Enterprise Modeling System: Inventory Exposure and Delivery Performance

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Manufacturing systems performance measures such as inventory exposure and delivery performance are affected by multiple interacting factors including forecast accuracy, material lead times and production planning process times. The Enterprise Modeling System (EMS) developed at HP Labs, which utilizes a simulation model and data exploration and visualization techniques, was used to study how these factors affected the performance measures in HP's Computer Manufacturing organization. This report presents quantified graphical relationships between these factors. The results indicate that: a) committed inventory is strongly correlated to both forecast accuracy and part lead times, b) reducing maximum part lead times can mitigate the effect of under forecasting on backlog, and c) reducing planning process time, by itself, has very little effect on inventory levels and delivery performance.

The recommended action leading to the most immediate benefits is to reduce the effect of long effective lead time among all the parts. This report includes an Executive Summary.

Executive Summary

Increasing profitability and improving order fulfillment performance are important areas of focus for HP. One potential source of help is the Enterprise Modeling System (EMS) being developed at HPLabs. This technology is specifically intended to model, simulate and analyze the complex, interactive behavior of material, information, and control flows in information intensive systems typical in today's manufacturing enterprises. Models of complex systems are primarily used to provide insight and deep understanding of how the many factors combine to affect system performance. While an individual factor by itself may have some impact, the combined effect is seldom a simple sum of the individual impacts. A prototype EMS system was used to model the *Order-To-Ship* process to learn more about the interactive effects of forecast accuracy, production plans, and other variables on delivery performance and inventory costs (1989).

The research described in this paper is focused on understanding the relationships between two key enterprise performance measures (inventory levels and delivery performance) and measures of environmental and procedural operating conditions (planning time, forecast accuracy, and material lead times). The work was a joint effort between HP Labs and Computer Manufacturing's planning team. It was conducted in two phases.

The initial phase (Oliver, Jan. 1993) focused on understanding the relationship between the length of the planning process and inventory levels for the Jupiter[1] computer workstation model 503. Various scenarios were simulated using the *Simple Model*, a discrete event simulation model developed on EMS. No simple or direct relationship between planning process time and inventory investment was found.

The second phase, the subject of this report, was initiated with an increased appreciation of the complexity of the issues. It expanded the scope of the analysis to explore how planning times, part lead times, and forecast accuracies combine to affect inventory levels and delivery performance. The EMS provided a means to rapidly and effectively model, simulate and compare a wide range of scenarios.

Powerful data analysis techniques quantified and showed graphically that:

- on-hand inventory is strongly influenced by order forecast accuracy,
- on-order inventory is strongly influenced by part lead times,
- delivery performance degrades if actuals are greater than forecasts, with this effect becoming more pronounced as part lead time increase, and
- planning process delays increase inventory levels when forecasts are high, and reduce inventory levels when forecasts are low.

The EMS made it possible to identify specific parts or groups of parts, with the longest Effective Lead Times, whose availability governed inventory levels and delivery performance.

While the results of this study are specific to the data used, the methodology embodied in EMS is applicable to a wide range of issues analysis.

1. Not real product number or name

Table of Contents

Executive Summary i

Table of Contents ii

Glossary of Terms and Abbreviations iv

1 **Introduction** 1
1.1 Context 1
1.2 Purpose and Scope of Document 2
1.3 Project Goals 2
1.4 Staffing 2
1.4.1 CM Team 2
1.4.2 HPL Team 2
1.5 Outline of Document 2

2 **Model Development** 3
2.1 Simple Model 3
2.2 Converting the Simple Model to the Planning Calendar Model 4
2.2.1 Modification I - Pre-On-order Category 5
2.2.2 Modification II - Pre-RPI Category 6
2.2.3 A Part's-Eye View 8

3 **Phase I Experiments** 8
3.1 Objectives and Approach 8
3.2 Data and Experimental Conditions 8
3.3 Results Analysis 10
3.3.1 Model Results 10
3.3.2 Observations on the Modeling Process 11
3.3.3 Benefits and Payoffs 11

4 **Phase II Experiments** 11
4.1 Objectives and Background 11
4.2 Data and Experimental Conditions 12
4.3 Results Analysis Process 13
4.4 Time Series Graphs 13
4.5 Assessing the High Level Situation 14
4.5.1 Multi-factor Plots 14
4.5.2 Start-up Data 15
4.5.3 Ordering-period Data 16
4.6 Reviewing the Landscape 19
4.6.1 Three Dimensional Surface Plots 19
4.6.2 Start-up Data 19

4.6.3 Ordering-period Data 19
4.7 Investigating the Details in the Current Operating Area 21
4.7.1 General Impact of Reducing MLT and PT on ELT 22
4.7.2 Impact on WIP, FGI, Backlog, and Shipment Performance 23
4.7.3 Impact on RPI 23
4.7.4 Impact on Pre-RPI 24
4.7.5 Impact on On-hand Inventory 24
4.7.6 Impact on On-order Inventory 24
4.7.7 Impact on Committed Inventory 24
4.7.8 An Interesting Observation 24

5 Conclusions 26
5.1 Revisiting the Phase I Results 26
5.2 Recommendation for Action 27
5.3 Comments on the Modeling Process 27
5.4 Possible Future Work 27
5.4.1 Further Analysis with Existing PC Model 28
5.4.2 Distributed Multi-Entity Factory 28
5.4.3 Changes to Production Planning and Material Ordering Policies 28
5.4.4 Production Capacity Constraints 29
5.5 Recommendation of the Planning Calendar Team Revisited 29

6 Acknowledgments 30

7 References 30

Appendix A Jupiter Bill Of Material (BOM) and Lead Times 31

Appendix B Multiple Plots 32

Glossary of Terms and Abbreviations

Abbreviations

BOM Bill of Materials

CM Computer Manufacturing

ELT Effective Lead Time - period between the time when the need for a part could first be identified to the time that the part is expected to be delivered for use.

EMS Enterprise Modeling System - a system developed in HP Labs for modeling and simulating the material, information and control flows in a manufacturing enterprise.

F/A Forecast to Actual ratio - this is the ratio of the forecasted orders to the actual orders received.

FAST Final Assembly and Test

FGI Finished Goods Inventory

LT Lead Time - the time between placing an order on the vendors and receipt of the part.

MLT Maximum Lead Time - the longest LT among all the parts.

PC Planning Calendar

Pre-RPI

Material delivered to the sub-assembly factory, but not yet available for use at the FAST factory.

RPI Raw Parts Inventory - raw material in stores waiting to be processed

SM Simple Model - a simulation model of a simplified manufacturing operation.

WIP Work In Process - material on the production line which is assembled into the final product.

Terms

Backlog

All products ordered by customers but not yet shipped.

Jupiter

Code name for Computer Workstation 503 (not real name or model number)

Committed Inventory

Total amount of inventory which has currently been committed to. It is the sum of on-order inventory and on-hand inventory.

Multi-factor Plot

The multiple plots of different responses on the same figure arranged side by side on the same figure. Each of these plots is "A plot of the mean of [some metric] at each of the levels of the factors in the [current] experiment" as described in the books on S. There does not appear to be a standard name or label for this kind of plot in S or S-PLUS.

On-hand Inventory

All physical inventory which is owned. It is the sum of Pre-RPI, RPI, WIP, and FGI.

On-order Inventory

Material ordered, but not yet delivered.

Ordering Period

The period in the simulation during which customer orders are received, from weeks 45 through to 124.

Orders Delivered

All orders that have been delivered to customers.

Orders Delivered Satisfactorily

All orders that were delivered to customers within the quoted lead time.

Orders Shipped

All orders that have been shipped to customers.

Orders Shipped Satisfactorily

All orders that were shipped to customers within the quoted availability minus the nominal transit time., i.e. those shipped to arrive in time to satisfy the availability specifications.

Pre-On-order Category

Material Orders that have been computed but not yet placed.

S and S-PLUS

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

Start-up

The point in the simulation runs just before the first customer order is received, which is the end of week 44.

1 Introduction

1.1 Context

The complexity of today's global business environment coupled with increasingly fierce competition and escalating customer expectation has created the need for companies to continually improve their business processes to remain competitive. Hewlett-Packard (HP) has seized this challenge by establishing programs to improve its order fulfillment processes and to increase profitability. Both of these are complex, multi-faceted issues that are viewed from many different perspectives by people within the company who are concerned with different aspects of the issues. These aspects encompass information, material and control flows that need to be understood at different degrees of abstraction and levels of detail.

Continual improvement and business process re-engineering increase the need to understand an enterprise more fully and to integrate these multiple perspective more effectively. In HP Laboratories (HPL) an Enterprise Modeling System (EMS) has been under development for several years. The guiding principle of this project is the belief that HP decision makers can make more effective choices by using interactive methodologies and tools to build, execute and maintain reusable models of a business enterprise and its environment. These models would enable them to understand the enterprise's behavior over time, and to rapidly explore the potential consequences of proposed actions. These models help to organize and manage information because they:

- encompass more information than any one person understands,
- cross functional, divisional and geographic boundaries,
- provide a multi-dimensional parameter space,
- represent complex relationships where behavior is not intuitive, and
- integrate information and physical domains.

Such enterprise level models coupled with the EMS provide the means of rapidly:

- exploring behavior of systems over time,
- exploring effects of rapidly changing environmental conditions,
- evaluating proposed actions prior to execution,
- determining system sensitivity to multiple parameters, and
- examining multiple scenarios.

Applying this process leads to better decisions because of greater understanding with more complete analysis and exploring more alternatives. These decisions are more readily accepted because they can be explained more clearly.

Better decisions are a major competitive advantage because they enable opportunities to be capitalized on more quickly, trade-offs to be understood more clearly, and changes to be made with greater confidence in the outcome.

1.2 Purpose and Scope of Document

This document describes the application of the Enterprise Modeling System (EMS)[1] and the enterprise modeling methodology developed at HP Laboratories (HPL) to the analysis of a manufacturing related problem encountered in HP's Computer Systems Organization (CSO).

1.3 Project Goals

The primary goal of the project was to develop a better understanding of how the interaction of the length of the planning cycle, part lead times, and forecast accuracy combined to affect inventory levels and delivery performance. The project was initiated in response to the Computer Manufacturing[2] (CM) organization's interest in understanding how delays in their hierarchical planning process affected inventory levels.

A secondary goal was to improve our understanding of how to apply the enterprise modeling methodology to problem analysis, and to explore ways to make EMS usable by people other than the tool developers in HPL.

1.4 Staffing

1.4.1 CM Team

- John Monroe - Project sponsor
- Kevin Oliver - Planning Calendar Team leader, planning domain expert and problem owner
- Lanny Meade - Planning Calendar Team member and inventory expert
- Mark Inkster - Modeling advocate in CM
- Charles Kozierok - MIT-LFM[3] graduate student

1.4.2 HPL Team

- Bob Ritter - Project manager
- Shahid Mujtaba - Model developer, implementor and owner

1.5 Outline of Document

The term *we* in this report refers to the authors of this report.

Section 2 begins with a brief description of the Simple Model (SM) which had been developed for a prior application. In Section 2.2 we discuss the jointly developed modifications necessary to adapt this model to the new analysis. This new, adapted model we named the Planning Calendar (PC) model.

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1. The Enterprise Modeling System is under on-going development at HP Laboratories. There are a number of HP Labs Technical Reports that describe this work [1], [2].
2. Computer Manufacturing is the manufacturing arm of the Computer Systems Organization.
3. LFM: Leaders For Manufacturing, an MIT program offered through the business and engineering schools.

Section 3 describes the Phase I experiments done by the CM and HPL Teams. The CM team provided the problem definition, domain expertise and executed the simulation experiments. The HPL Team developed and maintained the model and the EMS. Joint discussions were held to interpret the data.

Section 4 describes the follow up Phase II experiments done by the HPL Team, the basic analysis methods, the different graphical representations, and the results.

Section 5 begins with the observations and recommendation we made with respect to the CM Planning Calendar analysis. We go on to describe possible future work using the model to get more detailed insights into both the manufacturing and the modeling processes.

2 Model Development

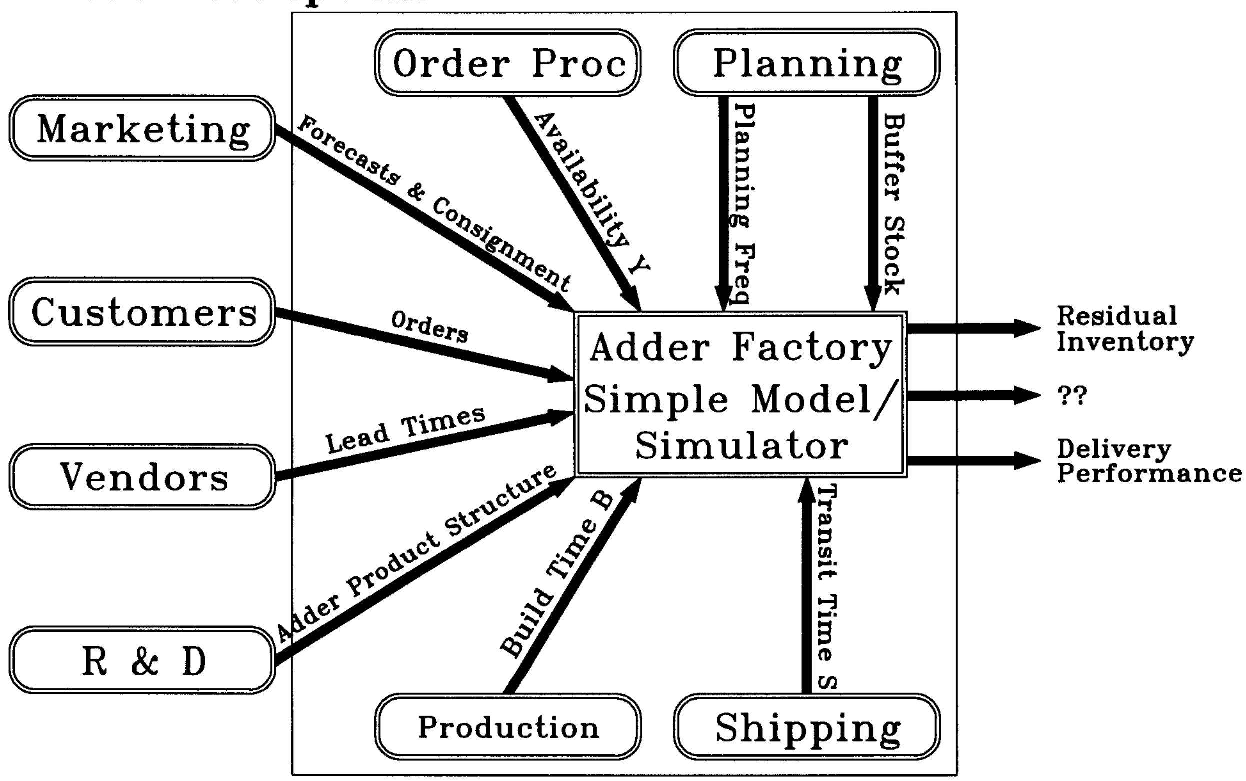


Figure 1. Conceptual diagram of Simple Model

2.1 Simple Model

The Simple Model (SM), diagrammed in Figure 1, was developed in 1991-1992 by HP Labs in conjunction with Jerry Harmon of CM. The SM was a simulation model of a fairly simple manufacturing enterprise that produced a single product from material it obtained from vendors and shipped the finished products to customers. It was implemented on the Enterprise Modeling System (EMS) at HP Labs. Products were built to forecast, and the lead times of some of the component parts were much longer than the production cycle time. The product was a single level assembly built in a single production facility. Production planning and material planning activities occurred periodically and took into account updated forecasts, the most recent actual orders, and the most recent data on inventory. The SM was used to understand how variations in the input parameters affected the performance measures of interest such as residual inventory and delivery performance. Initially, we wanted to limit the complexity of the model to facilitate the analysis. With subsequent use of the model we expected to expand its complexity. However, even in its most simple form, the SM provided a useful testbed for experimentation. Figure 2 shows the material/order flows for the Simple Model.

2.2 Converting the Simple Model to the Planning Calendar Model

The SM analysis used representative or typical values. We were interested in applying the model to a *real-world* situation. When the results of the SM analysis were presented to CM representatives at CCMO[1], the CM Planning Calendar Team proposed an application.

Historical data on sales and manufacturing for the 503 computer workstation product (code named Jupiter[2]) were used in the analysis of the Planning Calendar (PC) model. This product is built in a distributed manufacturing environment. HP sub-assembly factories fabricate components, which are shipped to the Final Assembly And Test (FAST) factory for inclusion in the product. Figure 3 shows the nature of the Jupiter product structure and supply chain. Vendors supply parts to HP factories. Each part

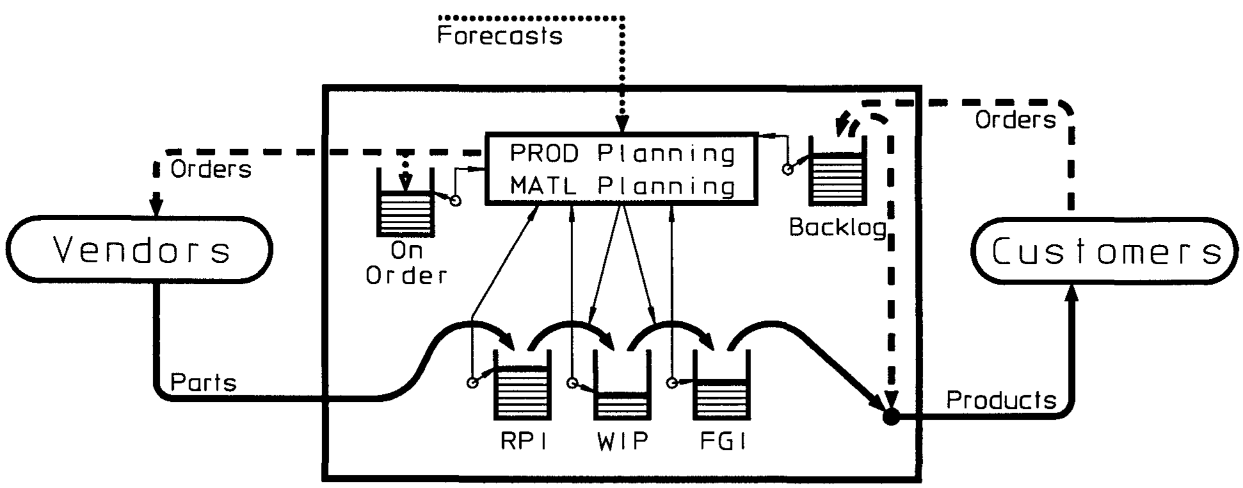
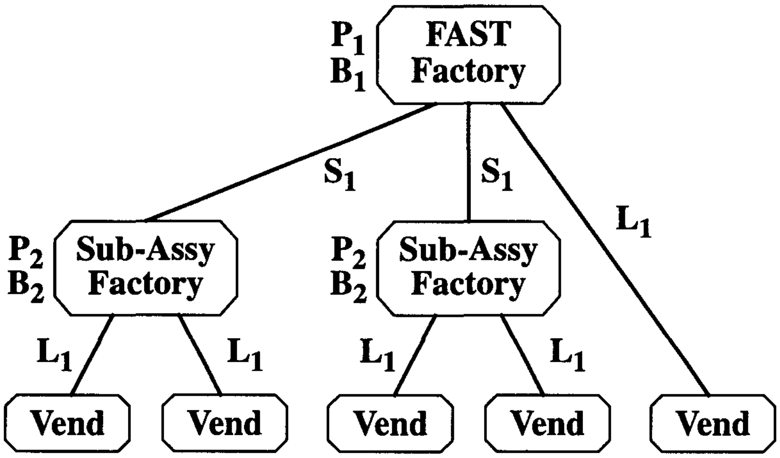


Figure 2. Material/Order Flow Diagram of the Simple Model

1. CCMO is the Colorado Computer Manufacturing Operation which is part of CM.
2. Not real name or product number

has its own lead time (L_1). Sub-assembly factories take time P_2 to plan, time B_2 to build sub-assemblies, and time S_1 to ship them to the FAST factory.



P_1 = FAST Planning Time
B_1 = FAST Build Time
S_1 = Shipping Time from sub-assy to FAST
P_2 = Sub-Assy Planning Time
B_2 = Sub-Assy Build Time
L_1 = Lead time from vendor to HP

Figure 3. Jupiter (503) Product Structure

Since the SM assumed a single level of assembly done at one factory, the Jupiter's multiple levels of assembly at different locations and time delays between them precluded the direct use of the SM. We made some simple modifications to parts of the SM to approximate the multi-level, multi-location assembly as a single-level, single-location product with effective lead times longer than the physical lead times. The modifications to the SM for the PC model are outlined with dotted rectangles in Figure 4 and described in Section 2.2.1 and Section 2.2.2.

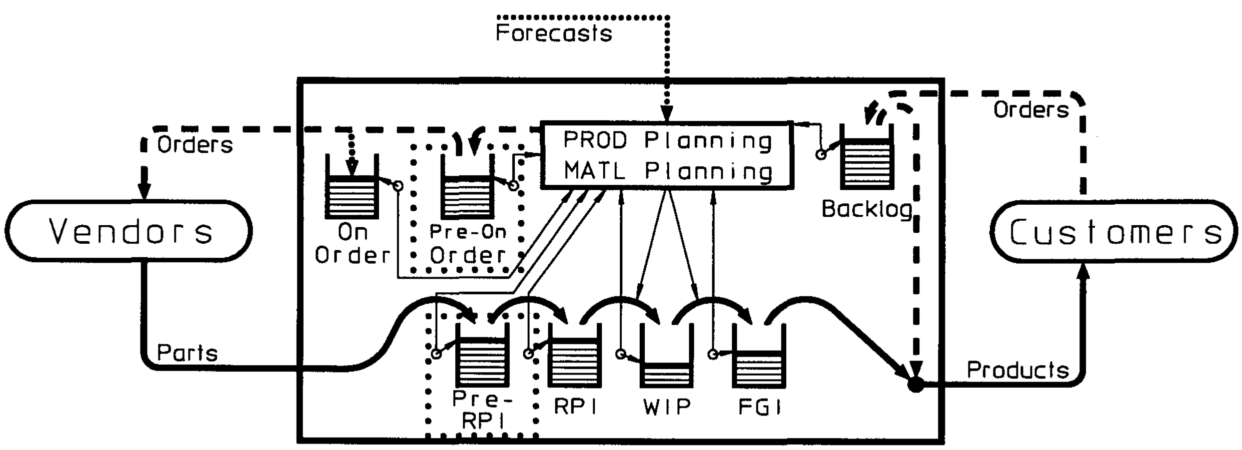


Figure 4. Material/Order Flow Diagram of Planning Calendar (PC)

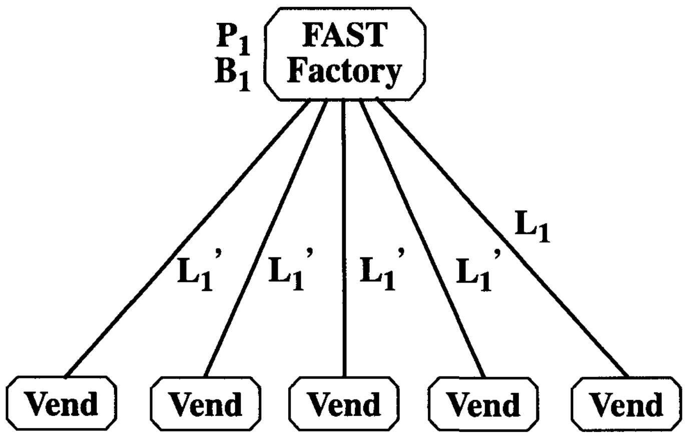
2.2.1 Modification I - Pre-On-order Category

Using the actual backlog and inventory state information from the end of the previous period the SM computed production and material requirements *instantaneously* and issued the material orders immediately thereafter. In real life, the period between the start of computations and the placement of orders could be a week or more. In the PC model, computations were also done immediately, but material ordering was delayed by the time needed for production planning in the real enterprise (i.e. planning time). This effect is equivalent to delaying the completion of the planning computation until the end of the planning period, while using the data that was current at the beginning of the planning cycle. To accommodate this difference we added the *Pre-On-order* measurement category (see Figure 4).

The *Pre-On-order* category accounts for the delay from the beginning of the planning process to the time that parts are actually ordered. This category represents all material ordering requirements estimated by the computations that have been planned but not yet ordered. Although the actual issuance of the material orders is delayed, the model does not review the proposed material orders with respect to the more recent customer orders and inventory data at the time of issuance as the PC model does not provide a mechanism for modifying material orders once they are planned. Consequently, once an order is planned, that order will be placed, and the material will be delivered.

2.2.2 Modification II - Pre-RPI Category

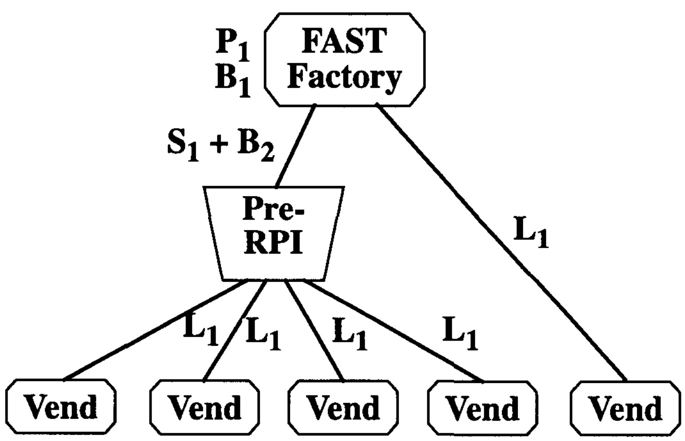
The multiple-levels of sub-assemblies were consolidated into a single-level assembly by separating the sub-assemblies into their component parts and assuming that these parts flowed directly into the final assembly with the other components from external vendors. Initially, we increasing the apparent lead times of the component parts associated with the sub-assemblies by including the time those parts spent in production and in transit between the sub-assembly factories and the FAST factory. The time these components spent at the sub-assembly factories in Raw Parts Inventory (RPI) and in Finished Goods Inventory (FGI) was ignored. This first approximation is shown diagrammatically in Figure 5. Consequence of this assumption compared to reality are that material appears to be in the pipeline longer, and the on-hand inventory in HP factories appears lower.



$$L_1' = B_2 + S_1 + L_1$$

Figure 5. First Approximation to Jupiter Product Structure

To make both the on-order and on-hand inventories more closely reflect the real world, we created an inventory category called *Pre-RPI*. This category represents inventory delivered to an HP sub-assembly factory and owned by HP, but not immediately available to the final assembly factory. Material was delayed in this category for a period of time equal to the build time at the sub-assembly factory plus the transit time from the sub-assembly factory to the FAST factory. It does not include the time these parts stay in RPI or FGI at the sub-assembly factories. This approximation is shown diagrammatically in Figure 6. All parts have their lead time



$S_1 + B_2$ = The time material is delayed in the *Pre-RPI* category

Figure 6. Second Approximation to Jupiter Product Structure

from the vendors (L_1). However, for planning purposes, we use the *effective lead times* (ELT) defined in Equation (1)

$$ELT = \begin{cases} P_1 + L_1 & \text{,for top level parts} \\ P_1 + P_2 + B_2 + S_1 + L_1 & \text{,for lower level parts} \end{cases} \qquad \text{EQ. 1}$$

where Top Level Parts go directly to the FAST factory from vendors, and Lower Level Parts go from vendors to sub-assembly factories and then to the FAST factory.

This approximation underestimates the RPI levels at the sub-assembly factories and does not correctly reflect the consequences of part outage at a sub-assembly factory. Nevertheless, both teams agreed that the model should give a good relative evaluation of the different options we would be considering.

2.2.3 A Part's-Eye View

Another way to think about these modifications is to consider how a typical part is incorporated into a product and shipped to the customer. Figure 7 shows the events in the life of Top and Lower Level Parts, and how these events indicate when a part moves from one inventory category to another. It also indicates that the dwell time of a part in RPI or FGI at a sub-assembly factory is assumed to be zero in the model. The ELT for the two classes of parts are also indicated in Figure 7.

3 Phase I Experiments

3.1 Objectives and Approach

The preliminary experiments done in October and November 1992 initially focused on increasing the understanding and acceptance of the model by the CM team members. To accomplish this goal, we ran the first simulations using the simplified Bill-Of-Material (BOM), the orders, and the order forecasts used in the SM experiments. Progressing gradually from simple experiments with the SM to the more complex experiments using the PC model helped increase the CM Team's understanding of the model's behavior, and validate that the behavior was an adequate approximation to reality.

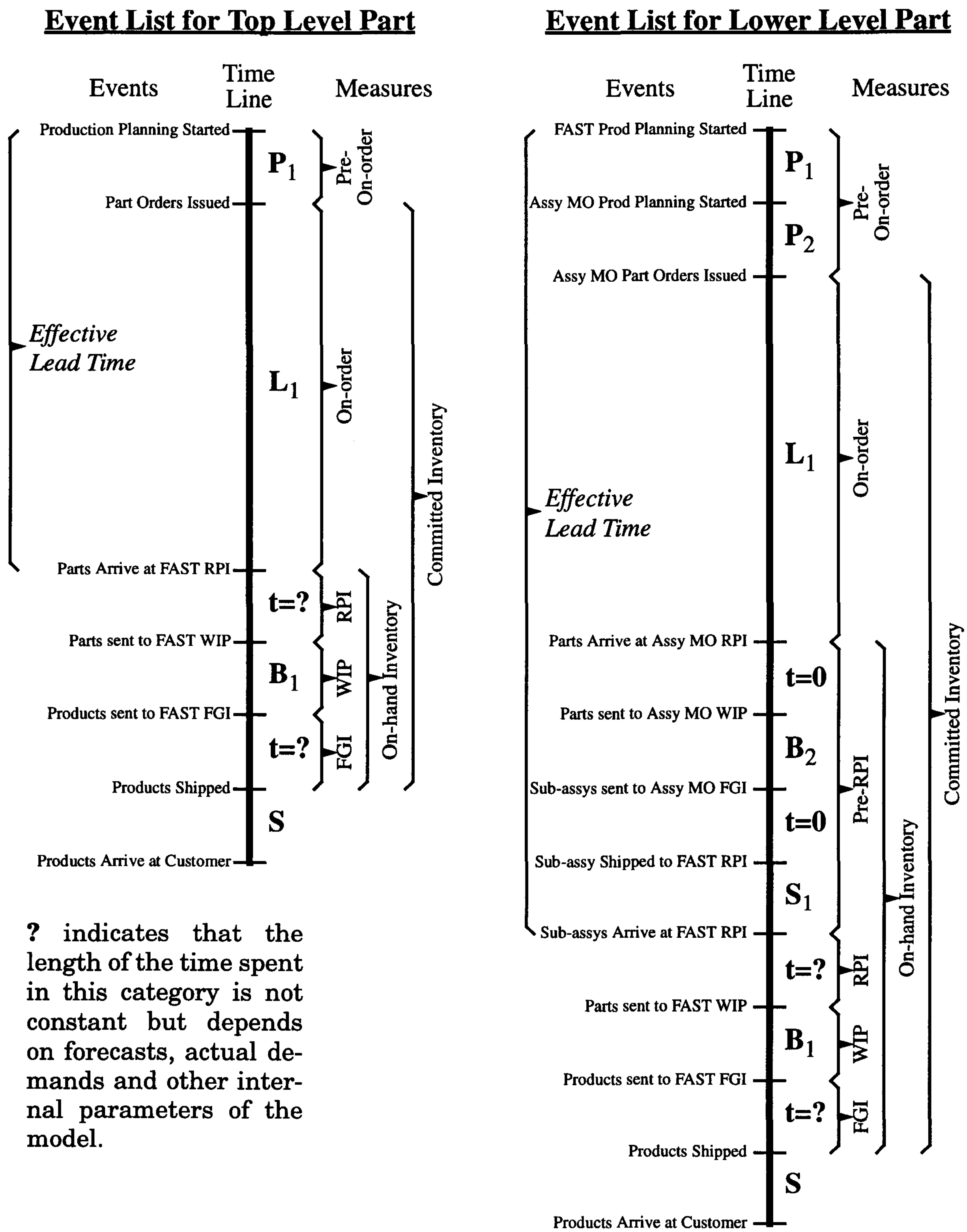
3.2 Data and Experimental Conditions

An abstracted BOM[1] (Appendix A, Table A-1 and Table A-2 for details) was used for the product structure. The actual order history for the Jupiter product from its first orders in October 1990 through September 1992 is shown in Figure 8. The heavy line shows the history of actual orders received. The series of connected light line segments show the rolling order forecasts that were made and updated monthly.

The following data and parameters were used in the experiments:

- Forecasts:
  - Equal to historical order Actuals

1. Parts with similar lead times were lumped together as single *representative* parts.



? indicates that the length of the time spent in this category is not constant but depends on forecasts, actual demands and other internal parameters of the model.

Figure 7. Events In the Life of a Part

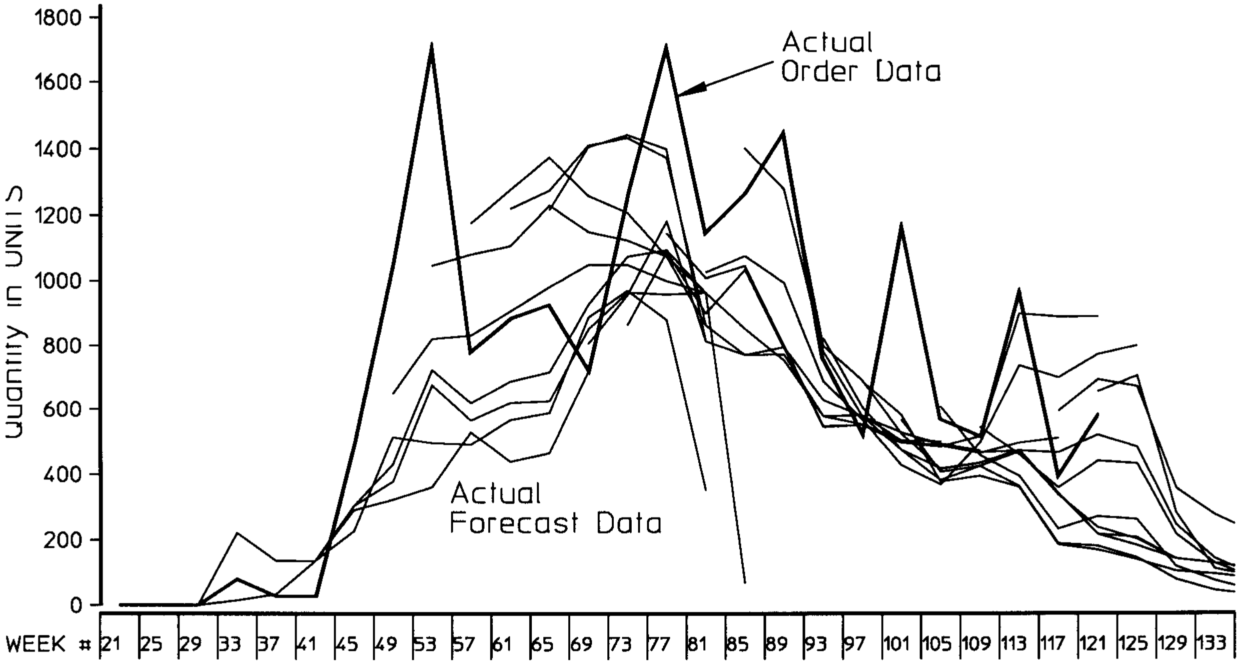


Figure 8. Historical Forecast and Order Data

  - Equal to a multiple of the historical order Actuals (F = cA; where c took the values 0.68, 0.80, 1.00, 1.25 and 1.5)
  - Equal to the historical order forecasts
- Planning cycle times of 0 and 1 week for both levels of planning.
- Planning frequencies of 1, 2, and 4 weeks. (SM data set only)

3.3 Results Analysis

The results of the simulation runs were displayed as time series graphs of the various inventory components for each simulation run. At the end of the experiment set, summary graphs were created using Lotus-123, to compare different simulation runs. A detailed description of the results of the Phase I experiments is given in [3].

The following were the major results and conclusions of the work [7]

3.3.1 Model Results

- Planning Time (PT) had the following effects:
  - When actual orders are less than forecasted, *Longer* PT increases inventory levels
  - When actual orders are greater than forecasted, *Longer* PT increases order backlog levels.

- PT is not the major cost component of the entire planning process. Part LTs are more significant. Furthermore, the relative cost of PT increases as part LT is reduced.
- There is no absolute or constant dollar value for the inventory due to the length of PT. The inventory *investment* depends on factors such as the level or volume of business, the fluctuations of forecast accuracy and the uneven nature of demand over time.

It was decided that further modeling effort was required to determine the appropriate amount of effort to be focused on reducing planning time.

3.3.2 Observations on the Modeling Process

- The initial set of learning experiments satisfied the CM team that the PC model provided a useful representation of reality with the assumptions made for planning delays in a multi-entity, multi-level planning environment. It confirmed and clarified, the Team's internal or intuitive *models* of how forecast accuracy, safety stock levels, lead times and planning times affect the planning process.
- Modeling processes as complex as the current CM Planning Process require time to understand the existing process, to determine the appropriate simplifying assumptions, to model the process, to design iterative experiments, and to analyze the results.

3.3.3 Benefits and Payoffs

- Modeling the planning process clarified the Team's implicit assumptions and increased common understanding of the process.
- Explicit assumptions now exist for understanding cause and effect relationships when considering the change of process variables.
- CM has greater certainty and understanding of the planning system behavior.
- Although the model does not indicate what to do or how to do it, it does provide the ability to compare and analyze alternative proposals and scenarios prior to their implementation.

4 Phase II Experiments

4.1 Objectives and Background

The Phase I work left the HPL Team with three unanswered questions:

- Why could we not find the inventory cost of PT?
- Would further data analysis give greater insight?
- Should forecast accuracy be dealt with in greater detail?

Furthermore, some questions were raised about enterprise modeling itself.

- How could we improve the modeling process?
- Could we use this experience to guide the development of techniques that improved data analysis, data reduction and visualization?

The fact that we had a validated model and ample data meant that knowledge acquisition and validation (generally time consuming processes) would be minor activities. Consequently, we could concentrate on the other aspects of our enterprise modeling methodology important for our research program.

4.2 Data and Experimental Conditions

The Phase I experiments revealed that the relationships we were exploring were not simple and that using all *real* data made it difficult to separate the effects of different factors. Consequently, we developed an experimental suite that gave us more control over the important parameters.

We developed a modified order stream with a smooth, two-month ramp-up, a flat thirteen-month mature volume and stepped decline over the last six months for which we had data. Figure 9 shows the *historical* and *smoothed* 503 order data that were

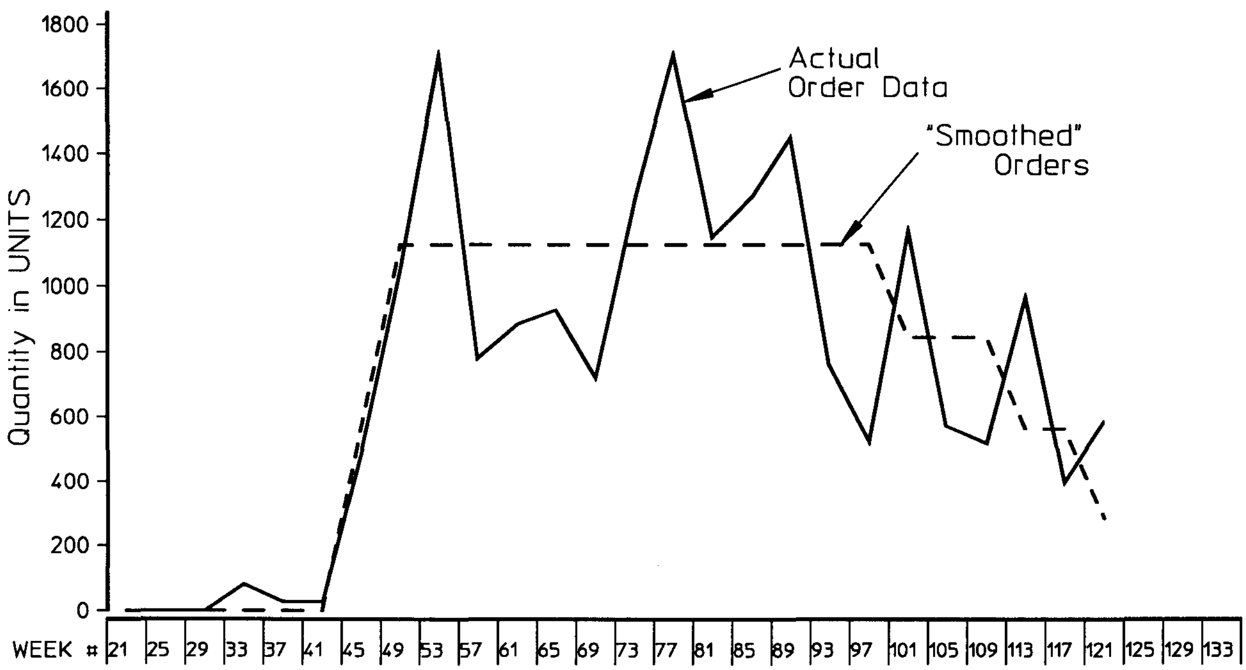


Figure 9. Historical and Smoothed 503 Order Data

used in Phase II. The total number of orders during the period October 1990 to September 1992 is approximately the same for both the *historical* and *smoothed* order data graphs. The demand in the mature period was 281 units/week or 1124 units/month.

While there are a number of different parameters that could be changed, the following ones were varied in our detailed planning calendar experiments:

- **Forecasts/Actuals (F/A):** The percentage ratio of forecasted orders to the actual orders (both measured in number of units).
- **Planning Time (PT):** The time it takes to conduct the planning process. In the PC model, the planning time can be specified in workdays.
- **Maximum Part Lead Time (MLT):** The longest lead time for any of the parts. This is specified in weeks, and comes from the product structure specification. We used the BOM from the Phase I experiments, except that the lead times of some of the parts were adjusted: when a MLT of n weeks was specified, all lead times longer than n weeks were set to n. All other parts kept their original lead times.

Table 1: Parameters and Values

Parameter	Values	Units
Forecasts/Actuals (F/A)	75, 80, 85, 90, 95, 100, 105, 110, 115, 120, 125	%
Planning time (PT)	0, 5, 10	work days
Maximum Part Lead Time (MLT)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 14, 17, 20	weeks

Table 1 shows parameters and their values used in the simulation runs, a total of $3 \times 11 \times 14 = 462$ simulations. The first 330 runs for the detailed experiments were made on the weekend of February 19-21, 1993 on two HP 9000/720 workstations, and the total run time was about 80 hours of CPU time. Another 132 runs were made on the weekend of April 2-4, 1993, and the total run time was about 29 hours.

4.3 Results Analysis Process

In the Phase II experiments, we used a more structured approach to the analysis than in the Phase I experiments. We:

- reviewed samples of time series graphs to ensure no unusual behaviors (Section 4.4),
- identified which input variables caused the greatest impact on the output variables (Section 4.5),
- reviewed the combined effects of the two greatest-impact input variables on the output variables (Section 4.6), and
- investigated the details close to the current operating area (Section 4.7).

4.4 Time Series Graphs

We use time series plots to display the raw data from simulation runs. These plots show system variables as a function of time, and enable us to investigate the details of an individual experiment run. A plot for the nominal experimental conditions is

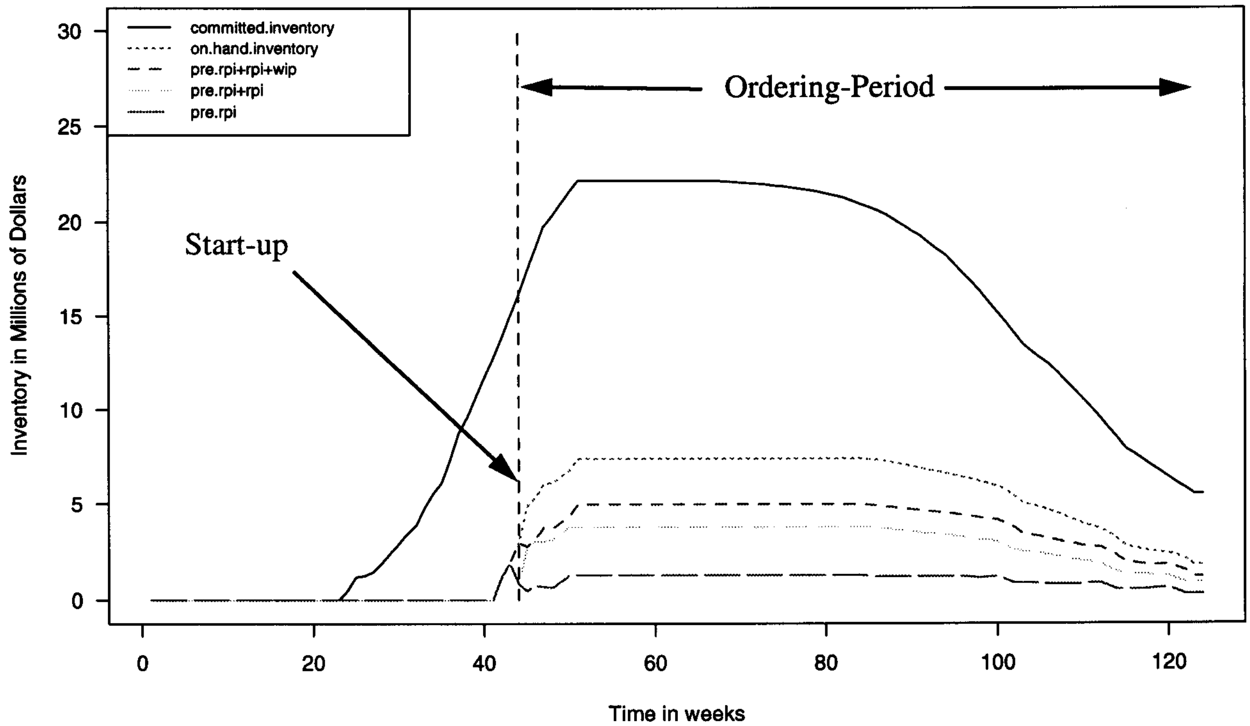


Figure 10. Time Series Plot

shown in Figure 10 in which orders start arriving at week 45. In analyzing the results of the detailed experiments we looked at the data from two perspectives:

1. **Start-up:** The state of the system just prior to the receipt of the first orders (i.e. end of week 44).
2. **Ordering-period:** The average of the state variable data values over the period that orders were received from customers (i.e. average over weeks 45 to 124).

Performance measures were computed for the start-up and ordering-period perspectives.

4.5 Assessing the High Level Situation

4.5.1 Multi-factor Plots

We used the *multi-factor*[1] data analysis and plotting facility in S-Plus[2] to produce the plots shown in Figures 11, 12, and 13. In these *multi-factor* plots an output variable is displayed on the Y-axis with the mean value over all runs of this variable shown as

1. *Multi-factor* plots designate the multiple plots of different responses superimposed on the same figure. Each of these plots is "A plot of the mean of... at each of the levels of the factors in the... experiment"[4]. There does not appear to be a standard name or label for this kind of plot in S or S-Plus.
2. S-PLUS is a product of Statistical Science Inc. [6]. It was originally derived from S [5].

a horizontal line. Along the X-axis, there are a vertical bars, one for each of the input variables: F/A, PT(P) and MLT(M). These vertical bars show how the range of values of the output variable changes with respect to the input variables. Each tick-mark on a vertical bar shows the mean value of the output variable for all runs where the input variable was kept at one value. The longer the vertical bar, the greater the impact of changing the associated input variable on the output variable. A *multi-factor* plot helps to prioritize the variables by degree of impact so that more attention can be given to the areas of greatest potential for change or control. However, such *multi-factor* plots must be used with caution. The following should be kept in mind when interpreting *multi-factor* plots:

1. When taking the mean we lose information about the range of values. The consequence is that we lose perspective on the curvature of the *playing-field.*
2. The results depend on the range and granularity of values used for the variables. An inappropriate range for one variable may distort the results.
3. If we are able to control one variable more effectively than another, then there may be value in keeping that variable in a range that limits the impact of the variables we are less able to directly control.

4.5.2 Start-up Data

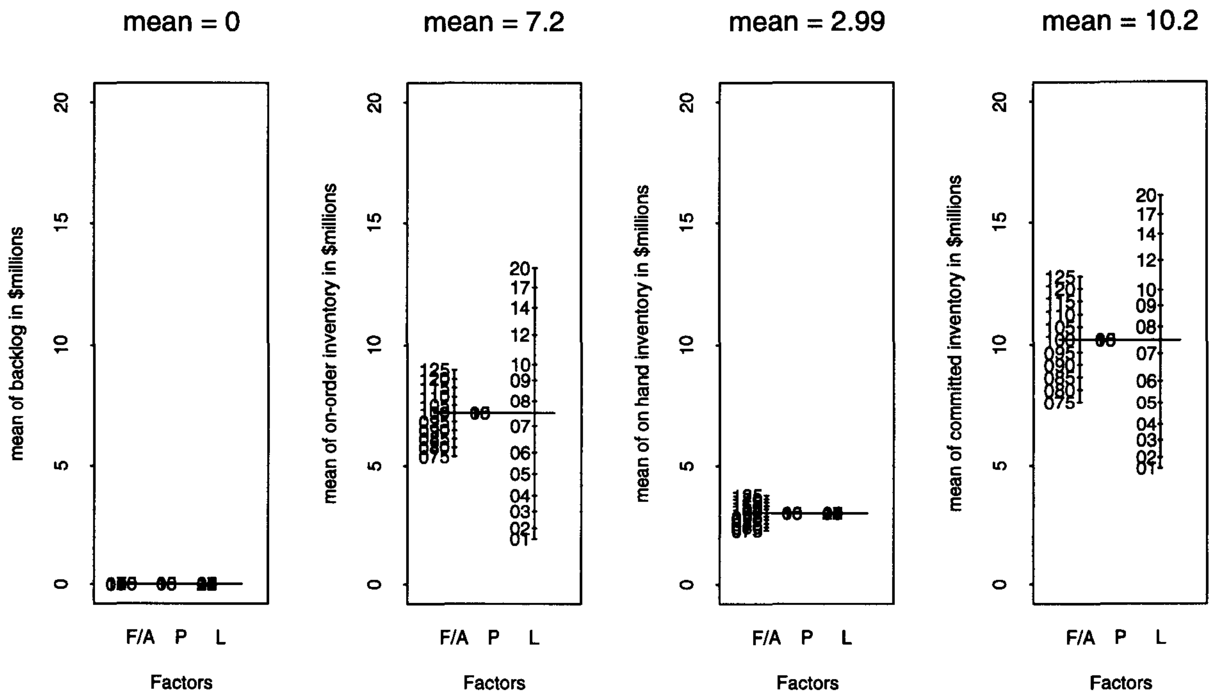


Figure 11. Multi-Factor Plots for Start-up Inventory Measures

In reviewing the *multi-factor* plots in Figure 11, which should be read in conjunction with Table 2, we determined the following:

1. Backlog is zero because no orders have been received.
2. On-order inventory, which is 71% of the committed inventory, is more strongly affected by F/A and MLT than by PT because F/A governs the early forecasts of incoming orders and PT determines how long the material is in the pipeline. As F/A goes from 75% to 125%, the mean on-order inventory ranges from $5.5m to $9m. As MLT ranges from 20 weeks down to 1 week, the mean of on-order varies from $13m down to $2m. As PT ranges from 0 to 10 days, the mean of on-order hardly changes.
3. On-hand inventory, which is the remaining 29% of committed inventory, is significantly affected only by F/A. Again, this is because F/A is an early estimator of incoming orders and determines the level of pre-RPI and WIP to support anticipated orders. Neither PT nor MLT have a significant effect.
4. Committed inventory is more strongly affected by F/A and MLT than by PT

Table 2: Summary of Measures - Start-up

	Impact of[a]			Component of	
	Forecast Accuracy	Plan Time	Lead Time	On-hand Inventory	Committed Inventory
Pre-RPI	0.43	0.00	0.00	29%	9%
RPI	0.00	0.00	0.00	0%	0%
WIP	1.06	0.00	0.00	71%	21%
FGI					
Backlog					
On-order	3.60	0.00	11.23		71%
On-hand Inventory	1.49	0.00	0.00	100%	29%
Committed Inventory	5.10	0.00	11.23		100%

a. The numbers in the **Impact of** column represent the range of values for a given variable, as shown in the graphs in Figure 11, measured in millions of dollars.

4.5.3 Ordering-period Data

The *multi-factor* plots for the ordering-period results are shown in Figure 12. Our main observations are listed below and summarized in Table 3.

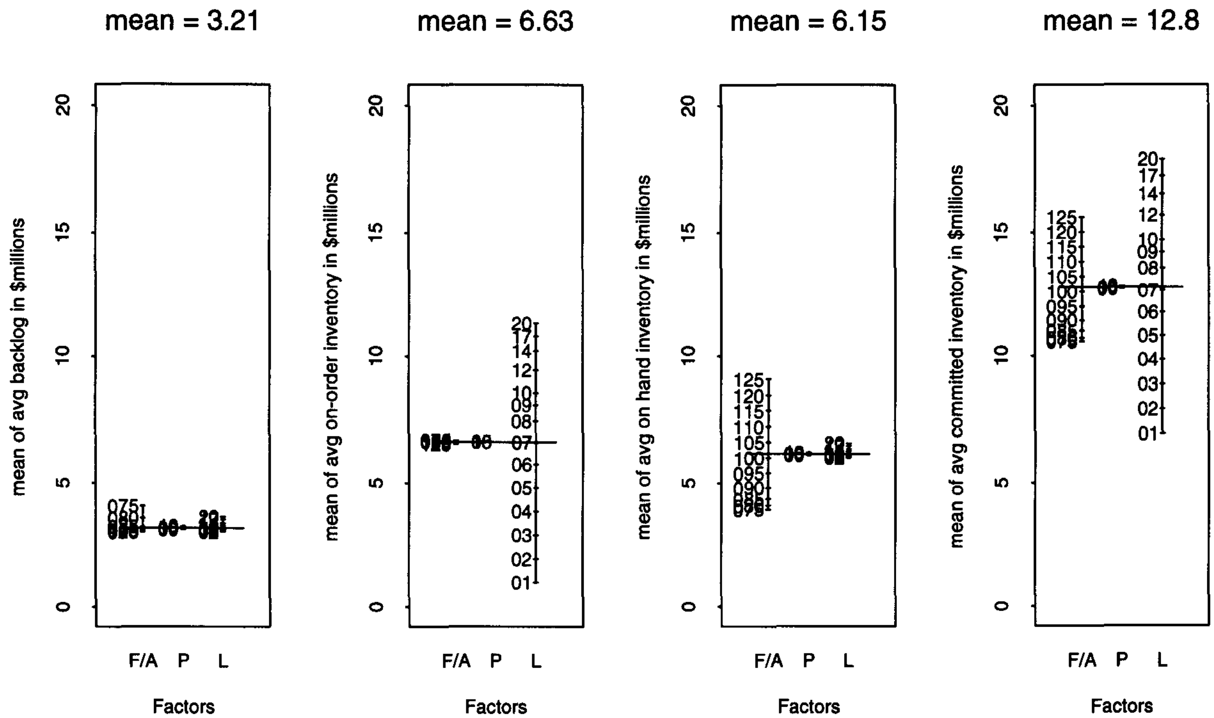


Figure 12. Multi-Factor Plots for Ordering-period Inventory Measures

Table 3: Summary of Measures - Ordering Period

	Impact of [a]			Component of	
	Forecast Accuracy	Plan Time	Lead Time	On-hand Inventory	Committed Inventory
Pre-RPI	0.02	0.00	0.00	17%	8%
RPI	3.26	0.22	1.00	40%	19%
WIP	0.02	0.00	0.01	16%	8%
FGI	1.99	0.11	0.40	27%	13%
Backlog	1.02	0.11	0.49		
On-order	0.13	0.00	10.37		52%
On-hand Inventory	5.18	0.11	0.59	100%	48%
Committed Inventory	5.05	0.11	10.96		100%

a. The numbers in the Impact of column represent the range of values for a given variable, as shown in the graphs in Figure 12, measured in millions of dollars.

1. Average Backlog was strongly affected by F/A, moderately affected by MLT, and slightly affected by PT.
2. Average on-order inventory, which accounts for about 57% of the committed inventory, is more strongly affected by MLT than by either F/A or PT.
3. Average on-hand inventory, which makes up the remaining 43% of committed inventory, is significantly affected only by F/A, and negligibly affected by PT and MLT.
4. Average committed inventory is significantly affected by F/A and MLT and slightly affected by PT.

For the order-period data we have some additional measures (i.e. orders delivered satisfactorily) that are not relevant for the start-up case. Figure 13 shows the delivery

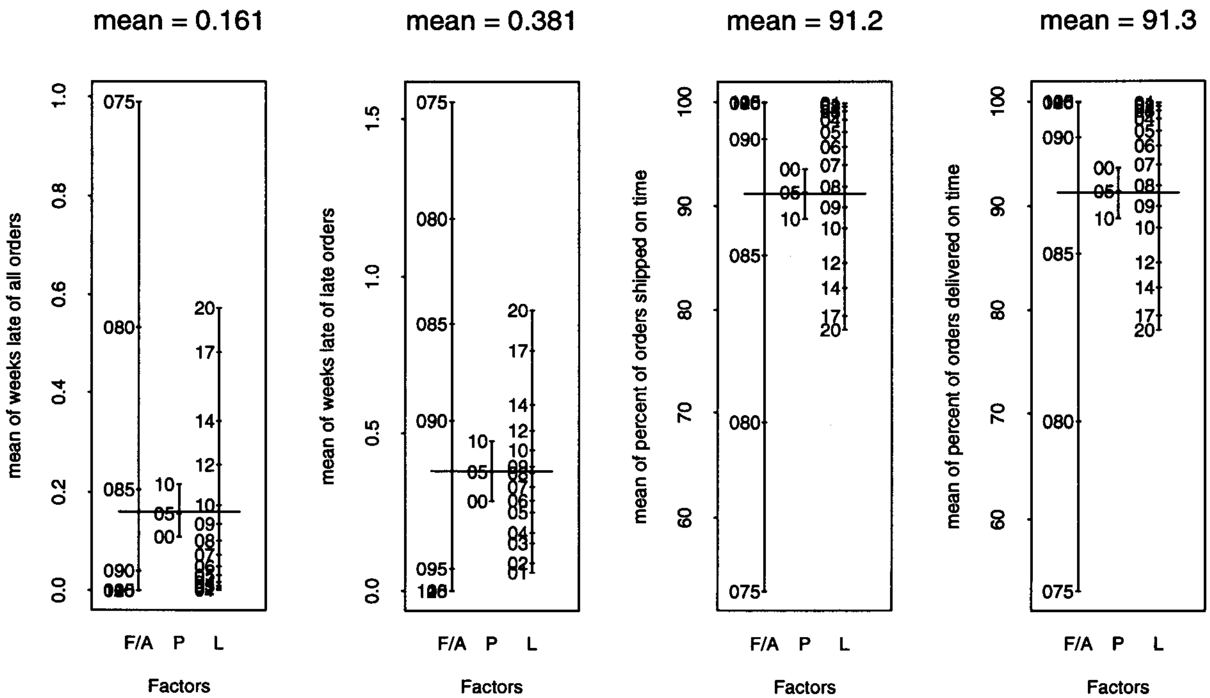


Figure 13. Multi-Factor Plots for Ordering-period Delivery Performance

performance measures for the ordering-period. All four of the measures shown in Figure 13 are most strongly affected by F/A, followed by MLT. PT has the least effect.

For both the start-up and ordering-period perspectives, changes in PT had very little impact on the primary performance measures. Both F/A and MLT had significant impact on one or more of the primary performance measure. These observations are consistent with the observations from Phase I.

4.6 Reviewing the Landscape

4.6.1 Three Dimensional Surface Plots

For the next level of analysis we kept PT constant at 5 work days, and investigated the response to changes in F/A and MLT, plotting the performance measures on the third (*vertical*) axis.

The 3-D surface plots[1] display graphically how two independent variables F/A and MLT jointly affect system response. The x and y axes form a *horizontal* plane with the z axis coming *vertically* out of the plane. Note that the sensitivity of z to either x or y depends on the location in the x-y plane. That is, *rules-of-thumb* will generally have limited application areas.

These 3-D surface plots are most useful when we try to determine the interaction of two independent variables. They become difficult to use when we try to see the relationships of more than two independent variables.

4.6.2 Start-up Data

The process for exploring the 3-D surface plots was similar for both the start-up and ordering-period data. For the purposes of this paper, we have chosen to discuss only the 3-D surface plots for the ordering-period data.

4.6.3 Ordering-period Data

There are a number of interesting 3-D surface graphs for the ordering-period data. In this section we will discuss several of them and point out what we believe are generally useful insights. The applicability of these insights to any real-world situation will depend on how well the PC model reflects that situation.

1. **Average Backlog:** This shows dramatically how F/A and MLT combine to produce a significant impact. The surface shown in Figure 14 is basically flat. When F/A is less than about 90% and MLT is greater than 6 weeks the average backlog begins to climb rapidly. At F/A = 75% and MLT = 20 weeks, the average backlog increases by about $3m over its value in the flat area. Viewed another way, if MLT < 6 weeks the system can tolerate F/A as low as 75% without any significant increase in backlog. While it is unlikely that MLT can be reduced to 6 weeks, any reduction in MLT will make backlog less sensitive to underforecasting (i.e. low forecasts).
2. **Average On-order:** The on-order inventory is not dependent on F/A, but dramatically affected by MLT. For the particular product structure we were working with, going from MLT = 20 weeks to MLT = 6 weeks reduces by more than half the amount of material on order.
3. **Average On-hand Inventory:** This measure is a composite of Pre-RPI, RPI, WIP and FGI. The two primary components are RPI and FGI. The FGI

1. Also known as perspective plots in S-PLUS.

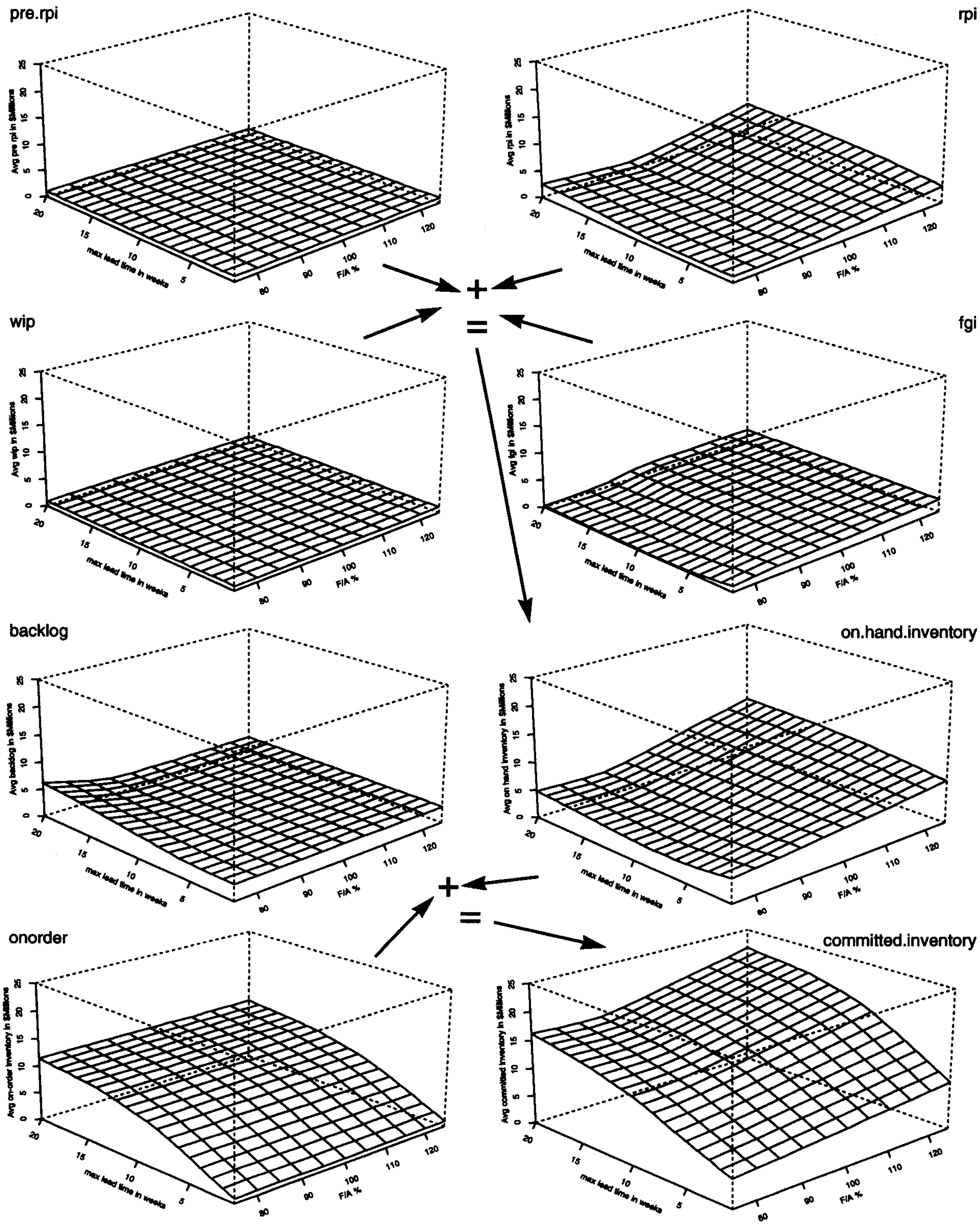


Figure 14. 3-D Surface Plots for Ordering-period for PT=5 days

surface has a fairly abrupt drop-off when F/A < about 95%. Changes in MLT have very little effect on FGI levels except when MLT < 8 weeks and F/A < 90%. In contrast, the RPI surface for MLT < 8 weeks decreases monotonically as F/A drops from 125% to 90%. Below 90% the RPI level is nearly constant. As MLT increases above 8 weeks, RPI levels tend to increase for all values of F/A. Since Pre-RPI and WIP are small, the on-hand inventory surface is approximately the combination of the FGI and RPI surfaces. On-hand inventory increases significantly (approx $5m) as F/A goes up, and decreases by about $600k as MLT goes from 20 weeks to 1 week. The numbers are extracted from Table 3.

4. **Average Committed Inventory:** This measure is the combination of on-order and on-hand inventory, and the 3-D surface reflects the attributes of the surfaces for its components. The sensitivity to F/A comes from the on-hand inventory component, and to MLT from the on-order component.

4.7 Investigating the Details in the Current Operating Area

While it is interesting and useful to review the landscape to determine the *best* operating points, a close look at the current operating state of the system can help identify possible first steps towards improvement. For this analysis we looked at the ELT of some parts as we altered conditions around the nominal state of PT = 1 week (5 work days) and MLT = 20 weeks. Table 4 shows some important attributes for the five parts with the longest lead times selected from the Jupiter BOM (Appendix A).

Table 4: Attributes of Selected Long Lead Time Parts

	Top Level Parts		Lower Level Parts		
Attribute	**TL1**	**TL4**	**SA12**	**SA20**	**SA01**
Unit Cost	$935.14	$136.71	$6.51	$4.31	$282.03
Quantity	1	1	5	2	2
Value	$935.14	$136.71	$32.55	$8.62	$564.06
Weeks RPI	3	3	1	2	1
BOM Vendor Lead Time	20	14	19	17	14

We reviewed the effects on these parts for the following four configurations:

1. **Case-1** (Nominal):.................... PT = 1 week...................... MLT = 20 weeks
2. **Case-2**: .... PT = 1 week...................... MLT = 17 weeks
3. **Case-3**: .... PT = 0 weeks.................... MLT = 20 weeks
4. **Case-4**: .... PT = 0 weeks.................... MLT = 17 weeks

Table 5 shows the changes in ELT (computed using Equation (1) defined in Section 2.2.2)[1], for the parts in Table 4, for cases-2, -3, and -4 with respect to case-1.

Table 5: Changes in Effective Lead Times

		Top Level Parts		Lower Level Parts		
Case	Attribute	TL1	TL4	SA12	SA20	SA01
1	LT	20	14	19	17	14
	ELT	21	15	23*[a]	21	18
	Δ ELT[b]	0	0	0	0	0
2	LT	17	14	17	17	14
	ELT	18	15	21*	21	18
	Δ ELT	-3	0	-2	0	0
3	LT	20	14	19	17	14
	ELT	20	14	21*	19	16
	Δ ELT	-1	-1	-2	-2	-2
4	LT	17	14	17	17	14
	ELT	17	14	19*	19	16
	Δ ELT	-4	-1	-4	-2	-2

a. * indicates maximum ELT
b. Δ ELT = ELT_i - ELT_1

For all four cases, the lower level part (SA12) is the critical part or gating item because it has the longest ELT and only one week of RPI (safety stock). The data is summarized in graphical form in Figures B-1, B-2, and B-3 in Appendix B. Analysis of the data lead us to the following observations.

4.7.1 General Impact of Reducing MLT and PT on ELT

Reducing only PT from 5 work days to 0 work days reduces ELT for the top level parts by 1 week, and for the lower level parts by 2 weeks, with no change in LT. Reducing only MLT from 20 to 17 reduces the LT and ELT of one top level part (TL1) by 3 weeks and one lower level part (SA12) by 2 weeks.

1. Where: P_1 & P_2 = PT, B_2 = 1 week, S_1 = 1 week, and L_1 = LT

4.7.2 Impact on WIP, FGI, Backlog, and Shipment Performance

When F/A >= 100%, material is always abundant; shortages never occur, and no parts become critical or gating.

However, for some F/A < 100%, there maybe one or more material shortages. The impact on WIP, FGI, backlog, products shipped and products shipped satisfactorily for a given F/A value is the same whether the longest LT is reduced to 17 weeks (case-2) or PT is reduced by 1 week (Case-3), as illustrated in Figure B-1 where the graphs for Case-2 and Case-3 are identical for these measures.

The five output variable listed above are controlled by the flow of material from RPI to WIP. This flow is regulated by the availability of the part with the maximum ELT, which is SA12 for all four cases we considered (see Table 5). Note that the ELT for SA12 is the same for cases-2 and -3 (21 weeks). In this particular BOM, the longest LT part TL1 is not the critical part.

As long as F/A >= 100%, Backlog is unaffected by reducing either MLT or PT, since shortages do not occur. However, for some F/A < 100% (more precisely close to 95%), backlog in general is reduced by reducing either the MLT or PT. This is illustrated in Figure 15.

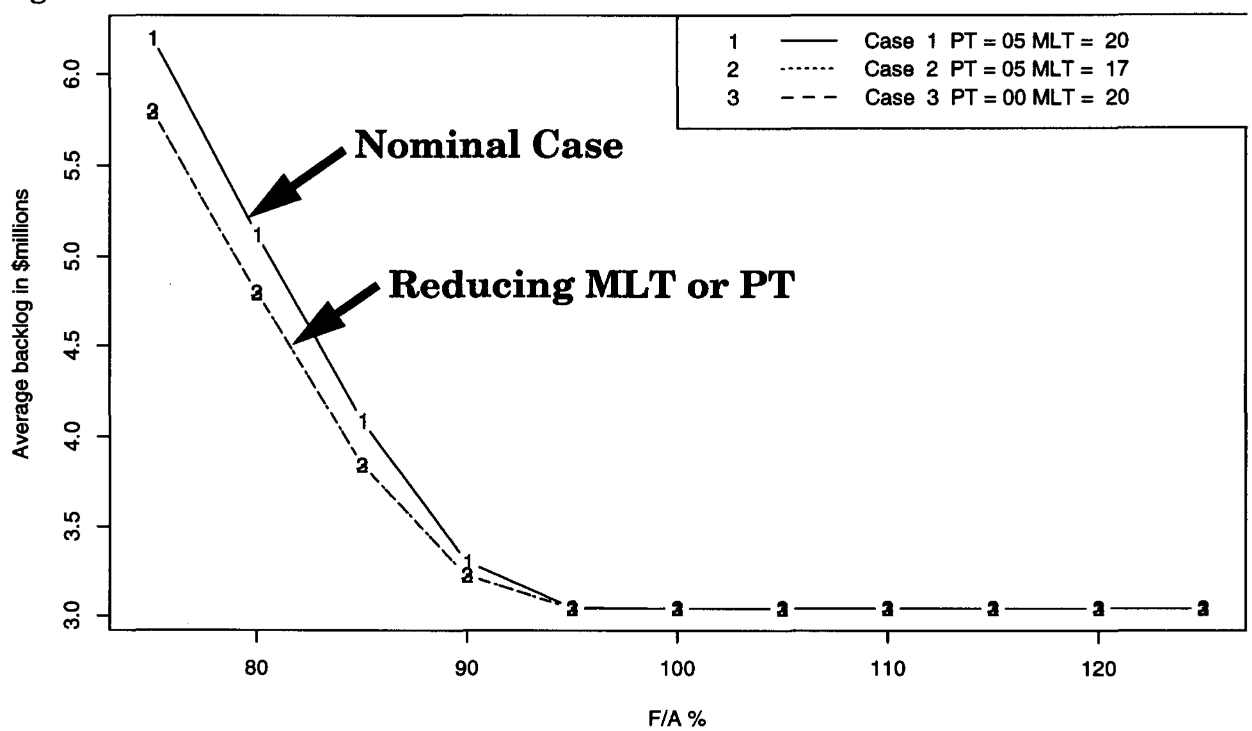


Figure 15. Average Backlog vs. F/A

4.7.3 Impact on RPI

When F/A >= 100%, reducing PT has more impact than reducing MLT. The implication is that for high forecasts, reducing ELT across the board has a bigger impact on RPI than reducing ELT for the longest lead time parts. For F/A < 100%, reducing MLT by 3 weeks has more impact than reducing PT by 1 week. The broader implication is that reducing ELT of the gating or critical item has a much bigger impact than reducing ELT across the board. These relationships can be seen in the graphs in Figures B-1 and B-2 of Appendix B.

We examined this behavior further by plotting the time responses of RPI for Cases 1 through 3 (see Figure B-3). For F/A = 100%, the RPI time profiles are identical for all three cases. For F/A > 100% the RPI profiles all increase over the 100% case, but Case-3 increases are less than Case-2 increases which are less than Case-1 increases. When F/A begins to fall below 100%, the RPI profiles initially decrease. However, as F/A continues to drop, the RPI profiles start to climb until at F/A = 75% the mean RPI level appears greater than the mean RPI level for F/A = 100%. For all F/A < 100%, the RPI level for Case-2 is always less than or equal to the RPI level for Case-3.

4.7.4 Impact on Pre-RPI

Reducing MLT (Case-2) has no impact on pre-RPI whereas reducing PT (Case-3) has some impact. However, the results are less interesting because pre-RPI is a much smaller component of on-hand inventory than RPI or FGI.

4.7.5 Impact on On-hand Inventory

The impact on on-hand inventory is the combined impacts on pre-RPI, RPI, WIP and FGI. We have seen that reducing MLT vs. reducing PT has different impacts on the different components. This gives rise to the interesting graph of on-hand inventory in Figure B-1 and the even more complicated shape of the delta graph in Figure B-2. This is illustrated in Figure 16.

4.7.6 Impact on On-order Inventory

On examining Figure B-1 again, we note that reducing MLT by 3 weeks has a very large impact on the average on-order (approximately $500k), whereas reducing PT by 1 week has a very small impact (close to 0).

The primary reason is that On-order inventory is directly affected by LT, and not by ELT. While reducing PT reduces ELT for all parts, LT is not affected. On the other hand, reducing MLT by 3 weeks reduces LT for the two parts. This is illustrated in Figure 17.

4.7.7 Impact on Committed Inventory

Finally, when we attempt to examine the impact of reducing MLT or PT on committed inventory, we note that the composite shape of the graph is the sum of the effects of on-hand inventory and on-order inventory (Figure 18).

4.7.8 An Interesting Observation

Figure 15 shows that backlog levels begin to increase when F/A decreases below about 95%. Figure 17 shows that on-order inventory increase as F/A decreases. Figures 16 and 18 show that on-hand and committed inventories begin to increase when F/A

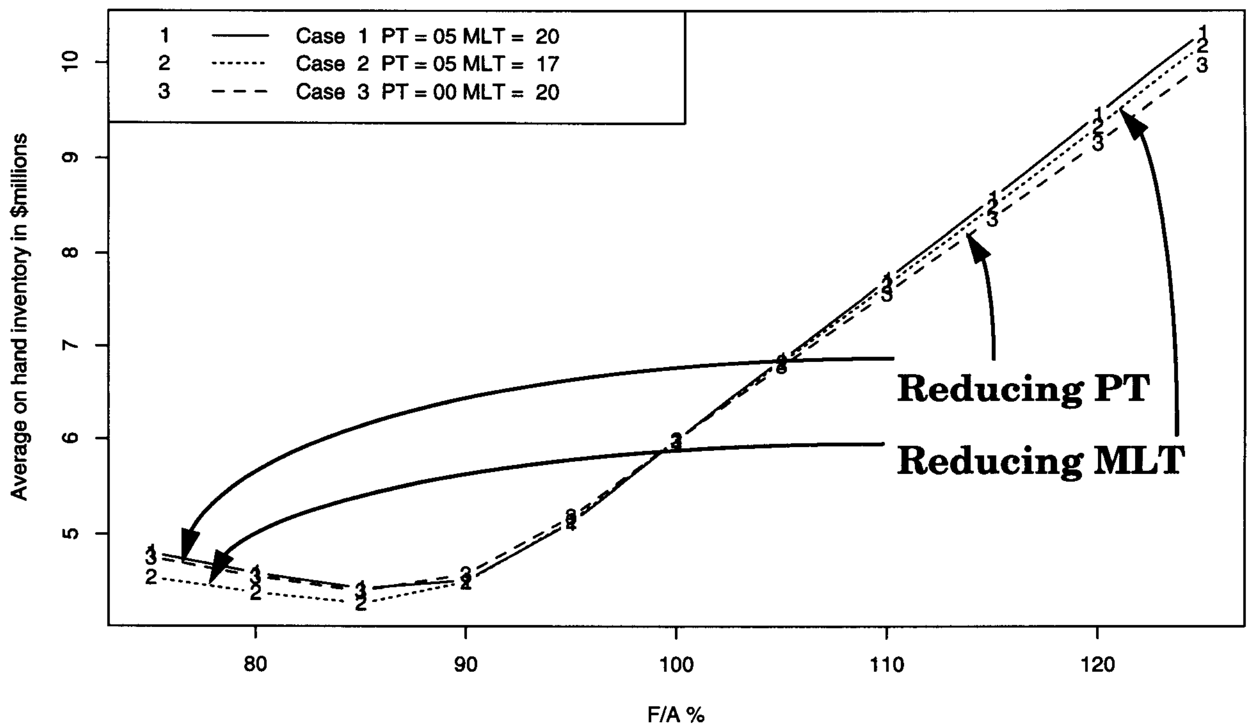


Figure 16. Average On-hand Inventory vs. F/A

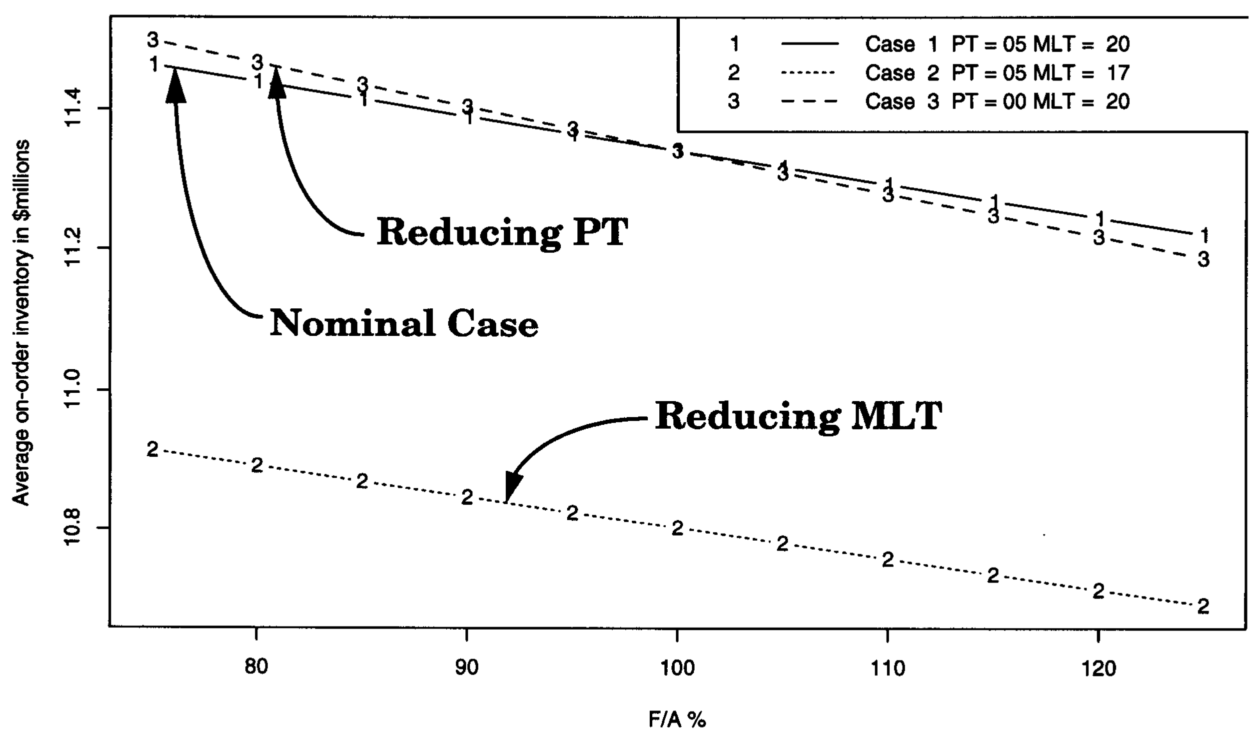


Figure 17. Average On-order Inventory vs. F/A

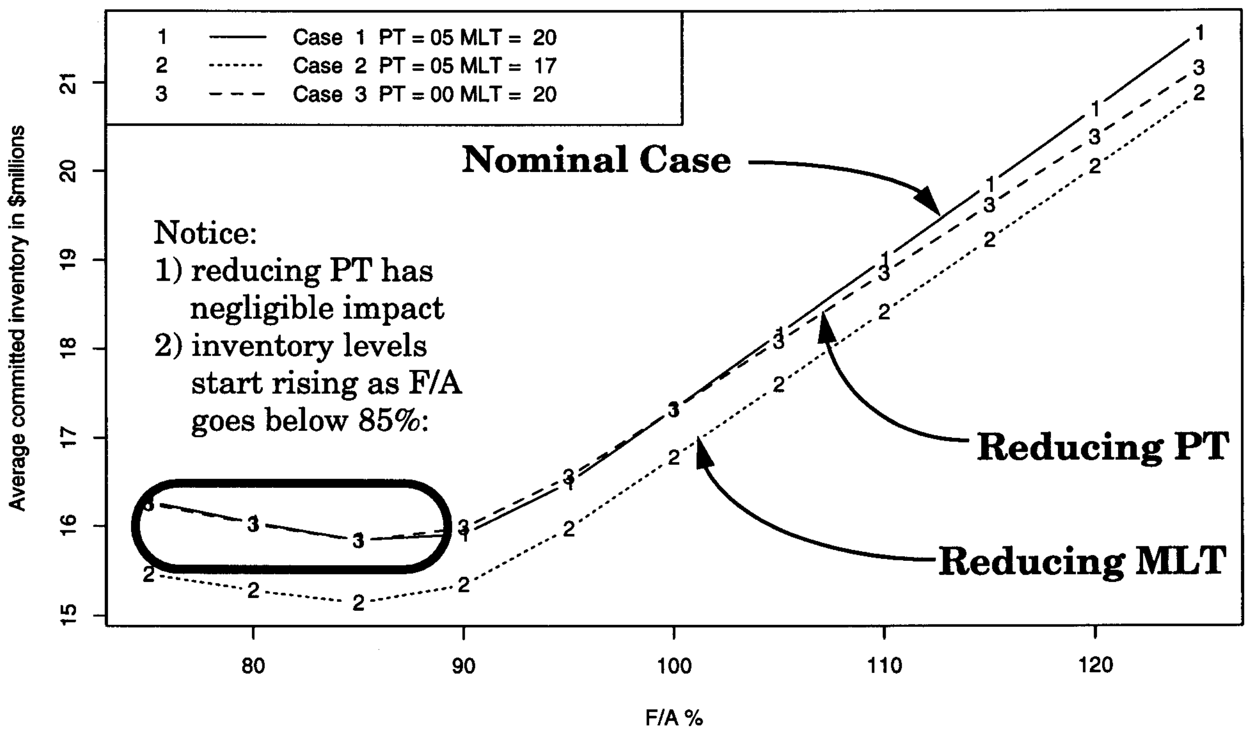


Figure 18. Average Committed Inventory vs. F/A

decreases below about 85%. The combination of these facts leads to the realization that when F/A is extremely low, both backlog and inventory levels are high, and shipments cannot be made. The following steps explain this phenomenon.

- Sustained low forecasts lead to depletion of material safety stocks which leads to production shortfalls and increased backlog.
- The response to material shortages is to order material quickly.
- Parts with long ELT take the most time to replenish safety stocks.
- Availability of the part with the maximum ELT will constrain production.
- Consequently, parts with shorter ELTs will accumulate in RPI.

For the Jupiter BOM, the longest ELT part is the relatively low value SA12 part. The high value of on-hand inventory is due, in part, to the more expensive TL1 part.

5 Conclusions

5.1 Revisiting the Phase I Results

The above detailed observations provide some insight as to why there was no definitive answer on the amount of inventory due to planning time at the end of the Phase I experiment set. Different values of the independent variables have different impacts on different components of inventory. The impacts also depend on the forecast accuracy. Using historical forecasts in the Phase I experiments provided a realistic and complex simulation configuration. However, as the graph in Figure 8 indicates, for the period of our analysis, forecasts were generally low. As Figure 18 shows, when forecasts are low reducing planning time has all most no impact. By smoothing the data and running multiple simulations in Phase II, we were able to get clearer insights into the relationships.

5.2 Recommendation for Action

The foregoing general and specific analysis argues for reducing PT and LT while driving F/A to 100%. While these are worthy long term goals, it is not possible to do all these things simultaneously. We recommend the following for immediate action:

- Reducing the lead times of SA12 and TL1 may provide the best improvement to inventory exposure in the near term. Our expectation is that reducing the lead times of these parts by a few weeks would be easier than cutting planning time to zero.
- Establishing an on-going process for reducing the effects of the maximum ELT across all parts by:
  - identifying the parts with the longest ELTs.
  - negotiating with vendors to reduce the LT for those parts.
  - incorporate design changes that eliminate the use of those parts.
  - increasing safety stock for those parts, especially if they are low value items, so that they do not become critical parts

5.3 Comments on the Modeling Process

It became very clear to us as we worked on this project was that we could conceive of changes to make to the model and new experiments to run much faster than we could implement those changes, run the experiments, and conduct the analysis. We have reached the stage where we have a robust model that can be applied to a broad range of problems, and we have just begun to scratch the surface. Our intent here is to provide readers with an indication of the potential and stimulate thinking on how it might help solve other important problems involving complex relationships.

Obtaining these insights required time for model building, experiment design and execution, and the analysis of large amounts of data. These processes cannot be rushed. While time pressures often do not allow for much detailed analysis, the dollar value of the decisions being made should be kept firmly in mind.

5.4 Possible Future Work

The following are areas of possible future work. While they are all technically feasible, academically interesting, and expand the EMS work in different dimensions, we look forward to comments from the reader to provide guidance on what value and benefit will be provided to HP by doing such work.

5.4.1 Further Analysis with Existing PC Model

By changing the input data files, and without modifying the PC Model, it would be possible to do further analysis. The following are some suggested directions:

1. Investigate the effects of modifying SA12 and TL1 lead times and safety stock levels.
2. Rerun the PC Model with the historical forecasts and orders with lead time and safety stock values suggested by 1 above.
3. Obtain a quantified estimate of F/A over time for the historical data.

5.4.2 Distributed Multi-Entity Factory

Section 2.2 described simplifying assumptions that enabled us to use the SM, with only minor modifications, to do the analysis for the PC project. The consequences of these simplifications include but are not limited to the following:

- Dwell times in sub-assembly factory RPI & FGI are ignored.
- Material procurement plans are not adjusted for the most recent inventory and customer order data.
- Visibility on availability of all parts exists. In the real system, sub-assembly factory part availability data is not used in the FAST factory planning.
- Orders to vendors can not be adjusted or modified as in the real enterprise.

Figure 19 shows a modification of the SM in which the single factory has been cloned into one final-assembly site and multiple[1] sub-assembly sites. The straight forward implementation of this concept is precluded by the fact that currently the SM does not generate forecasts or plans for use by its suppliers. In particular, we would need to consider at least the following questions:

- How do the sub-assembly factories use the plans generated by the final-assembly factory to create their own plans?
- What information on constraints at the sub-assembly factories, is provided to the final-assembly factory, and how does the final-assembly factory use this information?

5.4.3 Changes to Production Planning and Material Ordering Policies

If we were to address all the issues related to the PC model assumptions, the following questions would also need to be answered:

- How is current inventory and customer order data used to modify material orders at the time of issuance?
- What are the policies and procedures for changing orders already placed on vendors?

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1. One level sub-assembly is shown for illustrative purposes. By recursive cloning, it should be possible to model multiple levels of sub-assemblies.

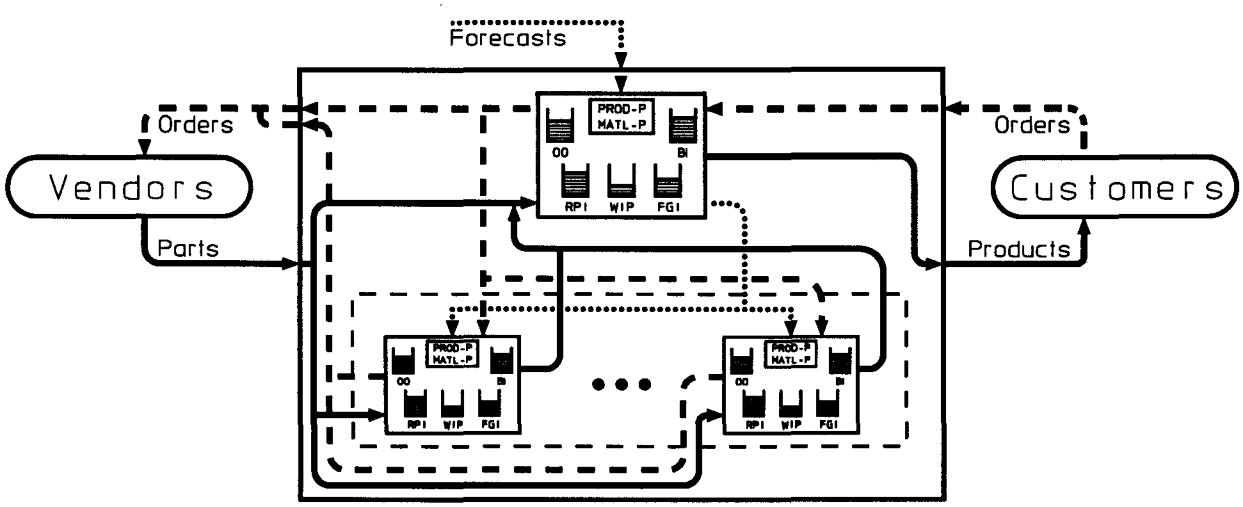

Figure 19. Material/Order Flow Diagram of Multi-Entity Distributed

5.4.4 Production Capacity Constraints

The SM and the PC models do not consider production constraints and rules dealing with expanding the constraints (e.g. how much can we increase production capacity in 1 month, 3 months, etc.). To date this has not been considered to be a major problem, as we have been modeling situations in which material constraints are the principle controlling factors. However, for completeness it would be necessary to add this capability to the EMS.

5.5 Recommendation of the Planning Calendar Team Revisited

The following observations and recommendations are extracted from [7]:

- Applying the models to CM's Planning Process yielded valuable information and the enterprise modeling methodology has further value.
- Awareness has increased that it is possible to reason explicitly and objectively about the outcomes of different actions rather than to rely only on implicit intuition.
- Three main areas for applying the model are:
  - CM Planning Process Redesign
  - CM Coordinated Inventory analysis
  - General Core Team[1] experiments
- As resources become available, include the analysis of models as a tool for providing verification of our production planning activities.

The authors of this report endorse and concur with these observations.

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1. The Core Team refers to the Computer Systems Organization Planning Process Redesign Core Team

6 Acknowledgments

The authors of this report would like to express their thanks to the management of CM and HPL for supporting the execution of this project. Among the participant, we would like to thank Kevin Oliver for coordinating the efforts of the participants in three geographical locations toward a common goal, Lanny Meade for providing his expertise with the planning process, Mark Inkster for the initial coordination that made this work possible, Charles Kozierok, a MIT graduate student in the LFM program, for collecting the data, running the Phase I experiments, graphing the results, and distributing them in a timely fashion to all the participants, and everyone for the many hours of discussions which established the foundation for the Phase II experiments.

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Appendix A : Jupiter Bill Of Material (BOM) and Lead Times

A.1 Top Level Parts (not real part numbers)

Table A-1: Top Level Parts[a]

Part Number	Quantity Required	Unit Cost (dollars)	Lead Time (weeks)	Weeks of RPI
TL1	1	935.14	20	3
TL2	1	657.21	8	3
TL3	1	125.73	6	3
TL4	1	136.71	14	3
TL5	1	100.00	8	3

a. Pre-RPI Time = 0 weeks and Pre-on-order = P1; total items 5

A.2 Sub-assembly Level Parts (not real part numbers)

Table A-2: Second Level Parts[a]

Part Number	Quantity Required	Unit Cost (dollars)	Lead Time (weeks)	Weeks of RPI	Part Number	Quantity Required	Unit Cost (dollars)	Lead Time (weeks)	Weeks of RPI
SA01	2	282.03	14	1	SA16	1	5.51	13	1
SA02	4	66.31	13	1	SA17	1	5.13	9	1
SA03	14	8.21	13	1	SA18	2	6.42	9	2
SA04	18	2.40	8	1	SA19	36	10.31	9	1
SA05	1	68.11	6	1	SA20	2	4.31	17	2
SA06	8	3.55	7	1	SA21	36	10.30	9	1
SA07	2	10.51	9	1	SA22	2	4.26	9	2
SA08	51	0.21	4	1	SA23	53	0.05	5	4
SA09	1	10.51	13	1	SA24	1	10.18	12	2
SA10	3	10.86	9	1	SA25	24	3.01	8	2
SA11	6	2.76	3	1	SA26	1	29.01	5	2
SA12	5	6.51	19	1	SA27	4	16.01	13	8
SA13	1	42.01	6	1	SA28	1	17.50	13	2
SA14	1	27.01	9	1	SA29	1	37.51	6	2
SA15	1	14.50	11	1					

a. Pre-RPI Time = B2+S1 = 2 weeks and Pre-on-order = P1+P2; total items 29

Appendix B : Multiple Plots

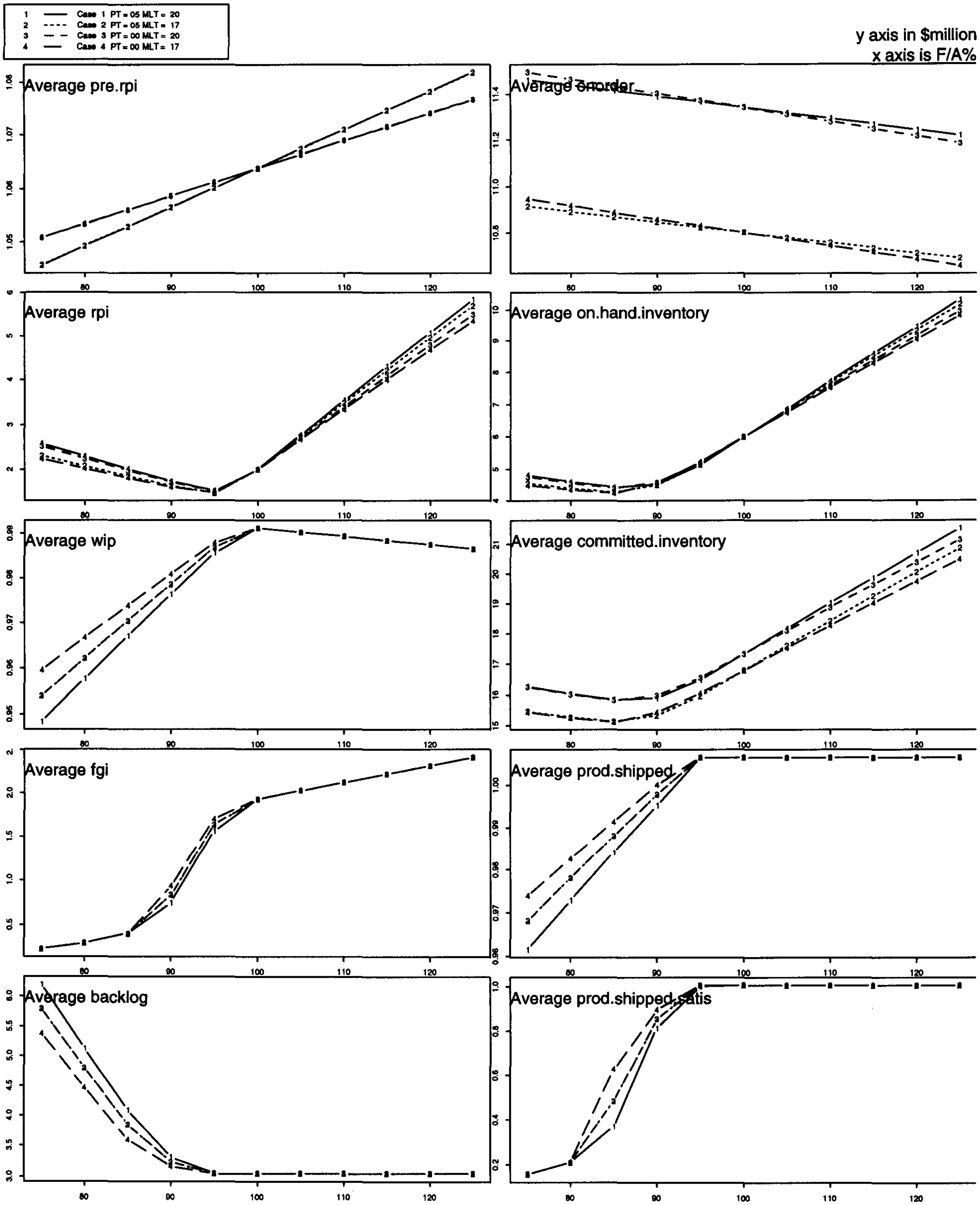

Figure B-1: Average metrics in $millions vs. F/A%

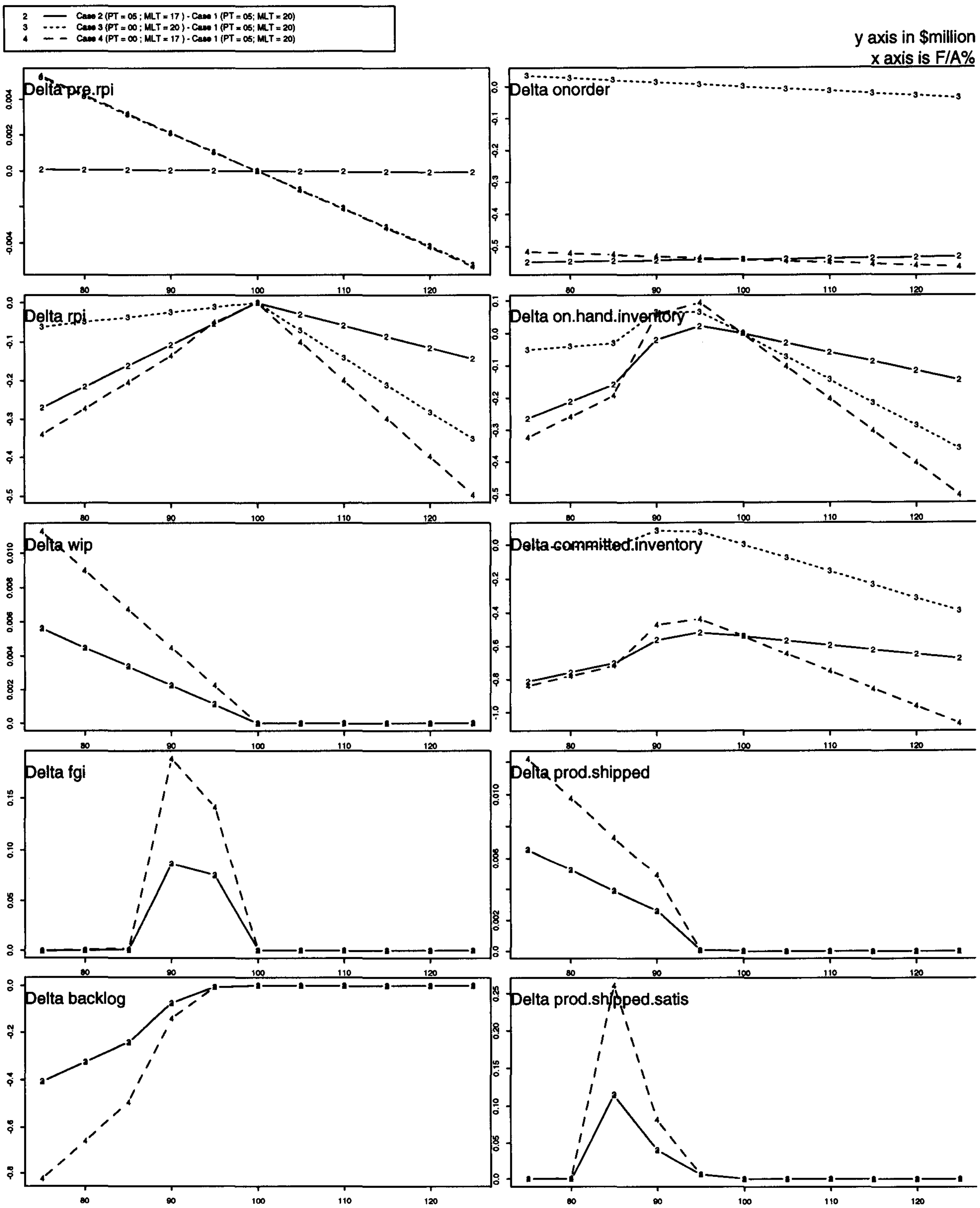

Figure B-2: Delta metrics in $millions vs. F/A%

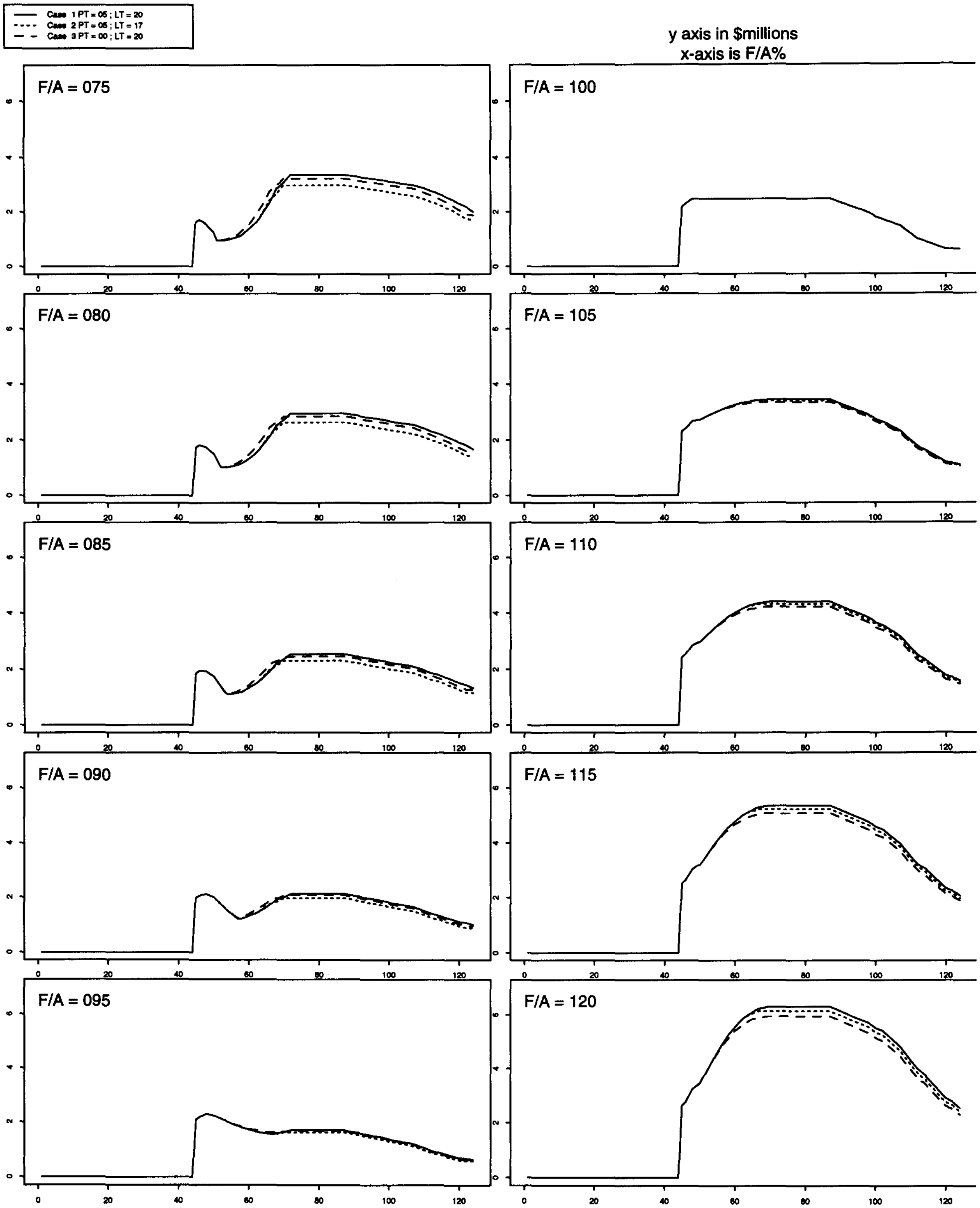

Figure B-3: Time History of RPI levels for Cases 1-3 for different F/A