Impact of Product Complexity on Inventory Levels

by
Ying-Lai (Chandler) See, csee@alum.mit.edu
Bachelor of Electrical Engineering, Honors (2001)
National University of Singapore

Jin Namkoong, jinnk@alum.mit.edu
Master of Business Administration (2004)
University of Virginia

Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

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Massachusetts Institute of Technology

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Signature of Author ....
Engineering Systems Division
12th May 2006

Certified by ....
Chris Caplice
Executive Director, Master of Engineering in Logistics Program
Thesis Supervisor

Accepted by ....
Yossi Sheffi
Professor of Civil and Environmental Engineering
Professor of Engineering Systems
Director, MIT Center for Transportation and Logistics

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Abstract

In this thesis we consider a manufacturing and distribution supply chain of a roll-based product whose width comes in 1-cm increments. We formulate a computer model subject to stochastic, inelastic demand to determine the relationship between width interval and finished goods inventory levels. Assuming that the supply chain operates with the same set of policies regardless of the width interval value, we illustrate that the value of risk pooling diminishes as the interval widens. Due to the presence of a counteracting effect, we also demonstrate that increasing the width interval does not always reduce the amount of inventory requirements. Lastly, we show that the supply chain can operate with lower inventory levels without compromising the service level by pushing the inventory down the chain.

Thesis Supervisor: Chris Caplice
Title: Executive Director, Master of Engineering in Logistics Program

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- Chandler

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- Jin

Dedication

For my mother who taught me the right things to do,

and

For my father who reminded me the wrong things not to repeat,

and

For my siblings who showed me how to forgive.

I love you all.

- Chandler

For my parents who have instilled strong values in me,

and

For my wife whose selfless devotion has allowed me to pursue my professional goals,

and

For my beloved two daughters who have been a source of support and joy.

- Jin

Table of Contents

List of Tables

List of Figures

1 Problem Statement

This research grew out of the belief that a wider product variety does not always lead to higher profitability. Conventional wisdom has it that product proliferation is an instrument for competitive advantage since it allows companies to better match their products to customers' requirements. However, this view is narrow because its implications on various operations have been largely ignored. In production, product proliferation will lead to a higher frequency of line setups and switching, degrading overall manufacturing efficiency. With a deluge of similar products, forecasting becomes difficult, and many manufacturers respond to that by building excessive safety stock. As a result of missed forecasts which in turn call for freight expediting, transportation cost is likely to be affected as well. Among other things, product proliferation also forces smaller orders for a larger array of goods, and complicates storage and shipment handling with the number of new cube and weight profiles introduced.

While the ramifications of product proliferation are extensive, the scope of this study is limited to the impact of product complexity on inventory holding levels. The research, conducted in collaboration with Emanon Inc.*, examines a specific product called Formax (more on this later). Available in a large number of configurations, this product provides a suitable platform for our analysis.

* The company name, the product name, and other details have been disguised for reasons of confidentiality

The purpose of this research is twofold. First of all, it serves to develop a deeper understanding of theoretical principles related to inventory management. Second, it is intended to shed light on how those principles, coupled with modeling techniques, could be used to develop insights into real-world applications.

The organization of this thesis largely mirrors the order in which the research is conducted. Chapter 2 provides an overview of the literature pertaining to this study. Chapter 3 introduces the partner company and Formax. The subsequent two chapters represent the main body of this research. Chapter 4 details the modeling approach taken, as well as several scenario analyses conducted. The model is then extended in Chapter 5, by taking into consideration the operations performed by a finishing center the company owns in Asia. Finally, we present our conclusions and recommendations in Chapter 6.

2 Literature Review

For years, SKU (Stock Keeping Unit) proliferation has been a subject of much talk for it represents a major operational challenge to manufacturing enterprises. To mitigate its negative impacts, researchers generally have the consensus that SKU rationalization is essential, however they differ in opinions with regard to the approach to take. As Edmunds and McSparran (1996) point out, any SKU reduction effort should be focused on low-volume items simply because the sheer number of them and the stress they bring to supply chain. On the contrary, since the financial contribution of low-volume SKUs is insignificant more often than not, Roberts (1999) argues that the tendency of concentrating on these SKUs is exactly what companies should avoid. Instead, he suggests, SKU rationalization will reap the most benefit if it is engineered around high-volume but low-profitability items or those that create a disproportionate number of production issues.

Some studies explore the issue of SKU proliferation from an entirely different perspective. They share the view that a growing portfolio is inevitable in the business environment, so the real issue is not to stop it but to learn to cope with it. Coupled with the fact that there is no straightforward means of telling whether a firm has come to a product variety saturation point, Bodegraven (2004) contends that having exit strategies in place (such as order termination, product returns, and early diversion into alternate channels) for a product that underperforms is more pragmatic as well as proactive. Postponement is also a recurring and widely recognized tactic for dealing with product complexity, which is usually less expensive to manage if it can be delayed until late in the production cycle.

Regardless of the approach, the fundamental principle underlying this segment of literature is essentially the same. The phenomenon was first documented by Eppen (1979) as "statistical economies of scale". More commonly known as risk pooling, it is the ability to reduce the total uncertainty by aggregating uncertainties that would otherwise be managed separately. Based on the assumption that demands are normally, identically and independently distributed, Eppen and Schrage (1981) demonstrate that holding and backorder penalty costs are lower in a centralized system than in a decentralized one with identical warehouses serving individual demands. Erkip, Hausman and Nahmias (1990) extend Eppen's model to allow for demand correlations. Their generalized model concludes that the safety stock requirement is higher when demands across products and successive time period are positively correlated. The benefit of pooling is dependant on the internal system parameters as well. Kim (2002) illustrates that such benefit diminishes with the increase in the loading of production system.

Zipkin's (1995) work on a multi-item production inventory system is one of the earlier papers that address the pooling effect by means of product offering reduction instead of location pooling. Considering a perfectly flexible manufacturing system with shared resources and zero switching time between items, Zipkin shows that the sum of the standard deviations of demands for different products are directly proportional to the square root of the number of products. In the case where setup times are substantial, the effect of product variety on inventory cost is significantly greater (Thonemann and Bradley, 2002). The finding is further corroborated by

Benjaafar, Kim, and Vishwanadham (2004) who extend the model without assuming any distributions associated with demands and setup times. They also show that the rate of increase in cost due to higher product variety decreases as demand variability goes up.

Literature that is closely related to our work includes the paper by Alfaro and Corbett (2003). Under the assumption that the inventory policy in place is optimal, they demonstrate that the value of pooling is sensitive to the concentration of uncertainty but is relatively robust across different types of distributions. Our research differs from the above study in that we focus on total inventory investment instead of inventory holding and penalty costs. In addition, demand is inelastic in our project due to the unique setting of the business. In other words, total demand stays constant even when certain SKUs are eliminated.

3 Background

3.1 Formax's Supply Chain Overview

3.1.1 Customer Segmentation

On the basis of application type, the customer base of Formax is divided two segments. By and large, sales are equally split between these two applications. Emanon also classifies its customers into four geographical regions, namely North America, EMEA (Europe, Middle East and Africa), Asia, and South America. On average, the first three markets comprise majority of sales.

3.1.2 Forecasting

Emanon adopts a top-down approach to generate sales volume forecast. Volume projection is first developed for an array of product families by region before it is decomposed into item-level information. By virtue of the pooling effect, forecast accuracy is high at the product family level. It hovers around 50% at the item level despite stable demand experienced by end customers.

3.1.3 Manufacturing

The manufacture of Formax begins with the mixing of core and additive. The process, marked by severe agitation, produces an intermediate compound which is subsequently introduced into an extruder. By raising the temperature of the core to its melting point and applying high pressure, the melted core gets forced through a nozzle to produce a continuous, uniform sheet that is immediately slit into rolls of desired width. The effective yield rate of the entire manufacturing process is high.

In general, Emanon adopts the make-to-stock policy for Formax's production. It holds the product in finished goods inventory and satisfies demand from that inventory as orders come in. The company makes use of MPS (Material Production Schedule) to facilitate its production planning. Taking forecast data, capacity data, and inventory data as inputs, the module works out when production will have to occur in order to meet the distribution schedule.

3.1.4 Distribution

Emanon distributes Formax through its many warehouses spanning the four geographical regions mentioned earlier. In general, each warehouse accumulates inventory coming from several manufacturing plants before the inventory is drawn by customers within the same region. Thus, the warehouses can be perceived as the push-pull boundary within the supply chain.

Between the manufacturing and warehousing facilities, goods are normally shipped by trucks or ocean carriers. As a result of long transportation lead time, a significant amount of inventory is in transit all the time. At the time of this writing, inventory in transit represents about 10% of the total finished goods inventory.

Emanon sets a target service level of 95% to measure its order fulfillment performance. More specifically, 95% of the orders should be fulfilled before the first promised date quoted to customers. To facilitate inventory control and distribution planning, a DRP (Distribution Requirements Planning) module is in place as part of the whole ERP (Enterprise Resource Planning) suite.

3.1.5 Trim Buy-Back

As a result of process limitations, a small portion of Formax is trimmed away by customers during their manufacturing stage. Currently, Emanon provides trim tubs to customers and buys the discarded material back for re-extrusion whenever the accumulated weight reaches a certain level. The reverse logistics cost is borne solely by Emanon.

Due to contamination reason, not all the returned material can be used for re-extrusion. In accordance with the agreements with customers, Emanon only pays for the portion that can be reintroduced to the extrusion line.

3.2 Product Attributes

Due to customers' varied requirements, Emanon produces Formax in a variety of widths, lengths, and colors. Some other attributes that characterize a SKU include:

- Formulation - It governs the chemical properties of the product.
- SQI - Special Quality Index, it refers to the special instructions a customer has pertaining to the construction of the product.
- Packaging Standard - It dictates the pallet type, the pallet size, the number of items on a pallet, and the item orientation.

4 Methodology

The goal of this research is to gain insights into how product complexity drives inventory levels. To achieve that end, we decided to use mathematical/computer modeling technique on the grounds that it often delivers needed information on a cheaper and timelier basis. On top of that, it offers the advantage of being scalable as well, and this comes in handy when we extend the model in Chapter 5.

Our modeling approach follows a simple outline. A model that represents the relevant characteristics of the supply chain of a specific product family is first constructed, forming the empirical basis for evaluating alternatives. Several what-if analyses are subsequently performed, each of which involves tweaking certain underlying structure or inputs. Most of the model inputs are extracted directly from the ERP (Enterprise Resource Planning) system. In cases where certain parameters are not available, estimates or proxies are used instead. For instance, due to the lack of actual demand information, we treat sales as its proxy throughout this research.

4.1 Profiling of Sales Data

Currently, Formax is available in over 10000 SKUs. To reveal the factors driving the complexity, we arbitrarily select the monthly sales data of Oct 2005 and plot its distribution (see Appendix A) by each of the product attributes listed in section 3.2.

The plots in Appendix A suggest that the complexity is induced primarily by different specifications in width, SQI, and packaging standard. The width, in particular, goes from a narrow 4 cm to a wide 322 cm, and is in increments of 1 cm for most of the range. Each of the remaining attributes identified also comes with at least 30 different values, and the number is likely to be higher since we only consider sales of a single month. Although interdependency between attributes exists, it should be apparent that the total number of possible combinations of attributes is massive (in the order of billions).

More importantly, the plots uncover the existence of dominant values. For instance, formulation "M" alone accounts for 62% of the total volume. This phenomenon is prevalent across the rest of the attributes except for the width, whose corresponding distribution exhibits a different pattern. As shown in Figure A6, over 80% of the total volume is spread out more evenly across the entire range of widths. Never is there an instance where a particular width value represents more than 20% of total sales.

This finding is important when we contemplate the option of SKU rationalization. Basically, the existence of dominant values dilutes the pooling effect, which is exactly what rationalization is trying to maximize. If a particular attribute value already represents 80% of the entire volume, trimming the value set along that dimension is similar to harvesting crops that are only 20% ripe. Therefore, even without any elaborate calculations, it should be fairly obvious that reducing the number of width offerings makes more sense than does decreasing the number of values of other attributes.

In fact, even if we ignore those distribution patterns, the issue of substitutability is likely to bring us to the same conclusion. For most attributes, alternatives are generally not available, so opportunities for rationalization are severely limited. Nonetheless, width rationalization does not suffer from such rigidity. Supplying wider rolls only means that the customers have to trim the excess material themselves, which is not a problem because it is part of customers' manufacturing process anyway.

4.2 Product Family Selection

To keep the scale of the model in check, we focus our analysis on one specific product family. Echoing the reasoning given in the preceding section, this particular product family comes in a large variety of widths. Its defining characteristics are given in the following table:

Attribute	Value
Formulation	M
SQI	FMS
Color	N.A.
Length	250 m
Packaging Standard	B4

Table 1: Characteristics of the Modeled Product Family

4.2.1 Data Sanitization

It is worth pointing out that not all the data associated with the family are relevant to our analysis. Depending on situation, Emanon does produce Formax to order at times. Since we are only interested in products that are made to stock, those that are not were excluded from the model.

Table 2 shows the monthly sales data of the 98 cm SKU in 2005. Notice that the SKU was sold through warehouse 5306 only in September throughout the year, so there is a high likelihood that it was produced to order. To do the filtering systematically, we assume that entries with sales in 4 months or less within the time frame were produced to order.

SKU Description	Warehouse	Volume (m^2)											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
FM,98x250,B4	5306	0	0	0	0	0	0	0	0	1960	0	0	0
FM,98x250,B4	5327	19845	14700	11515	9065	11270	10290	490	1715	1470	490	490	0
FM,98x250,B4	5380	[redacted]									11760	8820	9800
FM,98x250,B4	5383	15680	4900	1960	2940	6860	245	0	0	27930	14210	7840	16660

Table 2: 2005 Monthly Sales Data of the 98 cm SKU

Exceptions to the rule exist, however. For example, it is reasonable to assume that the company only began selling the SKU through warehouse 5380 after September 2005. Thus, the entry should not be removed, though it would have been under the filtering rule. To address this issue methodically, we stipulate that the rule does not apply to entries with at least 6 consecutive months of zero sales from January and at least 3 non-zero sales subsequently.

4.3 Modeling Tool

In this project, we make use of PowerChain Inventory software developed by Optiant to model Formax's supply chain. Designed for inventory deployment, the software allows users to establish inventory targets and policies in order to reduce overall inventory costs.

4.3.1 Terminology

Similar to any other software, PowerChain Inventory has its own unique terminology that translates to a moderate learning curve for most users. Not meant to be all-inclusive, we present a list of relevant terms as follows:

- Stage

  A stage represents a process or a series of processes that consume time and money. Procurement, assembly, and transportation are all quintessential examples of stages. Though inventory can potentially accumulate at the end of a stage, stages are item specific. Therefore, a stage can not be thought of as a location that holds multiple items.

- Link

  A link connects one stage to another, indicating the flow of product between the two. Item multiplier is the only property of a link. It defines the ratio between the source item and the destination item.

- Stage time

  The time it takes to complete all of the processes within a stage as soon as all of the inputs are available. This parameter must be a non-negative integer.

- Stage cost

  This is the unit direct costs added at a stage. It typically includes material, labor, tariff, and transportation costs.

- Service time

The lead time a stage promises to a subsequent stage to fill an order. It is assumed to be exact, meaning orders are filled neither too early nor too late. This parameter must be a non-negative integer.

- Net replenishment lead time (NRLT)

  Otherwise known as exposure period, NRLT is the period of time for which inventory coverage must be provided. It is used to determine the safety stock requirement at a stage. Mathematically,

$$NRLT = Inbound\ Service\ Time + Stage\ Time - Outbound\ Service\ Time$$

- Service level

  Service level is the probability with which demand in fulfilled within the quoted service time. Under conventional service definitions, it is also known as cycle service level.

- Total Inventory Investment

  The average dollar value of inventory residing in the supply chain. It represents the working capital expenditure required to fill the chain with inventory. It is the sum of pipeline stock investment and on-hand stock investment.

- On-Hand Stock

  On-hand stock is the sum of safety stock, early arrival stock, and cycle stock.

4.3.2 Underlying Principles[†]

In PowerChain Inventory, a supply chain is modeled as an acyclic network with stages (or nodes) and links (or directional arcs). Each stage represents a major process in the supply chain, and each link indicates a supplier-customer relationship between two stages. The network can be very complex in structure; there is no limit to the number of upstream or downstream stages a stage can have so long that the stages and links do not form any closed loops.

Some of the assumptions that underlie this modeling tool include:

- Every stage provides a guaranteed service time to its downstream stages.
- All stages operate with a periodic review inventory replenishment policy. In other words, the planner has the opportunity to review and replenish the inventory every period.
- External demand occurs only at nodes without successors.
- Demand is relatively stable over the long run.
- Demand every period is an independent normally distributed random variable with mean u and standard deviation σ.

By design, every stage is a potential location for holding safety stock. The calculation of safety stock requirements is not entirely straightforward; it relies on the software's ability to break a network into assembly and distribution sub-networks. (In an assembly network, a stage can only have one successor. Conversely, a stage can only have one predecessor in a distribution network.)

[†] See Willems (1996) for a comprehensive account of the fundamental basis of the software.

To illustrate the point, consider an assembly network in which a stage is connected to several upstream suppliers. The NRLT of the stage can be obtained by deducting the outbound service time of the stage from the sum of the longest service time of its suppliers and its own stage time:

$$NRLT = Max\{Inbound\ Service\ Time\} + Stage\ Time - Outbound\ Service\ Time$$

As a result of the above expression, the safety stock required by the stage is:

$$Safety\ Stock\ Level = k\sigma\sqrt{NRLT}$$

where k is the safety factor implied by the service level of the stage (e.g. $k = 1.64$ for a service level of 95%)

Now consider a distribution network in which a stage feeds several downstream customers. If we assume that the stage quotes a distinct service time to each of its customers i, the safety stock required by the stage can be expressed as:

$$Safety\ Stock\ Level = k\sqrt{\sum_i NRLT_i \sigma_i^2}$$

By treating the service time parameters between stages as decision variables, it is possible to formulate an optimization problem that minimizes the total inventory holding costs. Assuming there are altogether m stages,

$$\begin{aligned} &Minimize && \sum_m Safety\ Stock_m \times Holding\ Cost\ Rate_m \\ &Subject\ to && NRLT_m \geq 0 \quad \forall m \\ & && Service\ Time_m \geq 0 \quad \forall m \end{aligned}$$

Over the years, the software has evolved much and become relatively sophisticated. Many features have been added, and most of them are proprietary. Naturally, we have no visibility into the actual solution procedure. However, despite its simplicity, we want to emphasize that the mathematical model presented here doesn't differ considerably from the actual one contained within the software.

4.4 Base Case Model

Figure 1 shows the overall architecture of the model. Following a three-tiered structure, the supply chain begins with the procurement of raw materials, followed by the manufacturing processes, and ends with the shipping stages. Inventory accumulates at the end of every single stage, but as we are only interested in finished goods inventory, the procurement stages have to be excluded from the cost calculations. In other words, whenever we speak of total inventory investment in the context of this research, it does not include any raw material inventory but refers only to finished goods inventory, both in transit and in storage.

The software has the limitation that external demand can only be fed into stages without successors. In reality, demand is received directly at the manufacturing stages as well because in this case, the manufacturing plant is also a warehouse by itself. To circumvent that, we insert a zero-cost, zero-lead time stage between the manufacturing stage and its domestic customers.

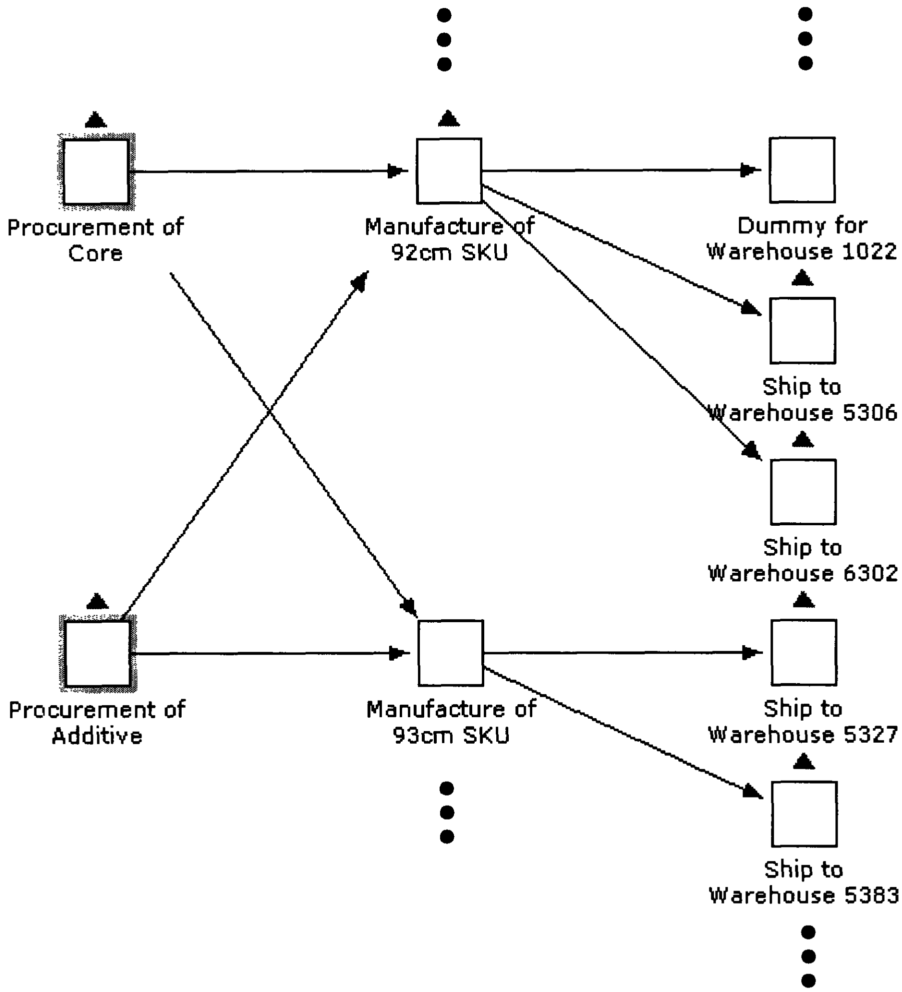

Figure 1: Model Architecture

4.4.1 Model Inputs

In Table 3, we provide a summary of the stage inputs needed to build the model. Take note that the stage costs reflect only the variable components because any fixed costs are irrelevant for comparison of different scenarios. We also want to emphasize that the base time unit of the model is business days rather than calendar days since customers place orders and receive material during weekdays only. Shipments on weekends are truly an exception.

Stages	Unit	Stage Costs	Stage Time (Business Days)	Service Time (Business Days)
Procurement of Core	kg	\$0.455/kg	11	0
Procurement of Additive	kg	\$0.3375/kg	19	0
Manufacture of x[‡]cm SKU	m^2	\$1.247/m^2	5	2
Dummy for 1022	m^2	\$0/m^2	0	0
Ship to 5306	m^2	\$0.11/m^2	5	2
Ship to 5327	m^2	\$0.11/m^2	5	2
Ship to 5380	m^2	\$0.11/m^2	10	2
Ship to 5383	m^2	\$0.11/m^2	3	2
Ship to 6302	m^2	\$0.14/m^2	10	2

Table 3: Base Case Stage Inputs

PowerChain Inventory either takes the standard deviation of demand or the standard deviation of forecast error to compute the safety stock requirement. Owing to the lack of exact forecast data at the item level but knowing that it stays around 50%, we assume that the forecast always misses by 50%. We also assume that overshooting and undershooting occur on an alternate basis such that the forecast error will not be biased in the long run:

	Volume											
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Sales	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}
Forecast Error	- $S_1/2$	+ $S_2/2$	- $S_3/2$	+ $S_4/2$	- $S_5/2$	+ $S_6/2$	- $S_7/2$	+ $S_8/2$	- $S_9/2$	+ $S_{10}/2$	- $S_{11}/2$	+ $S_{12}/2$

Table 4: Forecast Error Estimation

‡ Throughout this paper, x is a variable that represents the width of a roll

Last but not least, Table 5 presents a summary of link inputs. Put into words, the table suggests that it takes 0.545 kg of core and 0.21 kg of additive to produce 1 m^2 of the finished goods.

Source	**Destination**	**Link Multiplier**
Procurement of Core	Manufacture of x cm SKU	0.545
Procurement of Additive	Manufacture of x cm SKU	0.21
Manufacture of x cm SKU	Ship to Warehouse	1

Table 5: Base Case Link Inputs

4.4.2 Model Outputs

After specifying all the inputs for the model, the software automatically generates an assortment of outputs, many of which are extraneous to our research interest. Consequently, we provide only a subset of the outputs in the following table:

Cost of Goods Sold	\$3,492,373
Annual Stock Holding Cost	\$70,803
Total Inventory Investment	\$354,014
Days of Supply	26.4
Inventory Turns	9.9

Table 6: Model Outputs

4.4.3 Model Validation

To ensure the validity of the model, the inventory requirements generated by the model are compared against the actual inventory data:

	Actual	Calculated	Deviation
Inventory Investment at Manufacturing Plant	$162,915	$127,845	-21.5%
Inventory Investment at External Warehouses	$170,716	$220,227	+29.0%
Total Inventory Investment	$333,631	$348,072	+4.3%

Table 7: Inventory Comparison

In a nutshell, the model underestimates the inventory level for the manufacturing site but overestimates for the external warehouses. The deviation of errors varies within a range of $\pm$30%. However, the deviation reduces to only 4.3% if we consider the aggregated figures because the errors cancel out each other.

Although we are more concerned about the relative difference in these values when scenario analyses are conducted, we reckon that several factors could contribute to the disparity. First of all, we compute the actual average inventory investments by considering only four months (September 2005 through December 2005) of inventory data (which is all we have), although we feed into the model one full year (2005) of sales data. Obviously, the two sets of data are of different time horizon and therefore the accuracy should improve if we can get hold of the inventory data for the rest of the months in year 2005. Second, the model assumes that demand is normally, identically, and independently distributed. This is not entirely valid, because some of the demand data could not be explained adequately by any common distribution. Finally, we suspect that our assumptions about forecast error play a part in the phenomenon as well.

4.4.4 Sensitivity Analysis

So far, all the model inputs are numeric constants. Implicitly, we have assumed that the exact values of these inputs can be specified. Nevertheless, this is unlikely to be the case in the real world where the inputs might change from day to day or simply due to manual interventions. For instance, shipping goods to warehouse 6302 does not always take exactly 10 days. Depending on many factors such as carrier shipping schedule and port handling speed, this number can change.

On top of that, it was stated in the beginning of this chapter that some of the inputs are merely estimates of the actual values to the best of our knowledge. Therefore, in the following sections, we assess the sensitivity of total inventory investment to changes or estimation errors in several inputs such as stage cost, stage time, and service time.

4.4.4.1 Procurement of Core

Figure 2 shows the sensitivity of total inventory investment to changes in core procurement stage cost. Because stage cost itself doesn't affect the holding quantity of inventory but only the value of it, the relationship has to be linear. Expressed as a percentage of the original amount, total inventory investment varies within a small range of $\pm 16\%$ even when the stage cost swings wildly, suggesting that the model is relatively robust against changes or errors in this parameter.

The relationship can be represented by the following equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} = 0.164\left(\frac{StageCost_{New}}{StageCost_{Original}}\right) + 0.836$$

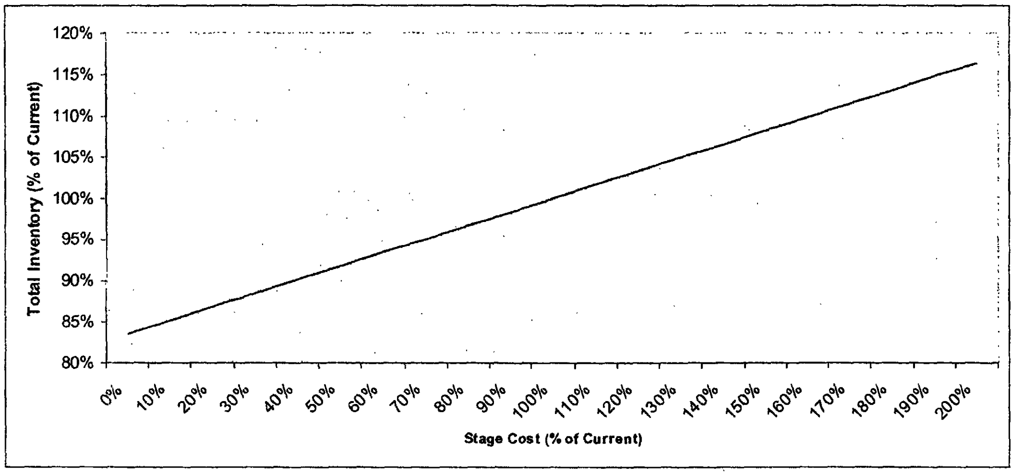

Figure 2: Total Inventory Investment as a Function of Core Procurement Stage Cost

Unlike stage time, the service time of a stage affects the inventory levels of both that stage and its succeeding stages. As shown in Figure 3, the curve manifests the property of diminishing effect, meaning that every incremental increase in the service time value will have less and less impact on total inventory investment. We can approximate the relationship by using the following linear equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} \approx 0.027(ServiceTime) + 1.017$$

We want to point out that Figure 3 does not suggest that a service time of 0 days is ideal from a system's perspective. Bear in mind the service time of this stage also affects the core inventory which is excluded from the calculation of total inventory investment. In fact, there is always a possibility that the core accumulation more than offsets the reduction in finished goods inventory when the service time of this stage decreases. Nonetheless, the way we define total inventory investment precludes us from seeing the trade-offs in the figure.

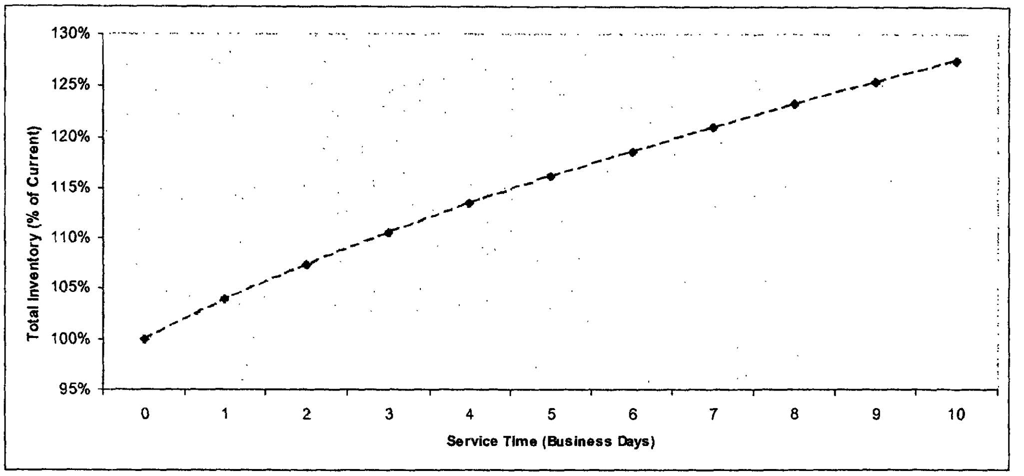

Figure 3: Total Inventory Investment as a Function of Core Procurement Service Time

4.4.4.2 Procurement of Additive

Having similar construction as the previous stage but only with different input values, the behavior of total inventory investment in response to changes in the corresponding inputs of this stage has to be similar as well. The associated equations are:

$$\frac{Inventory_{New}}{Inventory_{Original}} = 0.047\left(\frac{StageCost_{New}}{StageCost_{Original}}\right) + 0.953$$

$$\frac{Inventory_{New}}{Inventory_{Original}} \approx 0.039(ServiceTime) + 1.024$$

Given that the gradients of both lines above are small in comparison to the intercept values which are close to 1, we draw the logical deduction that the model is rather insensitive to estimation errors or changes in both the stage cost and the service time of this stage.

4.4.4.3 Manufacture of x cm SKU

Given the number of manufacturing stages in the model, it is infeasible to perform sensitivity analysis on each of the stages. Therefore, all of them are collectively considered as one cluster in this section.

Figure 4 shows the sensitivity of total inventory investment to changes in manufacturing stage cost. As before, the relationship is linear. What is different, however, is that the line is much steeper in this case. This is because manufacturing cost is the largest cost component in the entire chain, so modifying it will have a more significant impact on the inventory value. Expressed as a percentage of the original amount, total inventory investment varies within a wider range of $\pm 75\%$ when the stage cost alters from 0% to 200% of its current value. The relationship can be represented by the following equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} = 0.754\left(\frac{StageCost_{New}}{StageCost_{Original}}\right) + 0.246$$

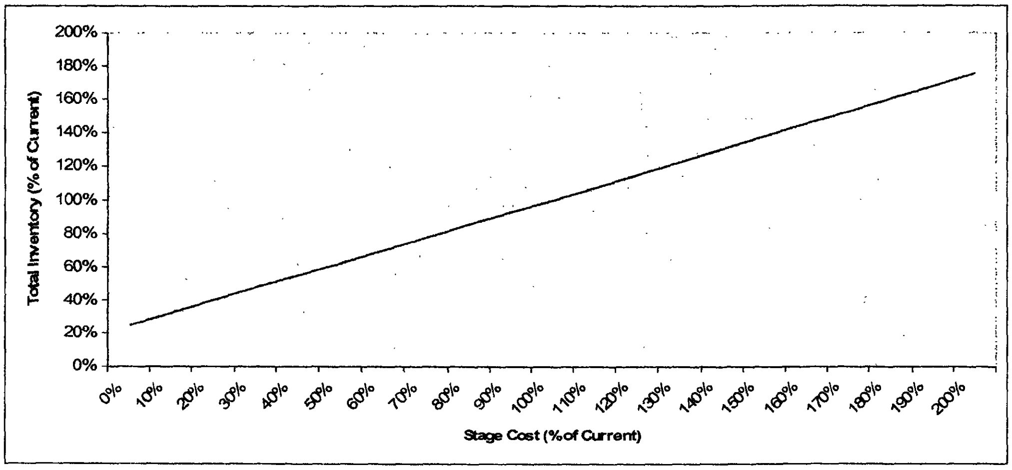

Figure 4: Total Inventory Investment as a Function of Manufacturing Stage Cost

Figure 5 shows the sensitivity of total inventory investment to changes in manufacturing stage time. Currently, manufacturing stages have an inbound service time and an outbound service time of 0 and 2 days respectively. Therefore, the NRLT is negative so long that the stage time stays below 2 days, which obviates the need to hold any safety stock at the manufacturing site. However, the inventory level does not stay constant within the range of 0 to 2 days because pipeline stock investment does increase mildly when the stage time rises. Beyond that range, the NRLT starts to assume a positive value, and the curve rises sharply because of safety stock requirements. The relationship can be expressed by the following equations:

$$\frac{Inventory_{New}}{Inventory_{Original}} \begin{cases} = 0.017(StageTime) + 0.705, & 0 \le StageTime \le 2 \\ \approx 0.059(StageTime) + 0.696, & StageTime \ge 3 \end{cases}$$

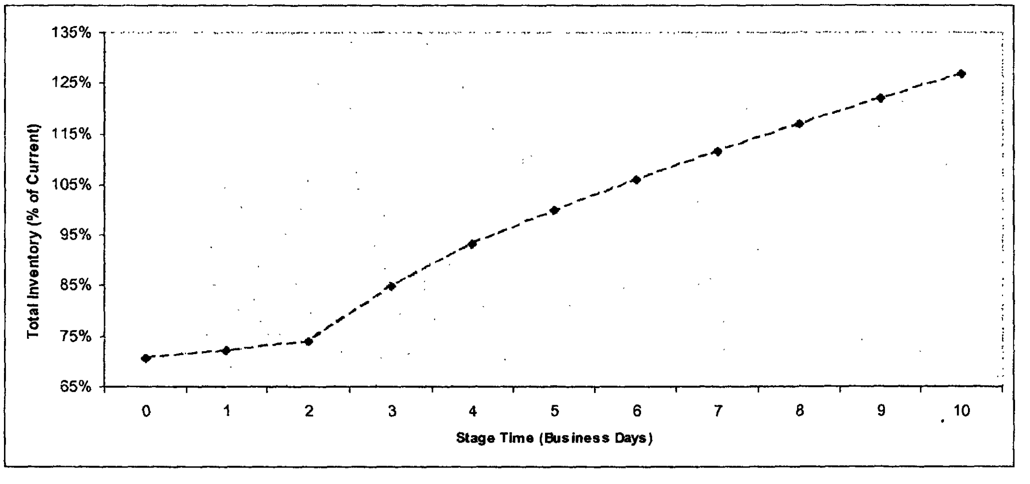

Figure 5: Total Inventory Investment as a Function of Manufacturing Stage Time

Figure 6 shows the sensitivity of total inventory investment to changes in manufacturing service time. Basically, increasing the manufacturing service time means a lower NRLT for the manufacturing stages but a higher NRLT for the shipping stages. In other words, the inventory requirements at the manufacturing and shipping stages go in opposite directions in response to the service time variation. Clearly, trade-offs exist. Take note that the inventory level at the manufacturing stages does not decrease indefinitely when the service time increases. In fact, when the service time goes beyond 5 days, the NRLT of the manufacturing stages begins to take on a negative value. As such, the manufacturing site is no longer required to keep any safety stock, and that is precisely the reason why the curve takes a dip when the service time equals 5 days. Beyond that, the increase shown in the figure is solely attributed to the increase in safety stock investment at the warehouses. The relationship can be approximated by the following equations:

$$\frac{Inventory_{New}}{Inventory_{Original}} \approx \begin{cases} 0.985, & 0 \leq ServiceTime \leq 4 \\ 0.065(ServiceTime) + 0.537, & ServiceTime \geq 5 \end{cases}$$

We also deduce from Figure 6 that there exists a specific manufacturing service time which minimizes total inventory investment. This mirrors our earlier assertion that the software comes with the capability of optimizing total inventory investment by treating service times as decision variables. We will look into this again when we optimize the model in later section.

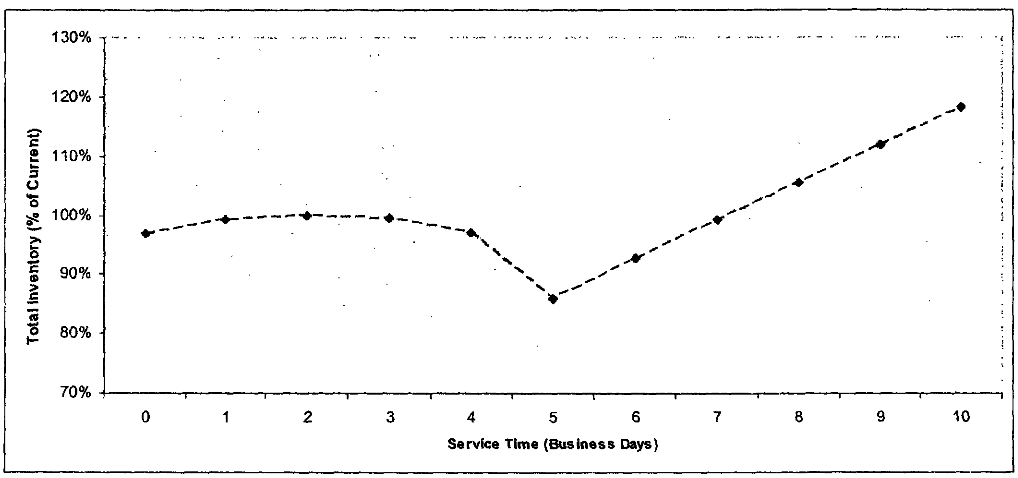

Figure 6: Total Inventory Investment as a Function of Manufacturing Service Time

4.4.4.4 Shipping to Warehouse

Similar to the manufacturing stages, all the stages in the third tier of the supply chain are jointly considered in this section. We first examine the sensitivity of total inventory investment to changes in shipping stage cost. As shown in Figure 7, total inventory investment varies within a tight range of $\pm 3\%$ when the stage cost alters from 0% to 200% of its current value. The relationship can be represented by the following equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} = 0.034\left(\frac{StageCost_{New}}{StageCost_{Original}}\right) + 0.965$$

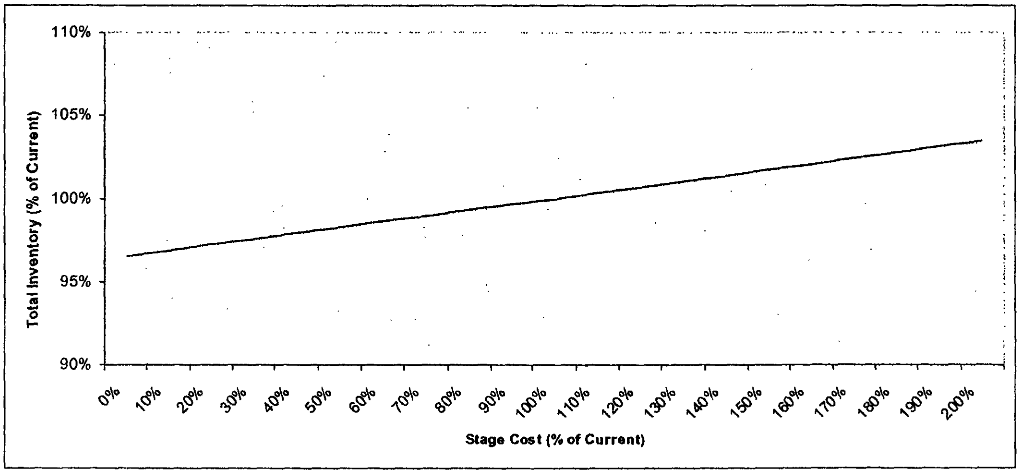

Figure 7: Total Inventory Investment as a Function of Shipping Stage Cost

Figure 8 shows the sensitivity of total inventory investment to changes in shipping stage time. The curve once again displays the property of diminishing effect, and the group's average stage time hovers around 6 days. The relationship can be approximated by the following equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} \approx 0.203(StageTime)^{0.67} + 0.378$$

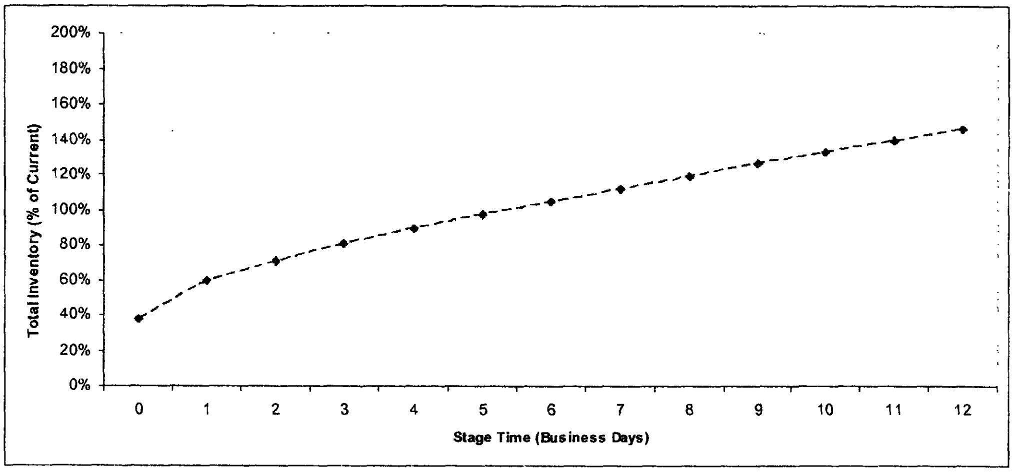

Figure 8: Total Inventory Investment as a Function of Shipping Stage Time

We can also consider both the stage time and the stage cost simultaneously by producing a chart like Figure 9, which can be used to determine the impact of other transportation means on total inventory investment. Consider a hypothetical shipping option that halves the stage time at twice the cost. Total inventory will increase due to the cost factor and decrease as a result of the time factor. The net result, from the figure, is a decrease in total inventory investment of around 17%.

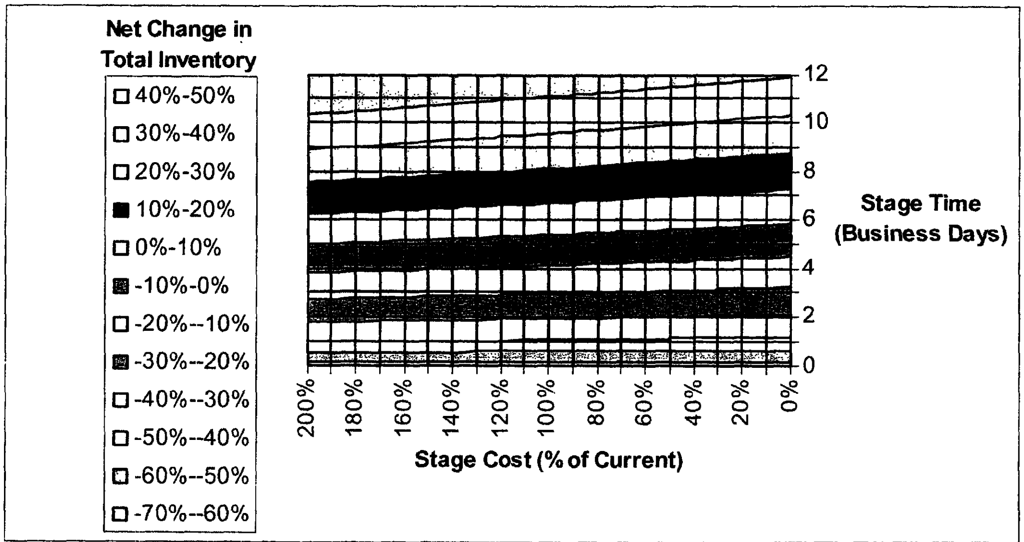

Figure 9: Time-Cost Trade-offs of Shipping Stages

Finally, Figure 10 shows the sensitivity of total inventory investment to changes in the service time promised by the warehouses. Notice that Figure 10 looks just like a mirror image of Figure 8, and this is because increasing the stage time has the same effect on the NRLT as decreasing the service time. Therefore, we can express the relationship by writing a similar equation:

$$\frac{Inventory_{New}}{Inventory_{Original}} \approx 0.1(7 - ServiceTime)^{0.7} + 0.679, \quad ServiceTime \leq 7$$

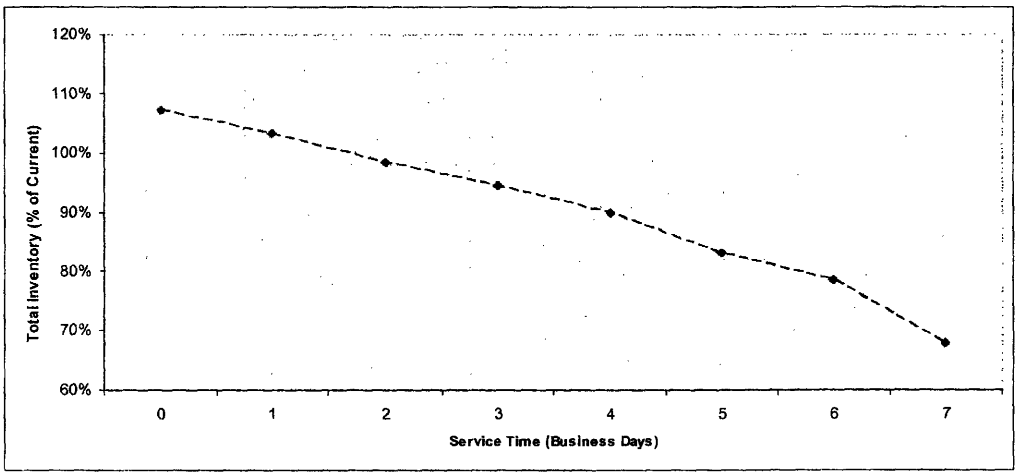

Figure 10: Total Inventory Investment as a Function of Shipping Service Time

In summary, the sensitivity analysis indicates that the model is relatively robust against changes or estimation errors in most of the inputs. In many cases, the output of total inventory investment varies within a small range even when the inputs change much. Besides that, the analysis also makes prioritization of inputs possible. By knowing the degree to which an input affects total inventory investment, one can decide whether it is worthwhile to expend more resources to fine-tune it. For example, in our case, it is reasonable to devote considerable amount of effort to get a more accurate representation of the manufacturing stage cost given its significant influence on total inventory investment. However, it is perhaps unwise to do the same thing for shipping stage cost.

4.5 Master-Sizing

We begin our scenario analysis by first considering the option of master-sizing – a form of width rationalization in which rolls would only be offered in increments of a larger value. Customers are expected to trim the excess materials themselves, which is not really an issue because trimming is part of their manufacturing process anyway.

On one hand, master-sizing has the advantage of pooling risks together to reduce inventory requirements. On the other hand, it forces the company to hold wider rolls in inventory. These two counteracting effects jointly determine the net impact of this initiative on total inventory investment.

In this research, we examine four specific interval (n) values, namely 5 cm, 10 cm, 15 cm, and 20 cm. Table 8 shows the actual width offerings in each case.

n	**Width Offerings (cm)**
5 cm	70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 125, 155
10 cm	70, 80, 90, 100, 110, 120, 130, 160
15 cm	80, 95, 110, 125, 155
20 cm	80, 100, 120, 140, 160

Table 8: Width of Master Rolls

4.5.1 Data Preparation

Due to the unique market power that Emanon has over its customers, demand is unlikely to be lost when the program of master-sizing is implemented (Bloemen, 2006). As a result, we assume that the demand of master rolls is simply the sum of demands of narrower rolls. We also assume that it remains normally, identically, and independently distributed after such aggregation. Table 9 provides an illustration for one particular master roll sold through warehouse y:

Item	**Width (cm)**	**Warehouse**	**Volume (Rolls)**
SKU_1	w	y	Vol_1
SKU_2	$w-1$	y	Vol_2
SKU_3	$w-2$	y	Vol_3
...	...	...	...
SKU_n	$w-n+1$	y	Vol_n
Master Roll	w	y	$\sum_i Vol_i$

Table 9: Demand Aggregation

The variance of forecast error for the master rolls can also be computed in a similar manner:

Item	**Width (cm)**	**Warehouse**	**Variance of Forecast Error**
SKU_1	w	y	Var_1
SKU_2	$w-1$	y	Var_2
SKU_3	$w-2$	y	Var_3
...	...	...	...
SKU_n	$w-n+1$	y	Var_n
Master Roll	w	y	$\sum_i Var_i$

Table 10: Variance Aggregation

4.5.2 Results

The blue curve in Figure 11 shows the impact of master-sizing on total inventory investment. Notice that the x-axis is not drawn to scale because the first value is 1 cm instead of 0 cm (the effect of so doing on the graphical interpretation of the figure is minimal). The curve shows that total inventory investment should reduce by roughly 10% when the interval value is widened to 5 cm. By stretching the interval to 20 cm wide, we can expect total inventory investment to further reduce to around 74% of its original value.

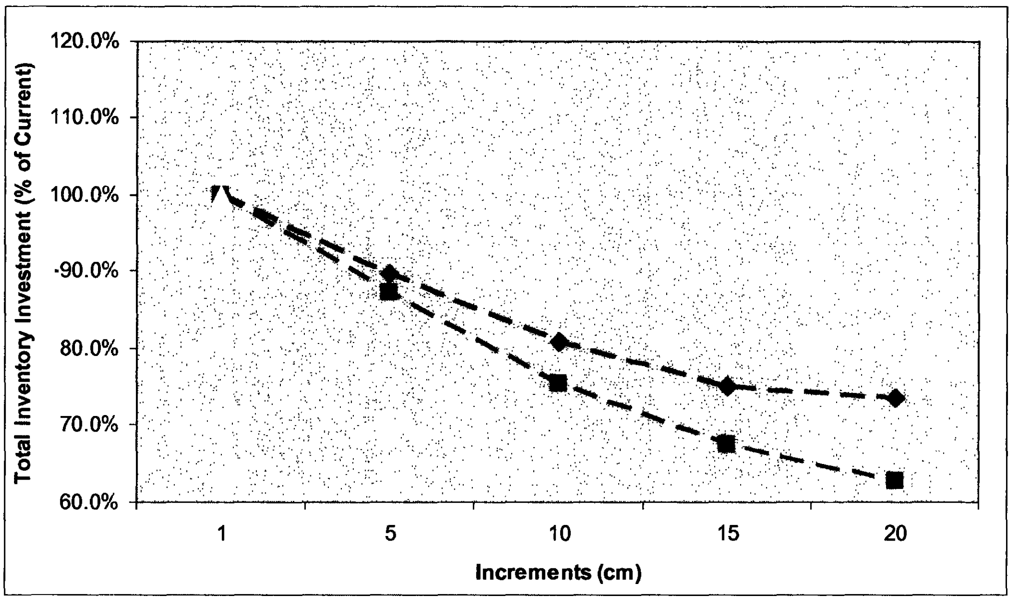

Figure 11: Effect of Master-Sizing on Total Inventory Investment

The fact that the curve stays below the level of 100% indicates that the value of pooling more than outweighs the wider-roll effect within the range of tested interval values. However, the relative strengths of the two counteracting effects do not stay unchanged across the range. To illustrate that, we decompose the results above and show the two effects separately. The yellow curve in the figure shows the impact of the wider-roll effect alone on total inventory investment.

As depicted, the wider-roll effect causes total inventory investment to rise linearly with respect to the width interval. The purple curve, on the other hand, shows the impact of the pooling effect alone on total inventory investment. The curve slopes downwards almost linearly initially but begins to flatten as the interval value widens, indicating an eventual wane in strength of the pooling effect.

Judging from the trends of the two separate effects, the blue curve in Figure 11 is likely to pick up when the interval value goes beyond 20 cm. In other words, the maximum achievable savings in total inventory investment by means of master-sizing is around 26%.

4.5.3 Incentives for Customers

From Emanon's perspective, master-sizing has the advantage of reducing total inventory investment. However, the customers will not favor the scheme because it forces them to buy more than they really need. Unless incentives are offered, implementing the scheme is likely to meet resistance from the customers.

To get around the issue, at least two distinct options are available to Emanon. The company can either reduce the unit price of Formax or increase the buy-back price for the trim return.

To examine how far the two parameters can be stretched and still keep the program of master-sizing favorable, we first let

p : Unit selling price of Formax

c : Unit COGS (Cost of Goods Sold) of Formax

b : Unit buy-back price

t : Unit transportation cost

i : Unit cost of raw materials

M : Savings in inventory investment due to master-sizing

r : Annual inventory holding cost rate

α : Trim return factor under the base case (the fraction of total volume sold that is returned), $0 \le \alpha \le 1$

β : Trim recycle factor (the fraction of trim return that can be re-extruded), $0 \le \beta \le 1$

P_B : Annual profit under the base case

P_E : Extra annual profit generated through master-sizing

V_B : Annual volume shipped under the base

V_E : Extra volume shipped due to master-sizing

Subsequently, we adjust the annual profit, annual sales volume, and annual trim return volume under the master-sizing case with respect to the corresponding items in the base case in the following manner:

	Base Case	**Master-Sizing Case**
Total Profit / Year	P_B	$P_B + P_E$
Volume Shipped / Year	V_B	$V_B + V_E$
Volume of Trim Return / Year	αV_B	$\alpha V_B + V_E$

Table 11: Profit and Volume Adjustments

If we were to increase the buy-back price to b',

P_E = Revenue received for selling V_E

- COGS associated with V_E

- Reverse logistics costs for V_E

- Buy-back cost for βV_E

- Extra buy-back cost for $\alpha\beta V_B$

+ Savings in raw material production associated with βV_E

+ Savings in inventory holding cost due to master sizing

$$= pV_E - cV_E - tV_E - b\beta V_E - \alpha\beta V_B(b'-b) + i\beta V_E + Mr$$

$$= V_E[p - c - t - \beta(b - i)] - \alpha\beta V_B(b'-b) + Mr$$

Since b' is always greater than b, the above expression shows that it is always desirable to have a smaller α. In other words, it is in Emanon's advantage to have a lower amount of trim return from customers even though a portion of it can be used for re-extrusion. That way, the transportation cost for the non-recyclable portion can be reduced. In the case where $b > i$, the equation also reveals that P_E is larger when β is smaller. This implies that a lower trim recycle factor is favorable from Emanon's perspective whenever the unit buy-back price is higher than the unit cost of raw materials.

Given that p = \$3.94/m^2, c = \$1.67/m^2, b = \$0.56/m^2, t = \$0.11/m^2, i = \$0.32/m^2, and assuming that $\alpha = \beta = 1$ (worst-case scenario), the maximum buy-back price can be determined simply by setting P_E to 0.

Now consider the case of decreasing the selling price to p',

P_E	=	Revenue received for selling V_E
	-	COGS associated with V_E
	-	Reverse logistics costs for V_E
	-	Buy-back cost for βV_E
	-	Decrease in revenue for V_B
	+	Savings in raw material production associated with βV_E
	+	Savings in inventory holding cost due to master sizing
	=	$pV_E - cV_E - tV_E - b\beta V_E - V_B(p - p') + i\beta V_E + Mr$
	=	$V_E[p - c - t - \beta(b - i)] - V_B(p - p') + Mr$

As before, P_E is larger when β is smaller whenever the unit buy-back price is higher than the unit cost of raw materials. Taking the worst case where $\beta = 1$, the minimum selling price can be determined by setting P_E to 0.

The results of both approaches are summarized in Table 12. Consider the interval value of 5 cm, Emanon can afford to increase the buy-back price by no more than 9% or decrease the selling price by no more than 1.3% and still come out ahead in terms of profit generation. Bear in mind that the values are obtained by considering the worst case scenario where $\beta = 1$ and $\alpha = 1$. Therefore, the absolute values of the allowable percentage variations are likely to be higher in reality.

Interval	5 cm	10 cm	15 cm	20 cm
V_B	1,866,222 m^2	1,866,222 m^2	1,866,222 m^2	1,866,222 m^2
V_E	46,090 m^2	101,102 m^2	140,090 m^2	200,077 m^2
M	\$36,211	\$67,622	\$88,164	\$93,706
Max b'	\$0.61/m^2 (9% increase)	\$0.67/m^2 (20% increase)	\$0.71/m^2 (28% increase)	\$0.77/m^2 (39% increase)
Min p'	\$3.89/m^2 (1.3% decrease)	\$3.83/m^2 (2.8% decrease)	\$3.79/m^2 (3.9% decrease)	\$3.72/m^2 (5.5% decrease)

Table 12: Maximum Buy-Back and Minimum Selling Prices

4.6 Model Optimization

We mentioned in section 4.3.2 that the software comes with the capability of minimizing total inventory investment by treating the service time parameters between stages as decision variables of an optimization problem. By using this feature, we see a 14.5% reduction in the total inventory investment, and the only change involved is that the service time of the manufacturing stages has to increase from 2 to 5 days.

Not surprisingly, the result is in agreement with our earlier observation derived from Figure 6. Increasing the service time implies a shorter NRLT for the manufacturing stages but a longer NRLT for the shipping stages. Implicitly, the optimization mechanism pushes the finished good inventory down the supply chain. In other words, it is more cost-effective for the finished goods to be held at the external warehouses than at the manufacturing site.

The appeal of this approach is that it reduces total inventory investment without introducing the wider-roll effect at all. However, it brings about the issue of inconsistency. Take note that the manufacturing site does serve domestic customers directly, so a service time of 5 days basically means a promised delivery lead time of 5 days for the domestic customers. On the other hand, since the service time of the shipping stages stays unchanged at 2 days after optimization, the international customers have the privilege of getting the goods sooner. This could be an issue if some of the domestic and international customers belong to the same company.

5 Model Extension

5.1 Overview of Asia Finishing Center

For certain Formax SKUs marketed in Asia, after manufacturing the company transports products by master-size of width, as WIP (Work in Process), to the company's Asia Formax Finishing Center (AFFC). As the customer's demand, particularly for width size, becomes more visible, the cutting processes for those WIPs begin at the distribution center to respond to the customer's specific requirements for width size.

This delayed customization allows the company to enjoy the risk pooling effect across time as well as across demand, thus improving forecasting accuracy, reducing lead-times and lowering FG (Finished Goods) inventory level. It is very similar to the supply chain management strategy HP (Hewlett Packard Company) successfully implements in distributing its laser printers localized to the European and North America markets (Lee, Billington, and Carter 2003).

From the 2005 sales data for Formax, we see that approximately 8.8 million SQM (Square Meters: unit measure for the product volume) in total were processed through the AFFC slitting processes, accounting for about 7% of the company's total sales for the year.

By extending the model we built in the preceding chapter to apply to the current operations at AFFC, we aim to analyze how "accompanying" risk pooling by SKU rationalization will play a role in affecting the inventory level obtained by the delayed customization already being put in place.

5.2 Model Architecture

In Figure 12, we depict the architecture of the foregoing processes. Extended from the base case model in Section 4.4, the overall architecture has one more tier, slitting at AFFC between manufacturing and shipping to customer.

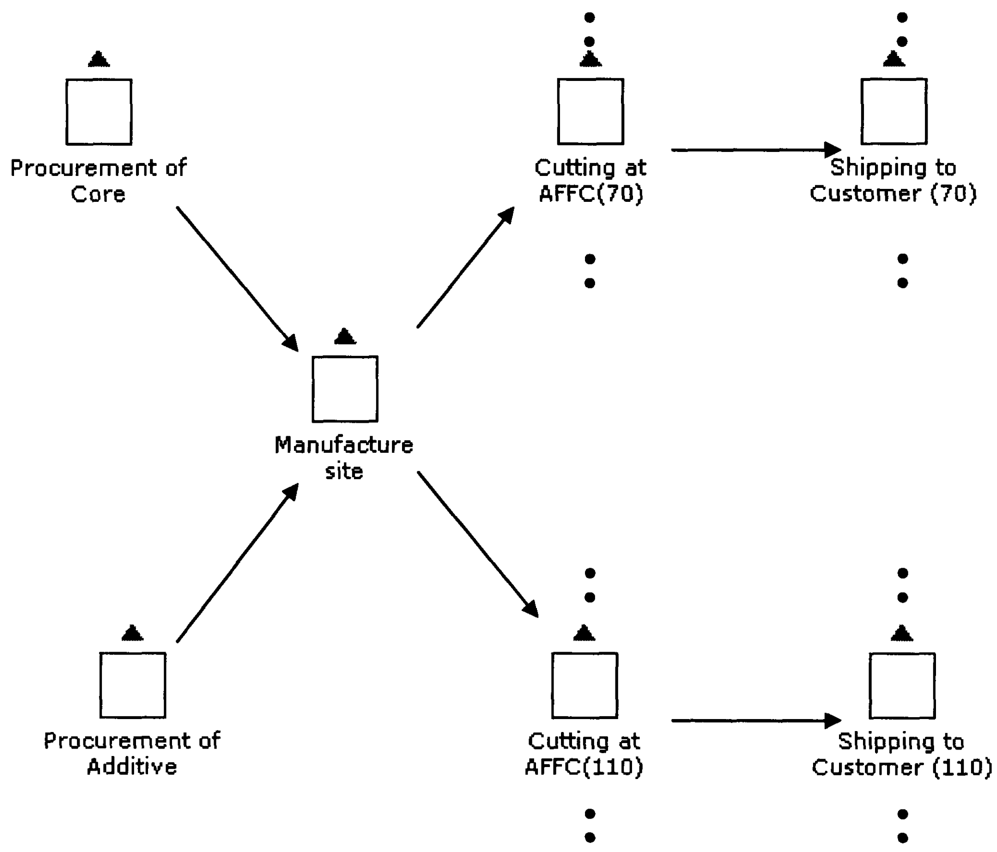

Figure 12: Extended Model Architecture

5.2.1 Model Inputs

We applied the same input variables for stage costs, stage time and service time of the procurement processes as in the base case model in Chapter 4. We made a modification to some variables and stage additions. Table 13 highlights those parameters and stages. Additional lead times for transportation (17 days) in the manufacturing process and the associated costs (freight and duty: \$ 0.34 per m^2) from the manufacturing site to AFFC are added in the manufacture stage.

Stages	Unit	Stage Costs	Stage Time (Business Days)	Service Time (Business Days)
Procurement of Core	kg	\$0.455/kg	11	0
Procurement of Additive	kg	\$0.3375/kg	19	0
Manufacture of cm SKU	m^2	\$1.59/m^2	22	0
Cutting at AFFC	m^2	\$0.15/m^2	3	0
Ship to customer	m^2	\$0.05/m^2	3	2

Table 13: Extended Model Inputs

The same methodologies applied to the modeling in Chapter 4 are also repeated in the model extension, except for a choice of inputs for standard deviation of demand. The forecasting accuracy (at the item level) rate of about 50%, on average, used for the base case in Chapter 4 is no longer applicable for this model extension case, because it is anticipated that the forecasting accuracy with the postponement policy at AFFC is much higher than 50%. Hence, we decided to use standard deviation of the historical data, which we computed from the monthly sales data for year 2005.

We calculated the coefficient of variation to be approximately 21% on average for a select product family at AFFC. We will explain the selection process for the SKU family in the following section. It is worth noting how sensitive total inventory costs are to the product demand in the model. To do this, we compared inventory level of applying the informed forecast error rate of 50% and coefficient of variation of 21% derived from the historical sales data. With the latter, the total inventory cost is 22% lower than using the forecast error 50%. This outcome is agreeable with our previous statement that the company carries fewer inventories for the products sold through AFFC because of the more accurate demand forecast.

5.2.2 Product Family Selection

For the analysis through the model extension, we chose a product family with the same approach as in the base case of Chapter 4. As explained in the chapter, focusing the width among the other attributes of the products makes much more sense in maximizing the pooling effect of aggregation because SKUs are well spread across the different width size while a few dominating SKUs with the other same characteristics represent the majority of volumes. Table 14 below illustrates a detail of the SKU family only with different width that goes through the AFFC operations. Also by using the data sanitization explained in Section 4.2.1, the number of SKUs in this model diminishes from 27 to 17.

Attribute	Value
Formulation	N
SQI	W2
Color	N.A.
Length	250 m
Packaging Standard	B4

Table 14: Characteristics of the Product Family for the Extended Model

5.2.3 SKU Rationalization

Master-sizing of width, as a means of SKU rationalization (same as the base case in Chapter 4), under this AFFC case, no longer provides any meaningful insights into the impact of inventory level because it is already in a form of master size in width when WIP is transferred from the manufacturing site to AFFC.

Accordingly, we took a different approach by aggregating SKUs on a basis of principles of (1) clustering SKUs with width being different in a narrow range and (2) integrating SKUs having less consistent sales over the months into a wider roll size of the SKUs whose sales pattern demonstrates otherwise. Table 15 supports to explain the methodology.

These three SKUs in the table fall under the same SKU family and the width of each SKU differs with a range of three cm. The width of 81 cm SKU and the 82 cm SKU show less consistent demand pattern over the period than the 84 cm does. Apparently, aggregation of the first two SKUs needs to be made into a width of 84 cm, becoming the 84 cm SKU. This aggregated master width measures the larger SQM, as shown in the table, than before the aggregation. The numbers in the bottom of the table, as highlighted in bold letter, represent the aggregated SQM of each month.

Width (CM)	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
81	0	0	0	0	0	2430	0	6480	7290	2430	4860	5670
82	4920	3280	1640	3280	2460	1640	1640	4100	1640	1640	1640	2460
84	5040	840	1680	1680	1680	2520	2520	2520	2520	2520	840	1680
Additional Volume	504	336	168	336	252	420	168	1092	924	420	672	840
84	**10464**	**4456**	**3488**	**5296**	**4392**	**7010**	**4328**	**14192**	**12374**	**7010**	**8012**	**10650**

Table 15: SKU Rationalization Process (1)

In the selected family product, the next width to the 84 cm is the 85 cm whose demand, however, occurs in three months in a row at the end of the year. Hence, rather than treating the 85 cm SKU as a master width for the 81 cm, 82 cm and 84 cm, we aggregated the 85 cm into the 87 cm that displays a steadier demand pattern across every month. Table 16 illustrates the calculation for aggregation between the two SKUs.

Width (cm)	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
85	0	0	0	0	0	0	0	0	0	850	850	850
87	2610	1740	1740	1740	2610	2610	2610	3480	1740	2610	2610	2610
Additional Volume	0	0	0	0	0	0	0	0	0	87	87	87
87	**2610**	**1740**	**1740**	**1740**	**2610**	**2610**	**2610**	**3480**	**1740**	**3547**	**3547**	**3547**

Table 16: SKU Rationalization Process (2)

Taking the same approach for the rest of SKUs, we came up with the number of SKUs reduced to seven in total. (Widths of 70, 79, 84, 87, 89, 94, 105, in centimeters)

5.2.4 Results

The risk pooling effect across demand by aggregating SKUs as explained in Section 5.2.3 returns a smaller decrease, about 6%, of total inventory investment, relative to the base case analyzed using the master-sizing methodology in Chapter 4. (About 10% to 26% reduction of total inventory cost with the different intervals of master sizing) It is also worth noting that the SKU aggregation based on the demand pattern, as compared with master sizing of width increment, produces less increased volumes. This result confirms our hypothesis that the products going through the AFFC slitting processes already gain the pooling effect by large amounts, through the delayed customization. In other word, the pooling effect on the demand is obtained enough, through the postponement policy at AFFC, that the combined pooling effect resulting from the SKU rationalization results in the smaller reduction in the inventory costs. Table 17 shows a comparison of outputs for the two models (Base case and SKU rationalization case) under the AFFC operations.

On the other hand, COGS (Cost of Good Sold) under the SKU rationalization case are higher than under the current case (about 3% increases). This leads to the same issue dealt in Section 4.5.3 about how to provide the customers with incentives on unit selling price and buyback price to the extent, which the marginal savings from less inventory investment could still end up exceeding the net effect on the bottom line.

Alternatives	SKUs	COGS (yearly)	% Diff	Total Inventory Investment	% Diff
Base Line Case	17	$ 889,179	-	$ 149,415	-
SKU Rationalization	7	$ 923,133	+3.4%	$ 140,277	-6.5%

Table 17: Output Comparison

5.2.5. Optimization

In this section, we optimized the base case model and compared the result of total inventory investment with the base case as well as with the SKU rationalization case. Figure 13 shows percent change in inventory investment after optimization against the base case as well as the SKU reduction. It demonstrates the largest cost savings on the inventory costs through the optimization are achievable.

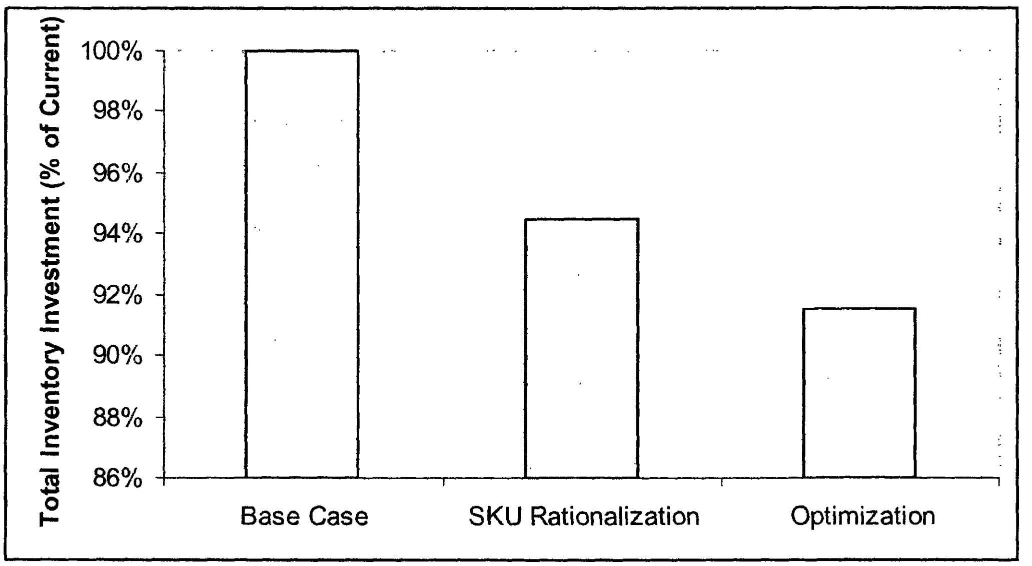

Figure 13: Comparison of Alternatives

The model optimization also suggests that the service time for the slitting operations at AFFC increase from 0 day to 3 days, so the NRLT (Net Replenishment Lead-time) for that stage becomes a zero. This means that the company does not need to provide any coverage and therefore does not need to carry any safety stock. In the meantime, the NRLT for the shipping to customer stage increases as the service time for slitting at AFFC does. That is, the NRLT for the shipping stage to meet the external customer service goal becomes four days, requiring more safety stock at that stage. Therefore, with the optimization, a substantial amount of safety stocks previously sitting at the cutting stage are pushed down to the next stage, closer to the customer.

5.2.5 Sensitivity Analysis

So far, throughout this model extension analysis, we assumed that all stages have neither variability nor uncertainty in each stage time. In the real world, however, that may not be practical. For an instance of manufacturing operations, when a company operates its own machine and facility, it may not choose to keep capacity and workforce enough to cover the peak or unexpected demand at any given time, as long as capital investment requirement is considered minimal. Therefore, capacity and facility constraints inevitably exist in the manufacturing operations.

As a means to fend off such limit, a company opts for farming out excess order fulfillment to contractors. Nevertheless, in that case a stage time for the same operations may not be identical to in-house operations. The transportation lead-time also varies depending on carriers and the weather conditions.

Keeping this argument in mind, we performed sensitivity analysis on the base case by varying the inputs of the stage time for manufacturing and cutting at AFFC respectively. Figure 14 and

Figure 15 represent outputs of total inventory investment graphically. (The line trend shows a linear relationship between inventory cost and stage time) As displayed below, the both cases account for a high sensitivity. With the stage time for the manufacturing site varying within 15%, the total inventory cost changes with a range of approximately 5%. On the other hand, with 33% change in the stage time of the slitting operations at AFFC, the total inventory investment varies within approximately 5%. This leads us to conclude that the stage time for the slitting operations responds less sensitively to the total inventory investment than the one for the manufacturing site does. From this, it is clear that a stage with a long exposure time needs to hold more stock than when with a short lead-time, and that the sensitivity to holding inventory level gets higher as an exposure time of the stage gets longer.

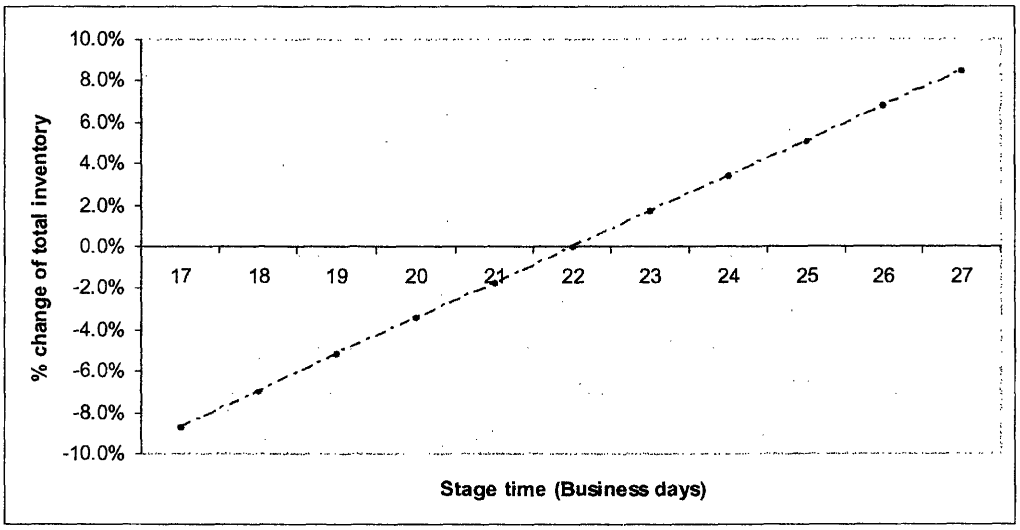

Figure 14: Total Inventory Investment as a Function of Manufacturing Stage Time

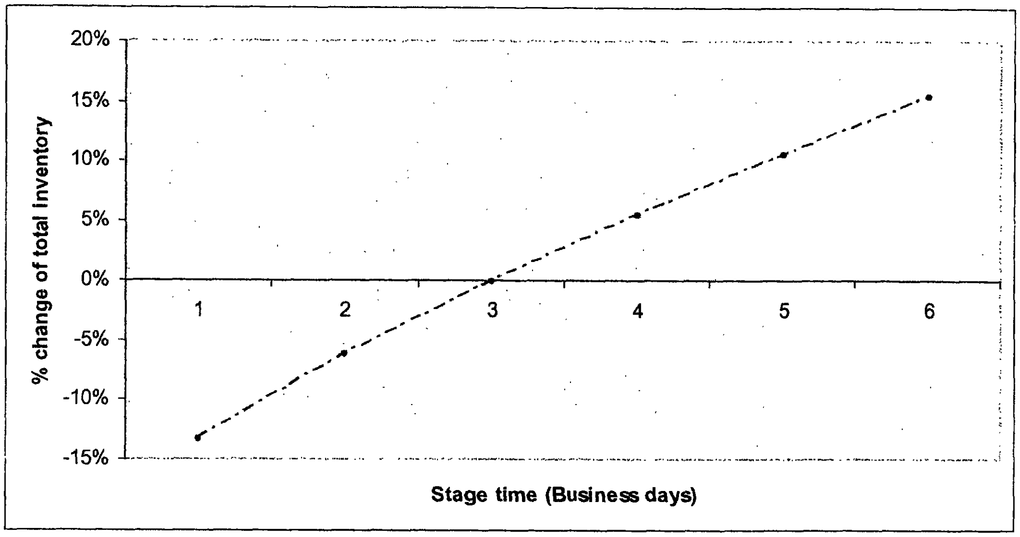

Figure 15: Total Inventory Investment as a Function of Cutting Stage Time

It is also interesting to note that if the stage time for the slitting operations is reduced to 2 days (from 3 days) or for the manufacturing operations to19 days (from 22 days), the savings of the total inventory investment are closely commensurate to the output of the SKU rationalization case.

In summary, the company already enjoys the pooling effect in the AFFC operations by capitalizing on the delayed customization, so the SKU rationalization adds less impact on safety stock as compared with the base case in Chapter 4. We also observed that the model optimization results in more savings on inventory costs, with no increase in COGS. Performing the sensitivity analysis of stage time provides us with an interesting insight to how influential the variability on the manufacturing and transportation lead-time is to inventory costs. Finally, the observations we made through the model extension lead us to an additional thought that improving the forecast accuracy, finding the optimal inventory location with inventory level, and reducing the stage time variability, are instrumental in saving inventory investment, at the same time with no requirement of incurring higher GOCS.

6 Conclusions

6.1 Findings and Recommendations

In this research we have constructed a supply chain model for determining the effect of width rationalization on inventory levels. We find that the value of pooling diminishes as the width interval widens. Because the product is available in rolls and its value determined by the surface area, there exists a wider-roll effect that offsets the pooling advantage. Although the total number of rolls held in inventory decreases as a result of width rationalization, the total worth of the inventory does not necessarily reduce accordingly. In other words, there is a definite range of width interval within which the rationalization effort is favorable in terms of total inventory investment. Beyond that range, the reverse is true.

The managerial implications of the wider-roll effect are significant. On top of causing a larger degree of mismatch between customers' needs and supply, master-sizing also creates more wastage of resources because a higher percentage of the product will traverse the supply chain back and forth without getting to serve any demand. In the face of ever-increasing petroleum costs, the wastage costs will become more evident in the future. Since such inefficiency comes at a price which neither the manufacturer nor its customers want to pay, the real challenge of the rationalization program not only lies in the selection of an appropriate width interval value, but also in preventing the perception that customers are footing the costs of increased wastage. Two readily available options accomplish that: reduce the product price or increase the buy-back price. Properly wielded, master-sizing can be a winning proposition for both parties.

Through model optimization, we also find for a product chain like ours, it is more favorable to push the finished goods inventory downstream. In other words, having the external warehouses rather than the manufacturing plant hold the inventory can effectively reduce the inventory requirements without compromising the service level.

6.2 Future Research

As with any research, our work ends with several unresolved issues and new questions. First of all, we assume in the model that demand is normally, identically, and independently distributed, although part of the actual demand data could not be explained adequately by any common distribution. Apparently, a model that allows mixed demand distributions and demand correlation will help us understand better how sensitive inventory levels are to product complexity.

Second, we assume that the monthly forecast error alternates between positive and negative values and its accuracy is always 50%. Even without the actual forecast data on hand, we know that this assumption is often not true. To rectify that, one could run the model under many scenarios with different error patterns and accuracy levels to observe the model behavior. Unfortunately, the number of possible scenarios could be so large that renders this approach impractical. Therefore, more research is needed to uncover better alternatives.

In our model, the selection of width offerings for any width interval value is arbitrary. Since the magnitude of the wider-roll effect is clearly tied to it, one possible extension of the model involves coming up an algorithm to determine the optimal width offerings that minimizes the wastage of resources for any given width interval value.

7 Bibliography

Alfrado, J., & Corbett, C. (2003). The Value of SKU Rationalization in Practice. Production and Operations Management. Vol. 12, Iss. 1; p. 12 (18 pages)

Benjaafar, S., Kim, J-S., Vishwanadham, N. (2004). On the Effect of Product Variety in Production-Inventory Systems. Annals of Operations Research. Basel. Vol. 126, Iss. 1-4; p.71

Bloemen, R. (2006). Minutes of Meetings, Meeting of February 1, at Zaragoza Logistics Center.

Bodegraven, A. (2004). Winning the Losing Battle of SKU Proliferation. Retrieved November 30, 2005, from http://www.theprogressgroup.com/publications/wp22_avb.html

Edmunds, K., & McSparran, K. (1996). Product Proliferation: Time for Action? Beverage World. Vol. 115, Iss. 1617; p. 114 (1 page)

Eppen, G. (1997). Effects of Centralization on Expected Costs in a Multi-Location Newsboy Problem. Management Science. Vol. 25, Iss. 5; p. 498

Eppen, G., & L. Schrage. (1981). Centralized Ordering Policies in a Multi-Warehouse System with Leadtimes and Random Demand in Multi-Level Production/Inventory Systems: Theory and Practice. L. B. Schwarz (ed.), North-Holland, New York, 51-67.

Erkip, Nesim, Hausman, Warren H., Nahmias, Steven. (1990). Optimal Centralized Ordering Policies in Multi-Echelon Inventory Systems with Correlated Demands. Management Science. Linthicum: Vol. 36, Iss. 3; p. 381 (12 pages)

Kim, J-S. (2002). On the Benefits of Inventory-Pooling in Production-Inventory Systems. Manufacturing & Service Operations Management. Linthicum. Vol. 4, Iss. 1; p. 12 (5 pages)

Lee, Hau L. (1999). Effective Inventory and Service Management through Product and Process Redesign. Operations Research. Vol. 44, Iss. 1; p. 151 (9 pages)

Lee, Hau L., Billington C., Carter B. (1993). Hewlett-Packard Gains Control of Inventory and Service through Design for Localization. Interfaces. Vol. 23, Iss. 4; p. 1 (11 pages)

Roberts, M. (1999). Using SKU Remediation to Eliminate Low-Value Products. Chemical Week. Vol. 161, Iss. 11; p. S9 (1 page)

Thonemann, U. W., & Bradley, J. (2002). The Effect of Product Variety on Supply Chain Performance. European Journal of Operational Research. Amsterdam. Vol. 143, Iss. 3; p. 548

Willems, S. P. (1996). Strategic Safety Stock Placement in Assembly/Distribution Systems. Master's Thesis, MIT Operations Research Center.

Zipkin, Paul H. (1995). Performance Analysis of a Multi-Item Production-Inventory System Under Alternative Policies. Management Science. Linthicum. Vol. 41, Iss. 4; p. 690 (14 pages)

Appendix: Distributions of Sales

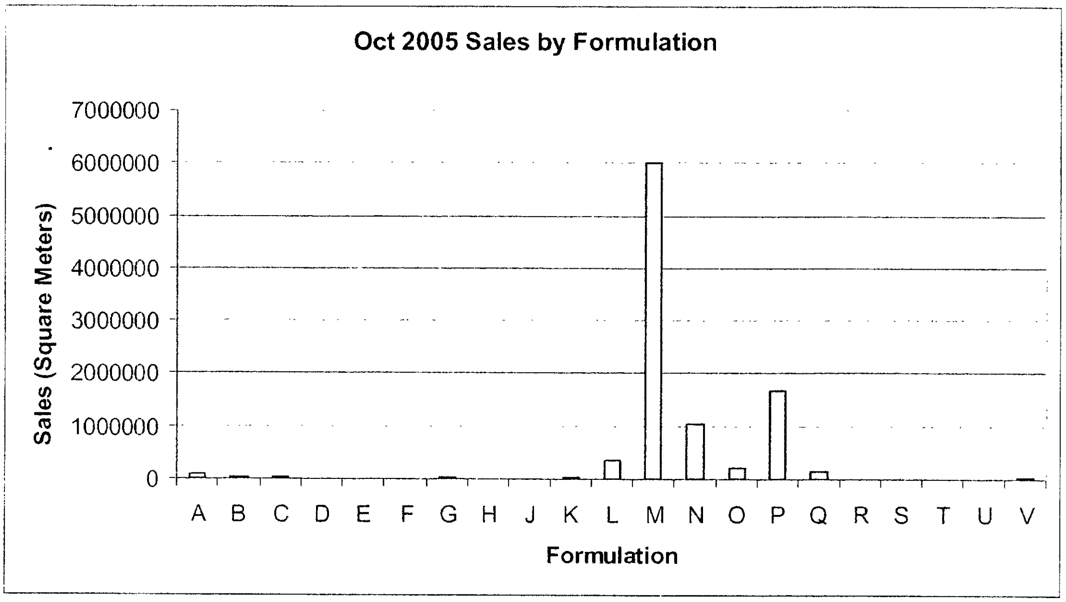

Figure A1: Oct 2005 Sales by Formulation

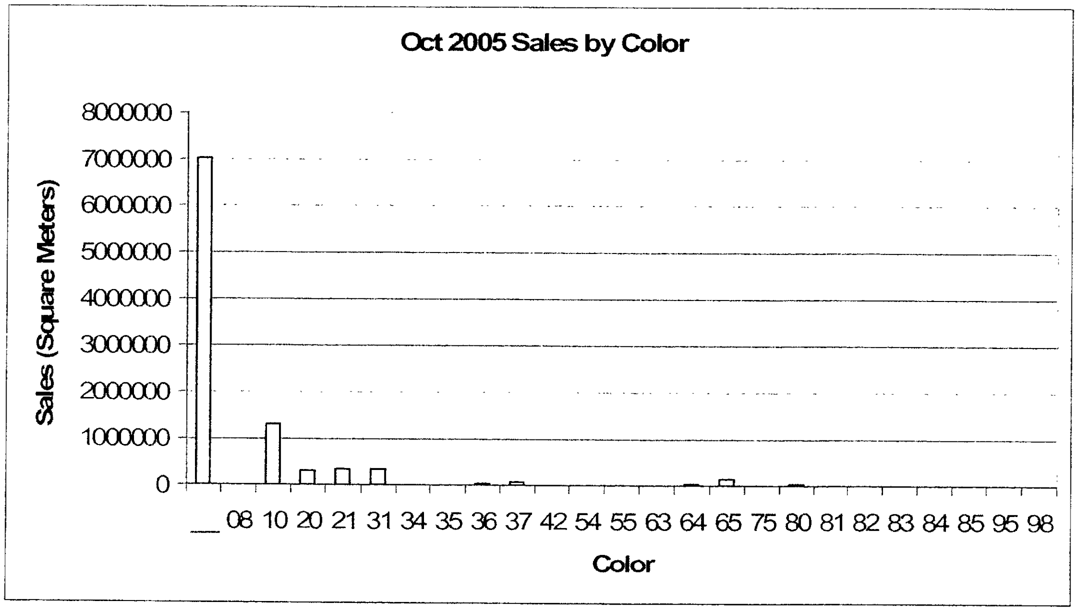

Figure A2: Oct 2005 Sales by Color

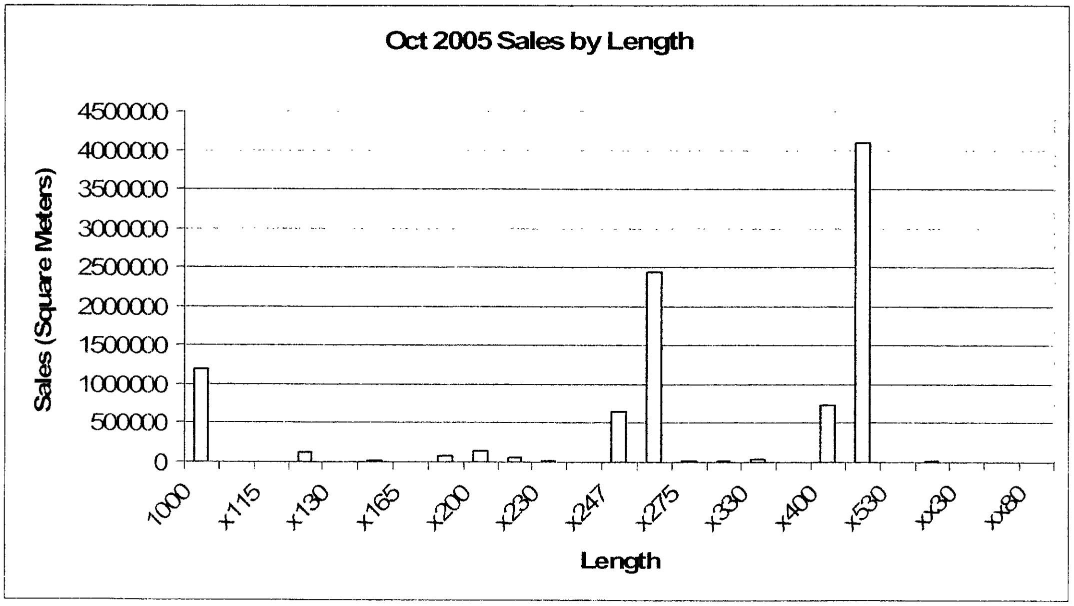

Figure A3: Oct 2005 Sales by Length

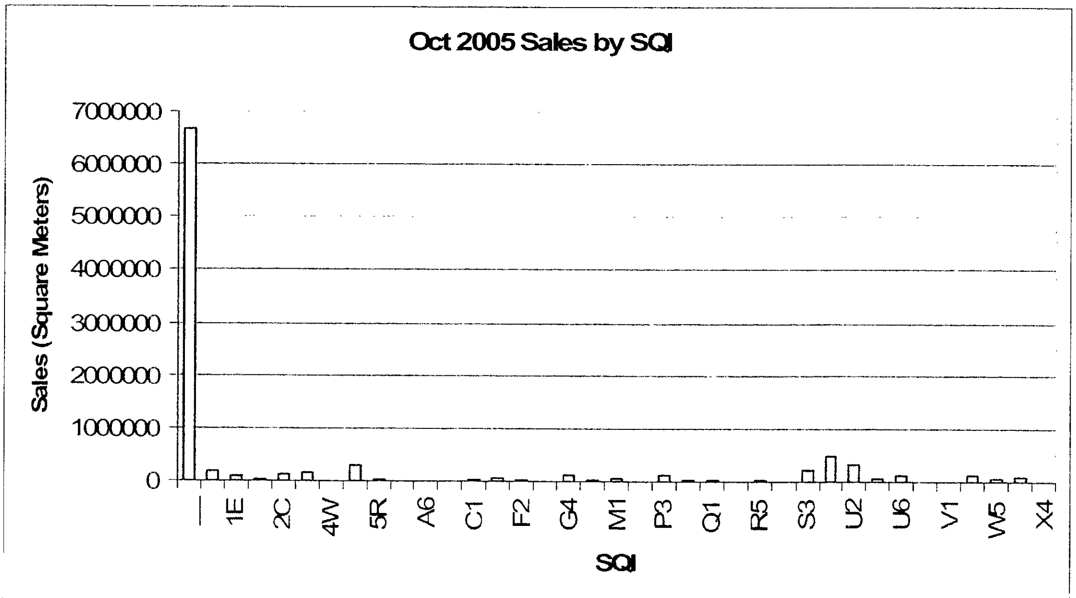

Figure A4: Oct 2005 Sales by SQI

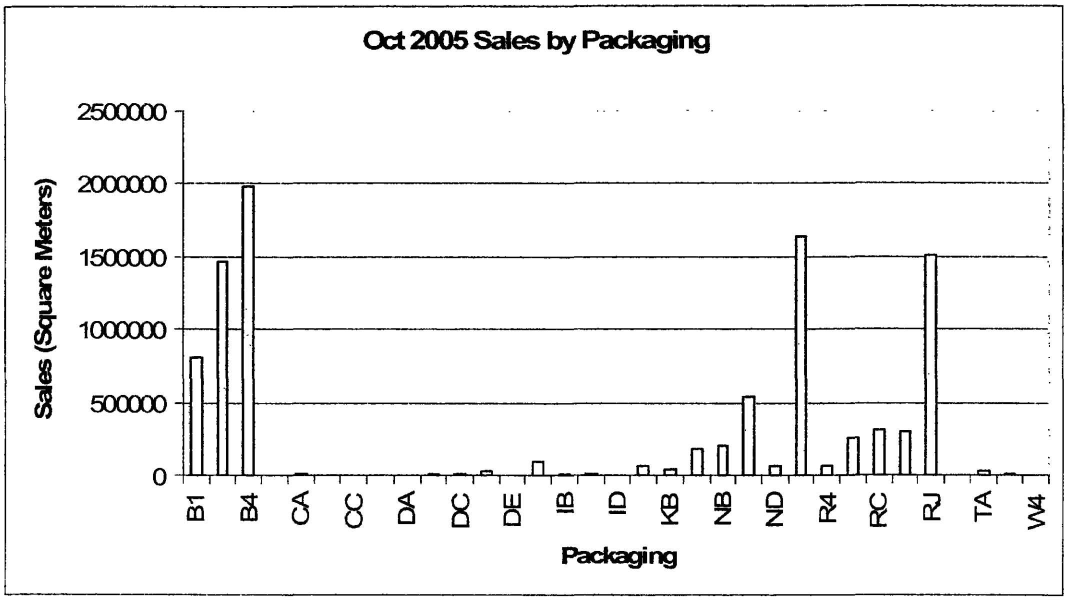

Figure A5: Oct 2005 Sales by Packaging

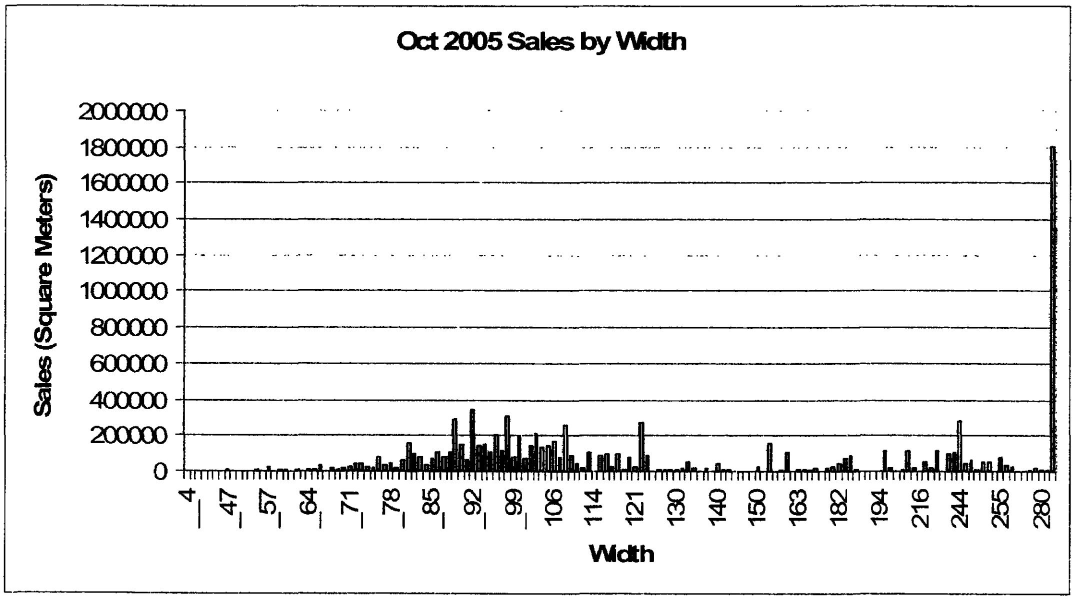

Figure A6: Oct 2005 Sales by Width