units down to 0 by the end of the product life cycle, the total new build must be less than that computed above, and hence there will be even more class C material left over.

In summary, one reason for the leftover class C material is that the safety stock computation requires holding more class C raw material in RPI 13 weeks before the end of life than can be consumed by orders received in the last 14 weeks of the product life cycle.

IV-5 Why Orders Cannot Be More than 14 Weeks Late for Experiment 1a

Assume that an order comes in during week x. In the worst case we have not yet ordered any material for the unit that goes with this order. The earliest the material can be ordered is week x+1, and the longest lead time part will be delivered during week (x+1)+14, which is week x+15. Since build time is 2 weeks, the unit is ready in week x+17. Since transit time is 1 week, the unit is delivered to the customer in week x+18. Since the quoted availability is 4 weeks, on-time delivery means the customer should receive it in week x+4. This means that the lateness is 14 weeks.