Inventory Strategies for Patented and Generic Products for a Pharmaceutical Supply Chain

by

Prashanth Krishnamurthy

Bachelor of Engineering, Electrical and Electronics Engineering
National Institute of Technology, Surathkal, 2001
MBA, Operations Management, S.P. Jain Institute of Management and Research, Mumbai, 2004

and

Amit Prasad

Bachelor of Technology, Mechanical Engineering
Indian Institute of Technology, Guwahati, 2006

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

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Signature of Author...
Master of Engineering in Logistics Program, Engineering Systems Division
May 11, 2012

Certified by...
Dr. Jarrod Goentzel
Director, MIT Humanitarian Response Lab
Thesis Supervisor

Accepted by...
Prof. Yossi Sheffi
Professor, Engineering Systems Division
Professor, Civil and Environmental Engineering Department
Director, Center for Transportation and Logistics
Director, Engineering Systems Division

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Abstract

This thesis presents a model to determine safety stock considering the distinct planning parameters for a pharmaceutical company. Traditional parameters such as forecast accuracy, service level requirements and average lead-time are combined with a nontraditional upstream uncertainty parameter defined as supply reliability. In this instance, supply reliability measures uncertainty in the supply quantity delivered rather than variability in the lead-time for delivery. We consider the impact of the safety stock using two products: a proprietary product that is patented and a generic product that recently went off patent. Sensitivity analysis is performed to provide insights on the impact of variations in input parameters. The study shows that there is a significant difference in safety stock between the proposed model and the current model used by the company.

Thesis Supervisor: Dr. Jarrod Goentzel
Title: Director, MIT Humanitarian Response Lab

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1 Introduction

Our sponsor company, referred to as Company A, is a leading pharmaceutical and healthcare company that operates globally. It develops, manufactures and distributes prescription medicines, vaccines and consumer healthcare products through numbers of research centers, manufacturing plants and distribution centers across the world. The management of Company A is evaluating the current inventory strategies of their finished goods, including patented product referred to in this thesis as Product-line P and off-patent and generic products referred to in this thesis as Product-line G. These product lines have different demand patterns, service level requirements, profit margins, and supply chain networks. Choosing the optimal combination of the operational parameters at the various distribution centers (DCs) requires an understanding of the trade-offs between inventory costs, working capital, and service levels. The objective of our research is to assess the distribution and inventory policies and identify opportunities to lower the working capital of Company A.

1.1 Problem Description

Company A maintains a large amount of inventory for both its patented and off-patented products at its regional distribution centers to maintain a very high service level target. As such, it puts a large amount of working capital into holding inventory. Company A holds inventories in forms of raw materials, packaged goods or finished products at several points in the supply chain, making it a multi-echelon network.

With several products going off patent, holding high inventory levels for off-patented product as well as patented products is expensive, which provides an incentive to study the current strategies and reduce total inventories. Cost reduction can come through a reduction in safety stock requirements, aligning inventory strategies with the service requirements, and improving the efficiency in the current supply chain distribution model. The reduction in cost has to be weighed against the effect on service levels and responsiveness of the supply and demand. Therefore, it is essential to consider various factors for each product such as:

- Demand volumes
- Demand variability
- Sales forecast accuracy
- Manufacturing lead times
- Lead time variability
- Service levels
- Physical locations of manufacturing plants and DCs
- Supplier reliability
- Product characteristics
- Cost of goods

1.2 Background

Company A is a leading pharmaceutical and healthcare company with a significant market presence in Europe and North America, including the United States.

The company has offices in more than hundred countries. The company produces medicines that treat major disease areas and cardiovascular and digestive conditions.

The company has a large number of patented drugs that are highly profitable. To realize this profits, the company maintains a very high service level that translates into high inventories. As an increasing number of these products go off patent, the company must focus on its supply chain to reduce inventories with lower margin products and achieve higher operational efficiency.

In order to understand the supply chain processes and policies used by our sponsor company, we conducted several interviews with executives and managers and made a site visit to their secondary manufacturing plant and one of their major distribution centers. In the following sections we discuss our interview process and give an overview of the distribution model that is currently in place at the company.

1.2.1 Interviews and Site Visit

Throughout this project we have interviewed several key executives, operations and category managers within several divisions of our sponsor company to develop a complete understanding of various aspects of product flow through the company's supply chain network. These aspects included the business process, manufacturing process, inventory policies, and distribution channels as well as understanding systems involved in sourcing, managing and distributing these products, and the management objectives in terms of service level requirements and related metrics for these products.

In addition to interviews, we conducted a site visit to a large secondary manufacturing plant and a distribution center in United States, which serves customer sites in North America. This visit was an important source of information as we were able to visually observe the various products, processes, and material flow from the secondary manufacturing plant in the form of raw materials to the finished products to the distribution centers and further downstream to the customers. This greatly enhanced our understanding of these operations:

- Manufacturing process cycle at secondary manufacturing plant
- Packaging of products into finished goods
- Possible bottlenecks in the process
- Transportation to regional distribution centers
- Inventory management in the distribution center
- Product flow from distribution centers to wholesalers, retailers and pharmacies

1.2.2 Distribution Model Overview

Company A distributes its high volume products and low volume slow moving products in North America through its largest distribution center in US, referred to in this thesis as RDC, which is very close to its secondary manufacturing plant (SMS). There is a smaller distribution center nearby, referred to in this thesis as KDC, which receives goods manufactured in the secondary manufacturing plant in UK. Each of the secondary manufacturing plants in the US and UK have a small DC referred to as MFG DC, attached to the site, where the products are stored temporarily until they are dispatched to the main DCs called RDC and KDC (refer Figure 1.1 and Figure 1.2).

The products are first procured and sent to the primary manufacturing site (PMS), for initial manufacturing. The products are then shipped to a secondary manufacturing (SMS), where they are processed and packaged into the finished product. The finished products are temporarily held at MFG DC for few hours after which they are shipped to two distribution centers RDC and KDC. The finished products from these DCs are finally distributed to the wholesalers or the customers.

A significant amount of intra-warehouse exchange of products takes place between RDC and KDC to meet the specific regional demands of the product across North America. Finished goods are shipped directly from SMS to RDC by truck. All the shipments between RDC and KDC are also carried by truck.

In this thesis, we consider subset of Company A's products distributed in North America region. For our quantitative analysis, we study two different products, one of which is a patented product-line (Product P) and the other a generic product-line (Product G) that has recently gone off patent. We analyze three SKUs of Product P and five SKUs of Product G distributed from the two DCs in United States shown in Fig 1.2.

Product P, which is a patent product, is manufactured in three configurations, referred to in this thesis as SKU P1, P2 and P3. Figure 1.1 shows how Product-line P for its three SKUs flows from the suppliers through the primary manufacturing plant, secondary manufacturing plant and DCs to customer sites. Post primary manufacturing, two SKUs of Product P, namely SKU P1 and P2 flow through a secondary manufacturing plant in the US (labeled as Secondary MFG Plant in the figure), referred to as SMS, and is then shipped to RDC in the US, while the third SKU called SKU P3 flows through a secondary manufacturing plant in the UK (labeled as UK MFG Plant in the figure) and is then shipped to KDC in the US.

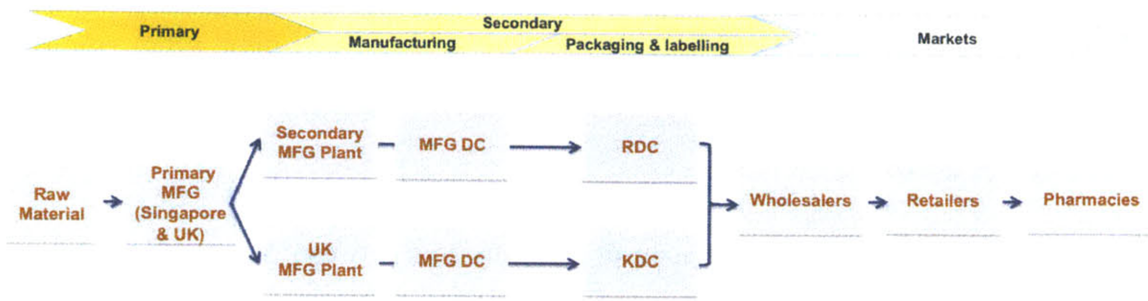

Figure 1.1 Supply Chain of Product P for its three SKUs

Similarly, Product G, which recently went off patent, has five configurations, referred to in this thesis as SKU G1, G2, G3, G4 and G5. Figure 1.2 shows how Product G for its five SKUs flows from suppliers to two primary manufacturing plants and then to a secondary manufacturing plant in the US where they are made into tablets and packaged. Product G is then sent to RDC and further distributed to customer sites directly or through KDC.

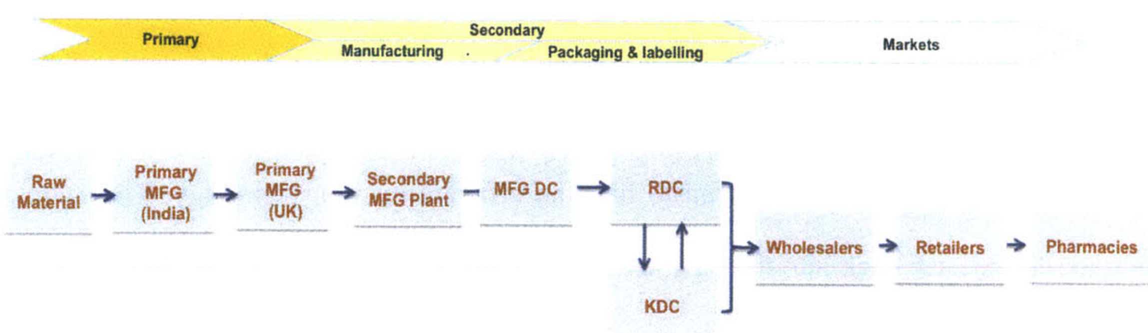

Figure 1.2 Supply Chain of Product G for its five SKUs

As mentioned earlier, a significant amount of intra-warehouse transfer of products occurs between RDC and KDC for both products P and G depending on the demand fluctuations and service regions.

1.3 Motivation

Over the last five years, our sponsor company held between180 to 200 days worth of inventory in its distribution centers. Availability and fulfillment are critical when it comes to medical drugs and products. This translates into a requirement of high service levels and high degree of responsiveness, which are currently achieved by holding a large amount of inventories in the regional distribution centers. However, keeping a high amount of inventories results in high holding costs and working capital.

Company A produces patented drugs that sell in high volumes as well the drugs that went off patent recently and hence went remarkably down in sales. A significant challenge lies in estimating the sales and maintaining the inventories of the off-patent products. Therefore, it becomes very interesting to understand the inventory strategies involving these products and the impact it makes on the working capital and service levels in the current model.

With demand for the greater service at lower costs even for slow moving products, it becomes very important to have an efficient inventory strategy. This would help to release cash back into the business and contribute to bottom line improvement.

1.4 Research Scope

This project uses quantitative analysis in conjugation with qualitative factors to evaluate the inventory strategies for a set of products in patented as well off patented categories. Our solution approach for recommending the best inventory strategy is based on analyzing the inventory data, lead times, service level requirements, demand patterns, manufacturing cycle, product flow and financial implications. It does not involve any optimization of the physical locations of distribution centers as their locations are fixed. Although the physical distribution network remains unchanged, for our study we aim to minimize the inventories without compromising with the service levels.

Based on our study we would like to propose a model with more efficient strategies in light of these parameters. The potential benefits of the new proposed model are likely to be the following:

- Reduction of inventories across the supply chain
- Verification of safety stock formulation in use
- Base lining of inventory levels
- Comparison of inventories suggested by their internal tool with the one they manage in practice
- Bottlenecks in the manufacturing lead times and overall supply chain process

The final deliverable to company A consists of a verified distribution model for their supply chain that should apply to other products. We also perform sensitivity analysis of safety stocks, varying factors such as desired service level, forecast accuracy, supply reliability and demand pattern. We also present a brief comparison of current model in practice and the proposed model with respect to safety stocks.

2 Literature Review

As we discussed in Chapter 1, our research problem focuses on assessing the inventory strategies at different points in the supply chain, and exploring the possibility to reduce the inventories in the current model. The models under the scope of our research are shown in Figure 1.1 and Figure 1.2. We approach the problem by surveying the research done in the field of inventory management in pharmaceutical industry based on analytical methods. We focus on literature in the three research areas listed below:

i) Strategic Positioning of Inventory

ii) Relevance of Supply Chain in Optimizing Working Capital

iii) Yield Uncertainty in Setting Safety Stock

The following three sections present our survey and relevant findings in the literature that ties closely to the scope of our thesis.

2.1 Strategic Positioning of Inventory

The literature on the strategic positioning of inventory focuses primarily on finding optimal replenishment policies by minimizing inventory levels at different positions as well as reducing inventory ordering and holding costs. Since the locations of the facilities of Company A in our research are fixed, we will restrict our survey to only those sources that assumed the facility locations are fixed. However we will survey different distribution models with varying inventory strategies and working capital with respect to the pharmaceutical industry.

Strategic positioning of inventory is very important to reduce the holding costs of safety stock in the supply chain without compromising the service level. This is crucial for companies in the pharmaceutical industry as inventory ties up a large amount of working capital, which can be released back into the business. At the same time, it is equally important to ensure that the organization meets the required service level. Graves and Willems (2000) developed an optimization-based framework to model a multi-stage production/distribution supply chain, subject to uncertainty in demand. Assuming that the lead-time and cost incurred at each stage are deterministic with no constraints in capacity, the model was developed to determine the strategic positioning of inventories in order to minimize holding costs of inventory across the supply chain. It was also assumed that each stage of the supply chain quotes a guaranteed service time to its downstream customer, provided the external customer demands were bounded. The model was successfully implemented at Eastman Kodak Company, where it helped increase the service performance and reduce total inventory through the supply chain. The primary objective of the research was to minimize the holding costs of safety stock in the supply chain and hence determine the safety stock levels in the network but the solution did not incorporate the transportation or other costs incurred in the supply chain.

A proper production planning and inventory management of the finished goods is often a concern for pharmaceuticals companies where the service level requirement is very high. Gupta (2007) developed a model for inventory management to reduce the amount of space required to store the inventory without affecting the production and customer service level as well as improve the material ordering and production planning process to help achieve the reduction in inventory. The model assumed the production rate as constant as well as the demand for each month being satisfied in the same month. The model was studied at TCG Pharmaceuticals, Singapore, and recommended for several scenarios. Though the model reduces the inventory but it does not find the optimal amount of inventory needed for the required service level. Also, the cost analysis had not been done during the study.

Sriram (2008) studied the process of consumables inventory management at Novartis Institute of Biomedical Research, Cambridge. His study showed the process for the inventory management was inefficient with stocks being maintained at three tiers. This problem is quite common across the pharmaceutical industry where the high service level leads to excess stock at several operating units of the company. His study further verified the lower inventory turn rates and often holding of duplicate stocks of SKUs at multiple storage locations. He also reviewed the factors responsible for poor inventory management and found that there was a lack of proper visibility to the inventories because there was no central process ownership and the central inventory manager was not always involved for inventory processes. Also, the performance was not measured on operational efficiency and hence there were no incentives to reduce inventory globally rather than locally. The study was primarily focused on the inventory management at the medical institute but the results and findings could also be related to a multi-echelon distribution model of a pharmaceutical company like our sponsor company.

Stark (2011) presented a model and tool to improve the inventory forecasting and resupply planning practices while taking into account several factors such as product seasonality, product expiration, and desired inventory service levels for the pharmaceutical industry, primarily for the vaccines. The model used a resupply point and resupply quantity methodology to create a resupply plan based on safety stock and lead-time. The quantity is correlated to total cost, shelf life, and minimum packaging quantity or resupply frequency. The model is useful for products with shorter shelf life, when the order quantity and inventory levels can be optimized and when scenario planning is necessary.

The author conducted two main case studies that were considered to demonstrate the validity and effectiveness of the model. The first case examined the products with a long shelf life and minimum sales fluctuation, while the second focused on products with a short sellable shelf life. Stark also considered a case that concentrated on seasonality and market trends. The model and tool showed improved inventory and resupply methodology in all three cases, which was an interesting finding. They did not, however, thoroughly address inventory holding costs; nor were the data validated against any accurate benchmarks.

Besides minimizing the inventory costs and working capital across the supply chain, it is very important to consider the impact of responsiveness of the supply chain in terms of time taken by the product to reach the customer. Responsiveness to the customers is of very high priority in the pharmaceutical industry so that they capture high profit margins. In order to quantify the responsiveness to customers, Gaur and Ravindran (2006) proposed a measure of responsiveness as a product of the volume that travels through the network from supplier to customer and the distance travelled. Increasing the service level to serve the responsiveness to customers often results in increasing the inventory and hence the working capital.

2.2 Relevance of Supply Chain in Optimizing Working Capital

Company A aims to find and use the model of distribution that employs the least working capital for a predetermined service level. Hence, it is important not only to understand the linkage between supply chain competence and working capital but also to empirically establish the role of supply chain competency and the financial performance of the firm.

Matson (2009) identified the supply chain as the major area of leverage in improving the cash position of a company. With the drying up of the credit market for businesses during the recession, companies have to take a conservative approach towards cash and have to tap internal resources within the company to extract cash. The supply chain offers plenty of opportunities to take out cash and reduce working capital. Matson advises companies to systematically look into inventory investments, accounts receivables and accounts payables to release cash. Changing the performance measure from an income statement metric like Return on Sales to a metric that ties together balance sheet and income statement items like Return on Invested Capital (ROIC) is the first step towards working capital conservation. Also, using an end-to-end metric that cuts across sales, manufacturing, procurement and planning teams will facilitate the reduction of cushions each team builds into its own forecasts.

The need for working capital varies by the industry and the business model employed. While some companies fund their operations on vendors' cash, some rely on debt and others on subsidies. Recognizing the business model becomes an important step in understanding how competitive making the supply chain work hard can create advantage. John (2010) prescribes ten steps to consider the supply chain: understanding inventory basics, benchmarking within and outside the industry, educating finance on the language of operations, establishing a hierarchy of metrics that free up cash, automating cash reporting and establishing a senior management cash council. A collaborative effort will go a long way in ensuring a sustainable competitive "cash" advantage.

Wheatley (2009) has identified working capital management and supply chain management as tools to help a company survive and prosper through the downturn. In this article, Wheatley argues that working capital management and supply chain management are two potent weapons for cost and cash management. Rather than the old school methods of exuberance during easy times and austerity during difficult times, it is important to follow consistent cash and cost management practices for long-term advantage. Regular stock reporting and meetings, better procurement practices and better credit evaluation of prospective customers enable companies to operate better and reduce working capital investment. Automation in the supply chain, consolidation of support services, review of business models, review of production, distribution, planning and forecasting are several other operational excellence levers identified.

Ellinger et al (2011) have tried to establish an empirical link between supply chain competency and firm financial performance. While it is generally known in the industry that a better supply chain performance leads to a better firm financial performance, the linkage between the supply chain performance and financial performance has not been established historically. Ellinger et.al developed a method to link supply chain performance to Altman's Z score statistic, a widely accepted measure of firm's financial success. It also demonstrates that the firms recognized for supply chain competency tend to outperform their rivals financially.

While the first and the second papers recommended looking at the supply chain to improve the financial performance through reduction in working capital and better ROIC for the firm, the third paper has empirically established that companies regarded by experts as relatively more competent in managing supply chains have better financial performance. Hendricks and Singhal (2003, 2005) empirically established that supply chain disruptions have a significant negative impact on both the operating performance and the stock price of firms.

2.3 Yield Uncertainty in Setting Safety Stock

There are several critical factors that affect the inventory levels and the safety stocks in a pharmaceutical company. The safety stock calculation as widely practiced in this industry is dependent on demand patterns, forecast accuracy, lead-time, lead-time variability and stock availability target. Our sponsor company uses another factor called supplier reliability into their safety stock calculation.

Pharmaceutical manufacturing has batches of process production where the yield is uncertain. They make MRP (Material Resource Planning) several weeks ahead and cannot change the batch size in process. If the yield is low, the supply reliability is low. We surveyed the literature to find the relationship between the supplier reliability and safety stock calculation used in any industry. The issue of supply uncertainty has not received much attention until late in the literature. According to Inderfurth (2009): "Regarding the yield risk, there is no clear advise from literature or from practice how to incorporate it in the MRP concept. Recommendations are found to do it by adjusting the scrap allowance or the safety stock (Silver et al., 1998)". The term “supply uncertainty” have appeared in the analytical literature through different interpretations like disruptions, yield variation, random capacity, and stochastic lead times. Tomlin and Snyder (2007) reviewed other inventory with supply reliability literature very well. Parlar and Berkin (1991) presented an EOQ-like model with deterministic demand but stochastic disruptions and repairs with the aim of finding the optimal order quantity.

Brian (1998) utilized the principles and implications of the base stock model to improve the supply chain performance of a medium-volume electronic product manufacturer with yield uncertainty. The base stock model was further extended to accommodate the yield variation for the product during the manufacturing process. The yield variation caused the uncertainty in supply. The extended model balanced the supply to probable demand over the coverage time. The random variables were characterized as follows:

$$\mathrm{E}(Demand) = \mu_D * (r + l) \quad (1)$$

$$Variance(Demand) = \sigma_D^2 * (r + l) \quad (2)$$

$$\mathrm{E}(Supply) = FGI + \mu_S * Q \quad (3)$$

$$Variance(Supply) = \sigma_S^2 * Q \quad (4)$$

where μ_S and μ_D are the mean supply and demand respectively, Q is the number of lots in the process, σ_D and σ_S are single period standard deviation of demand and supply, FGI is the finished good inventory, and $r + l$ is the coverage period.

To assure that supply available over the coverage time exceeded demand over the coverage time, the following equation was required to hold true:

$$FGI + \mu_S * Q - \mu_D * (r + l) - z * \sqrt{\sigma_D^2 * (r + l) + \sigma_S^2 * Q} \geq 0 \quad (5)$$

where z denotes a safety factor that determines the probability that safety stock will cover the gap between expected supply and expected demand. If the equation holds then expected supply during lead-time exceeds the expected demand by the amount greater than or equal to the safety stock. The above equation (5) was used to determine the value of Q for the planning purpose of the product.

We use a similar approach below in formulating the safety stock equation for Company A where the safety level is a function of demand variability and supplier reliability. In the model used by Brian, the lead-time corresponds to one lot, i.e. it takes $r + l$ to produce Q while in the model used in Company A, the time period is assumed as monthly.

3 Methodology

In this chapter we provide methods to address the key questions that our sponsor company is facing: What is the inventory-service level tradeoff in the current distribution model? Can the current model be made more inventories efficient? We attempt to answer these questions by first investigating the inventory strategies, working capital, service levels and policies in the current distribution model at various points in the supply chain and base lining this model. We then continue our research by assessing the scope of inventory reduction in the current distribution.

The study is based on the analysis of two different products: one proprietary product (Product P) that is patented and one generic product (Product G) that recently went off patent, in the North American region. Product P has three different SKUs and Product G has five different SKUs that sell in the North American region. The raw data obtained from the Company A is cleaned into more relevant and meaningful representation. The data is first filtered and organized into different categories like forecast, orders, sales or receipts, inventory ending balance on hand (EBOH) and intra warehouse transfers. The organized data is then processed by aggregating the days of data into monthly values for all SKUs whenever required. The data is further consolidated and broken by SKUs to compare the patterns of each SKU with the rest.

The baseline models are run on each of the products P and G and for each SKU with the effects of different parameters on the inventory levels. We study the demand patterns for the all the SKUs for past two years and also the forecast of these products for next two years. This helps us understand the order patterns of two different categories of products, patented and off-patent product.

We study the sales or receipt patterns for each SKU at both DCs as well as for Company A in total. We then look at the inventory balance at hand for each of the SKUs for product P and G and determine the average inventory levels on daily, weekly and monthly basis. We also examine the inter warehouse transfer of these SKUs between RDC and KDC. In order to understand the total lead-time for both the product lines, we study the upstream value chain and evaluate the time spent at each of the sub processes in manufacturing.

The four planning parameters that influence the level of safety stock for a given annual sales volume forecast are studied in order to understand the right combination of these planning parameters. These parameters are k (safety factor), LT (lead time), FA (forecast accuracy) and SR (supplier reliability). The safety stock calculated is used in assessing the inventories to hold at the DCs in alignment with the DRP (Distribution Requirement Planning) system. It also helps us to determine the gap between planning and execution at Company A.

We then propose a model that helps minimize the inventories further using our research and understanding of the Company A's supply chain. We run the model with product P and G and compare the results with the baseline model both at planning as well as execution. We also perform sensitivity analysis of safety stocks, which provides insights on the impact of variations in input parameters on the average inventory and the working capital using a largest selling SKU in each of the product. The output of each run will help us assess the impact of the models on service levels and the working capital, and thus point to recommend the correct inventory strategy to the sponsor company in order for maximum cost benefits. We further generalize our quantitative and qualitative results to other products having similar characteristics across the pharmaceutical industry.

The subsequent chapters comprise of our analysis on the data for the existing model and interpretation of result to propose a new model.

4 Data Analysis and Interpretations

In this chapter, we analyze the data for the two product-lines, product P and G, for the baseline distribution model of the company A and interpret the result of the analysis for the impact on the service levels, inventory levels and working capital. As mentioned in the pervious chapters, Product P is a proprietary patented product while Product G is a generic product of Company A that recently went off patent.

The demand management team is responsible for inventory planning beyond manufacturing and coordinates the sale to wholesalers. They meet with the warehouse team on a monthly basis and reforecast the volumes, if necessary. They decide on the safety stock levels at the DCs using an in house planning tool, referred to in this thesis as Planning Tool S.

Planning tool S has an inbuilt safety stock calculation equation, which is used for deciding what the safety stock should be. The tool also runs the EOQ (Economic Order Quantity) equation to decide the order quantity to be ordered from the manufacturing plant. But since the monthly sales volume is more or less constant for the three SKUs of this product, the manufacturing plant works out a fixed repeating schedule for production and produces accordingly. As soon as the production is done, the finished goods are shipped to the DCs.

Our objective was to question the planning activity on two levels: First, to determine if all the planning parameters used as inputs to the equation were correct. Second, to determine if the equation itself had a sound theoretical basis and relevance to the planning activity at our sponsor company.

As discussed in the Literature Review, we did not find enough literature in support of the equation used for planning. We tried transforming planning equations used in industry and the ones that are popular in the literature to be able to give a better planning model to our sponsor organization. That is the heart of the next section titled Proposed model.

The four planning parameters that influence the level of safety stock for a given annual sales volume forecast are k (safety factor), LT (lead time), FA (forecast accuracy) and SR (supplier reliability). The central question of this section is: What is the right combination of planning parameters to be used for the product under study.

i) **Safety Factor (k):** Currently, since the product is classified as a class A product for planning purposes, the safety factor is set at a higher level of 2.57 (corresponding to service level of 99.5%).

   The question we raise is: What is the right safety factor for this product? How should we incorporate the fact that while we expect Company's A downstream partner the wholesaler, to be able to give a higher service level to the retailer, do we need to give an equally higher service to the wholesaler since he carries a buffer inventory to accommodate demand shocks from the retailer. Due to the multi echelon nature of the inventory, we believe that the service level our sponsor company needs to give to their downstream partner is much lower.

ii) **Lead Time (LT):** Lead-time is a factor that certainly influences the safety stock levels and figures characteristically in all the safety stock calculations in the literature. But the definition of lead-time in the literature and the way it is employed in the safety stock calculations in our sponsor company are different.

The definition of lead-time in the literature is the time elapsed between ordering and receiving that order. However, in our sponsor company, there is a continuous replenishment of goods at warehouse for the product under study based on a predetermined manufacturing plan. Hence, the definition of lead-time should be suitably modified.

Since the level of safety stock is directly proportional to the square root of lead-time, sensitivity to lead-time is an essential component of our data analysis.

iii) **Forecast Accuracy (FA):** Forecast accuracy directly affects the fulfillment ability of DCs. Low forecast accuracy results in higher safety stock required to fulfill the demand. The forecast accuracy of Product P under study is so high that it may not be possible to improve it substantially.

iv) **Supplier Reliability (SR):** Typically, upstream uncertainty appears in the literature as lead-time variability and measures the spread of actual lead times around the mean over a period of time. However, in this case, upstream uncertainty is based on uncertain quantities delivered with fixed lead-times.

Historically, Company A had two approaches for calculating this supplier reliability factor. The first approach was based on the concept of perfect orders where they measured the factor based on the percent of order lines that did not deviate from the plan by more than 5%. The second approach was based on the VMI concept where it was measured as the percent of days over a period, quarterly or annually, where the inventory position was not in "low stock" or "out of stock". Currently, however, Company A does not use either of these approaches and assumes the supplier reliability equal to 80% for all products. We were not able to identify the reasons behind this step from our interviews with the key managers in our sponsor company.

4.1 Data Analysis for Product P

The patented product we discuss here is the highest selling product for Company A in the US market. The top selling SKU of this product contributes to approximately one fourth of the revenue of the pharmaceutical part of the company in the US market. The three top selling SKUs contribute to 34% of revenue for the pharmaceutical part of the company. Because the SKUs are pharmaceutical products, none of them exhibit seasonality.

At the US SMS, the total cycle time for manufacturing Product P is about 33 days, whereas the cycle time at the UK SMS is 58 days. The travel time between SMS in US and RDC is about 4 hours by truck. The output of the SMS in UK is shipped to KDC by two modes – most of it by ship, which takes about 28 days and urgent shipments through air, which takes 7 days. The expected days of inventory for SKU P1 and SKU P2 at the two DCs – RDC and KDC is about 30 days.

4.1.1 Demand Forecast

We study the demand patterns for three different SKUs of Product P namely SKU P1, P2 and P3 for its distribution in North America region.

(a) SKU P1

This SKU has relatively stable expected demand with coefficient of variation of monthly demand under 10%. In the long term, however this SKU exhibits a declining trend. The forecast for 2014 is 19% less than the 2012 forecast, as Figure 4.1 shows.

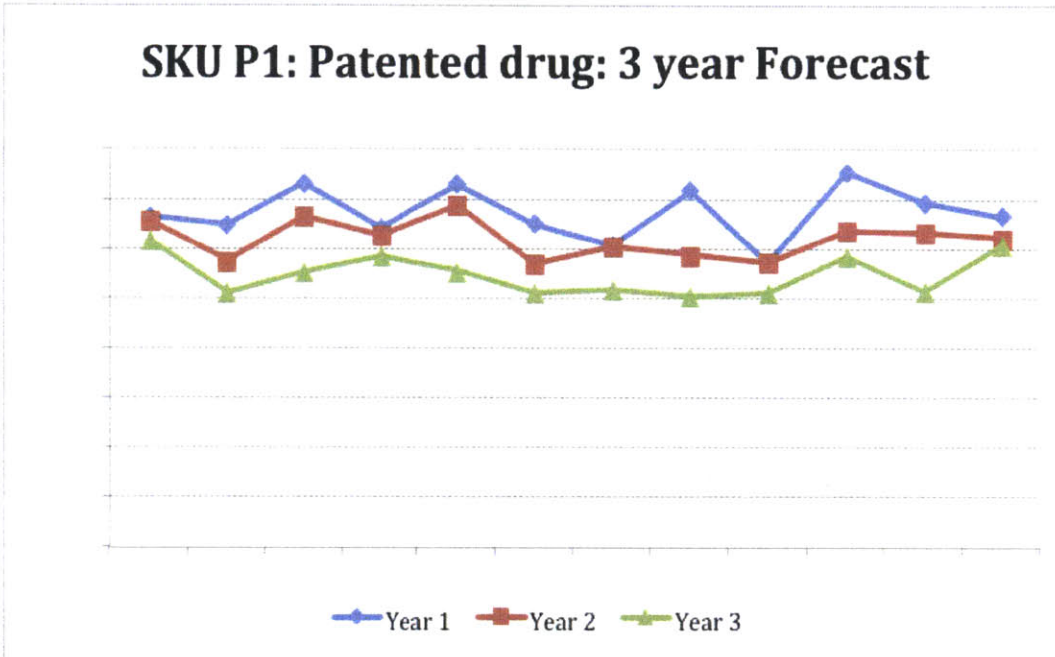

Figure 4.1 Demand forecast for SKU P1 of the under patent drug

(b) SKU P2

This is the highest volume SKU with an expected decline in the long term, but relatively stable demand within a given year. The coefficient of variation of demand is less than 10% in each of the next three years. The Year 3 projected average volume is 7% lower than the Year 1 demand. Figure 4.2 shows this forecast.

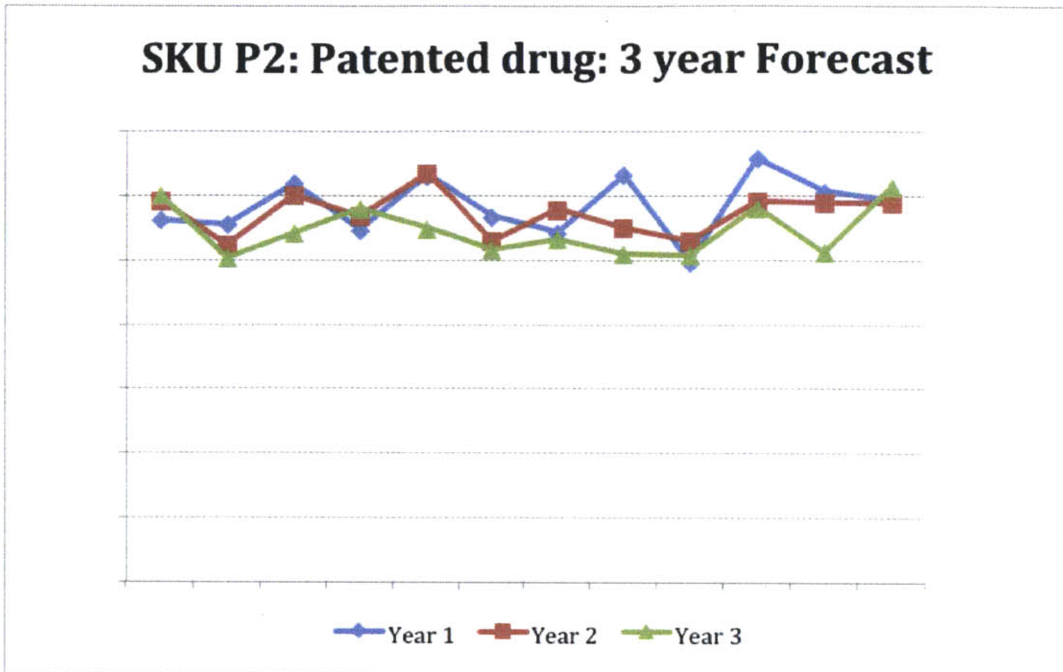

Figure 4.2 Demand forecast for SKU P2 of the under patent drug

(c) SKU P3

This is another SKU that has a relatively stable demand within each year, but has a declining trend. This SKU is expected to decline by 9% by the third year.

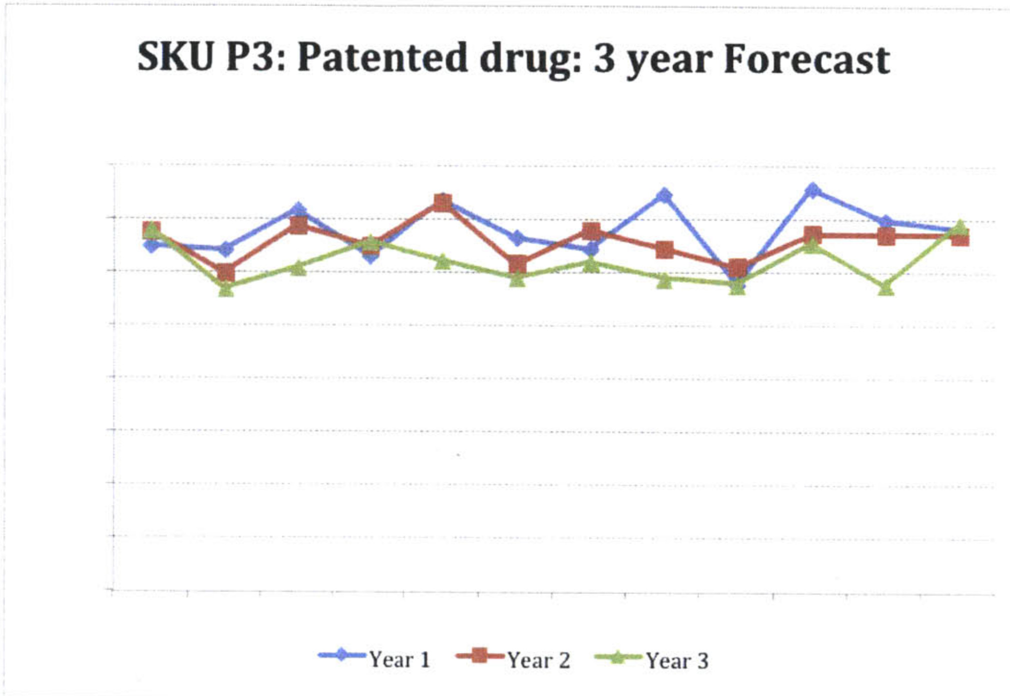

Figure 4.3 Demand forecast for SKU P3 of the under patent drug

4.1.2 Sales Pattern

The sales for this product to wholesalers from both the warehouses have been analyzed to understand if there is a significant variation between sales quantities across weeks.

The sales pattern for all three SKUs from both the warehouses is stable, as shown in the Table 4.1. On a monthly basis, the coefficients of variation are less than 20% in both warehouses. This signals that there is not much of variation in orders between weeks.

The tables show weekly average, minimum, maximum sales on a weekday basis as well as statistics like standard deviation, coefficient of variation on both a weekly basis and a monthly basis.

The coefficient of variation of SKU P1 at RDC on a monthly basis is 0.11, which is a relatively low number and shows stability of demand. The highest demand is experienced on Wednesdays, when shipments are made to a large wholesaler from RDC.

Table 4.1 Weekly order summary for SKU P1 for RDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	5,406	6,392	29,679	1,143	14,222	56,935
S.D.	2,568	9,929	9,459	4,735	9,464	13,281
Max	13,440	52,754	41,593	27,915	46,081	96,843
Min	2	3	4	1	2	37,664
Median	5,954	3,145	31,455	315	11,524	53,038
Number of weeks	33	37	37	34	35	36
CV	0.47	1.55	0.32	4.14	0.67	0.23
CV-Monthly	0.23	0.75	0.15	2.00	0.32	0.11

Although RDC is the primary warehouse for this SKU, KDC also sells significant volumes and experiences highest demand on Fridays. It can be observed from Table 4.2 that the coefficient of variation is 0.16, a low number that indicates a stable demand.

Table 4.2 Weekly order summary for SKU P1 for KDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	3,807	4,017	5,701	312	19,442	32,002
S.D.	1,637	2,299	2,588	245	7,457	10,335
Max	8,592	12,660	11,590	1,056	44,640	58,749
Min	2	3	4	5	6	438
Median	3,944	3,395	5,976	216	21,120	33,849
Number Of Weeks	32	37	37	31	34	36
CV	0.43	0.57	0.45	0.78	0.38	0.32
CV-Monthly	0.21	0.28	0.22	0.38	0.18	0.16

SKU P2 is the largest selling SKU and RDC is the primary warehouse for this SKU. Table 4.3 shows that the coefficient of variation of demand at RDC is 0.08 and hence the demand is stable. Also, again Wednesday is the day when highest volume order is fulfilled.

Table 4.3 Weekly order summary for SKU P2 for RDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	16,797	15,196	100,914	1,180	39,109	175,766
S.D.	7,280	9,755	20,007	963	16,038	30,728
Max	38,400	38,991	124,963	3,996	92,166	259,465
Min	56	-	6,010	6	39	134,784
Median	16,393	11,702	103,114	1,041	35,529	170,145
Number of weeks	32	36	36	35	34	36
CV	0.43	0.64	0.20	0.82	0.41	0.17
CV-Monthly	0.21	0.31	0.10	0.39	0.20	0.08

Table 4.4 shows that the volume of orders for SKU P2 fulfilled from KDC are also significant. But compared to RDC, the average demand is smaller and the standard deviation of demand is higher. The coefficient of variation at 0.2 is higher than the coefficient of variation of SKU P1.

Table 4.4 Weekly order summary for SKU P2 for KDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	16,011	14,082	19,470	836	62,988	107,547
S.D.	5,884	7,208	8,473	600	24,898	37,903
Max	27,224	30,264	40,644	2,164	136,320	222,148
Min	480	360	48	48	188	600

Median	16,236	12,676	19,686	624	63,360	111,655
Number of weeks	31	36	36	31	34	36.0
CV	0.37	0.51	0.44	0.72	0.40	0.4
CV-Monthly	0.18	0.25	0.21	0.35	0.19	0.2

For SKU P3, the primary warehouse is KDC, from which a higher share of the units is sold. Table 4.5 shows that the coefficient of variation in demand at RDC is higher than 0.2. What is also to be noted about this SKU is that the secondary manufacturing happens in UK, after which it is shipped to US.

Table 4.5 Weekly order summary for SKU P3 for RDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	4,477	4,360	11,758	319	9,844	29,696
S.D.	2,044	2,090	13,625	259	4,159	14,394
Max	9,600	9,164	33,844	1,351	23,041	55,495
Min	15	1,186	30	2	25	8,071
Median	4,184	3,784	1,999	315	9,601	21,316
Number of weeks	32	36	36	34	34	36
CV	0.46	0.48	1.16	0.81	0.42	0.48
CV-Monthly	0.22	0.23	0.56	0.39	0.20	0.23

The coefficient of variation of demand for SKU P3 at KDC is much lower than RDC at 0.15 and hence the demand can be considered stable.

Table 4.6 Weekly order summary for SKU P3 for KDC

	Mon	Tue	Wed	Thu	Fri	Week
Mean	5,454	5,590	22,895	278	19,078	53,617
S.D.	2,256	5,859	16,374	228	5,878	17,167
Max	9,600	35,496	53,634	1,056	38,688	84,037
Min	2	3	4	5	6	18,774
Median	5,441	4,086	25,446	227	19,224	56,752
Number of weeks	31	35	35	30	34	34
CV	0.41	1.05	0.72	0.82	0.31	0.32
CV-Monthly	0.20	0.51	0.34	0.40	0.15	0.15

The high CV for Wednesday orders is explained by the drastic reduction in volume at RDC and almost an equal increase in Wednesday orders at KDC, which points that fulfillment for some customer/s was shifted to KDC from RDC. Figure 4.4 shows the relationship.

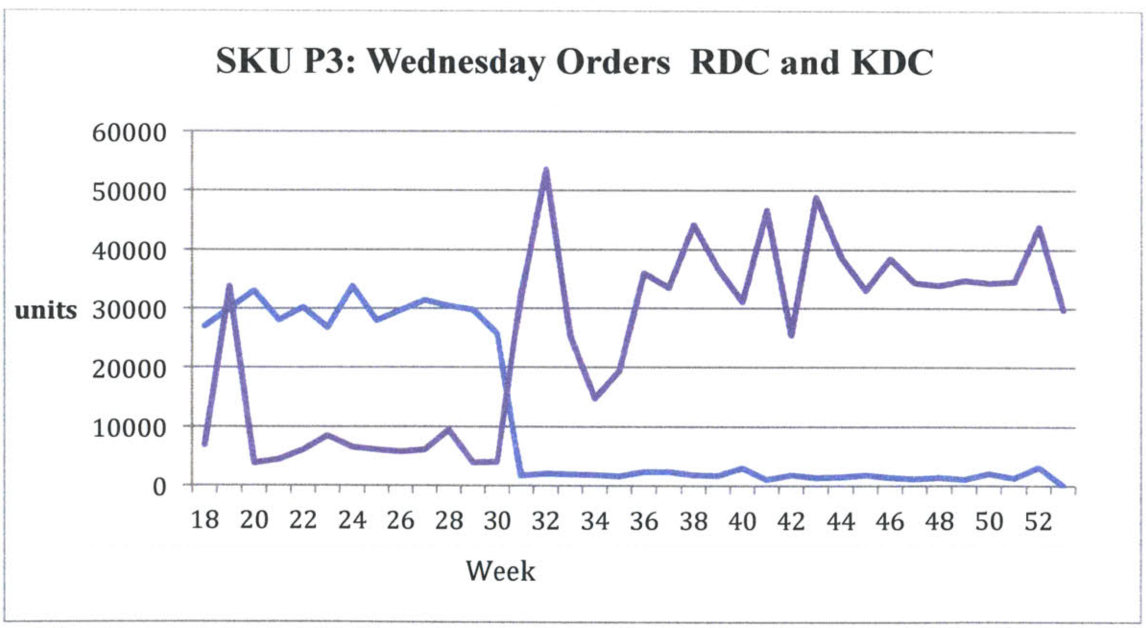

Figure 4.4 Wednesday Orders for RDC and KDC

An interesting question that arises is that if there exists a correlation between the demand variability and the forecast accuracy for the three SKUs of this product. Generally, it would be expected that an inverse correlation between demand variability and the forecast accuracy exists. They are tabulated in the following table.

In the following Table 4.7, it appears that the correlation doesn't hold. While the relationship holds true for SKU P1 (higher variability, lower accuracy) and SKU P2 (lower variability, higher accuracy), SKU P3 becomes an outlier with higher forecast accuracy with higher demand variability.

Table 4.7 Forecast Accuracy and Demand Variability

SKU	Forecast Accuracy	CV - RDC	CV- KDC
P1	0.91	0.11	0.16
P2	0.95	0.08	0.20
P3	0.95	0.23	0.15

4.1.3 Receipt Patterns at DCs

Receipt pattern at DCs over a two-year horizon is an important element of our study. It can be seen from the Figure 4.5 that there is a drop in receipts in July for SKU P1 and SKU P2, as manufacturing maintenance is run during this period. Other than this, receipts for SKU P1 and SKU P2 show less variation. It is also noticed that the supply of SKU P3 was stopped to RDC in July 2010, but was resumed in March 2011.

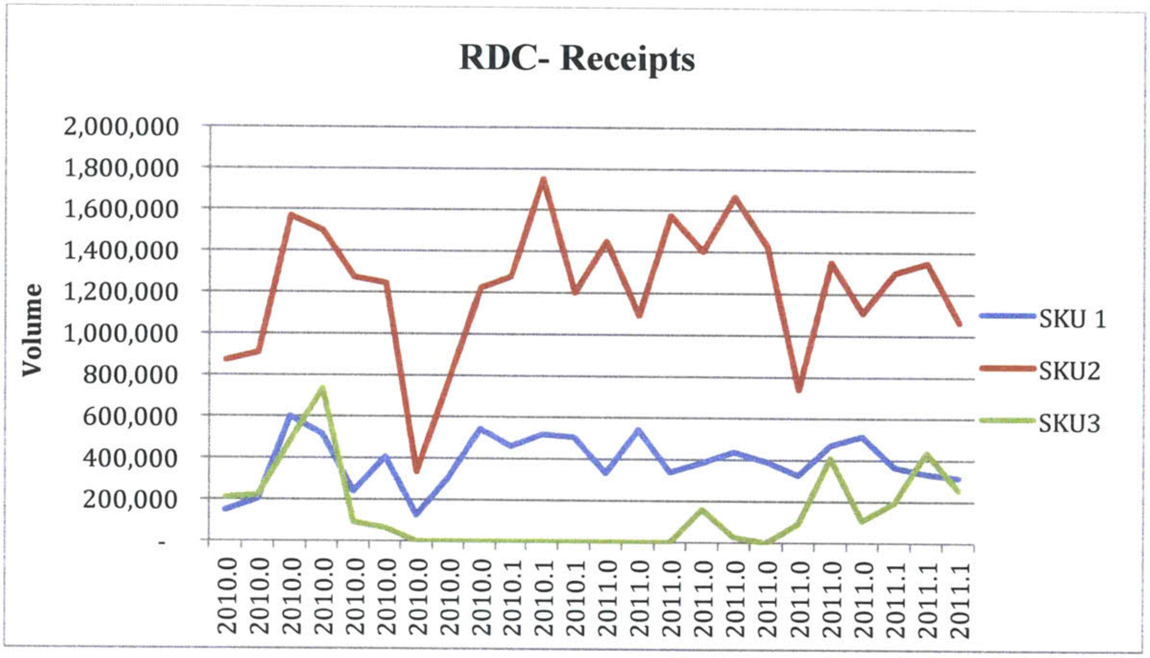

Figure 4.5 Receipt Patterns for Product P at RDC

Figure 4.6 shows the variation in the receipts for SKU P1 and SKU P2 at KDC. It can be seen that the supplies to KDC of these SKUs were stopped by July 2010. Since the company has resumed stocking SKU P3 at RDC too, in the last few months, the inventory level has gone down at KDC.

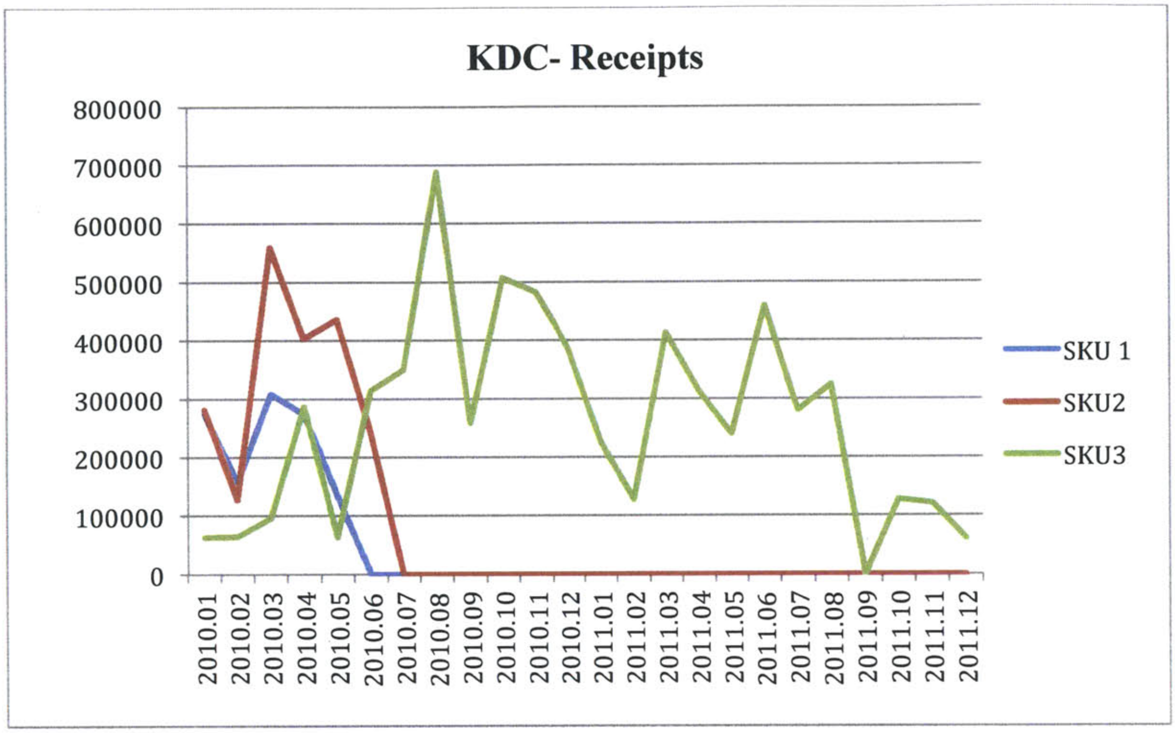

Figure 4.6 Receipt Patterns for Product P at KDC

Figure 4.7, 4.8 and 4.9 are the inventory and sales graphs for all three SKUs. The graphs also show the average number of days of inventory held in the warehouses.

Figure 4.7 shows that the average monthly inventory is much higher than the monthly sales volume for SKU P1.The average inventory has fluctuated over the last two years and has been at about two times the monthly sales level for the last three months for the period of study. The sales can be seen to be exhibiting a slow decline over the last two years.

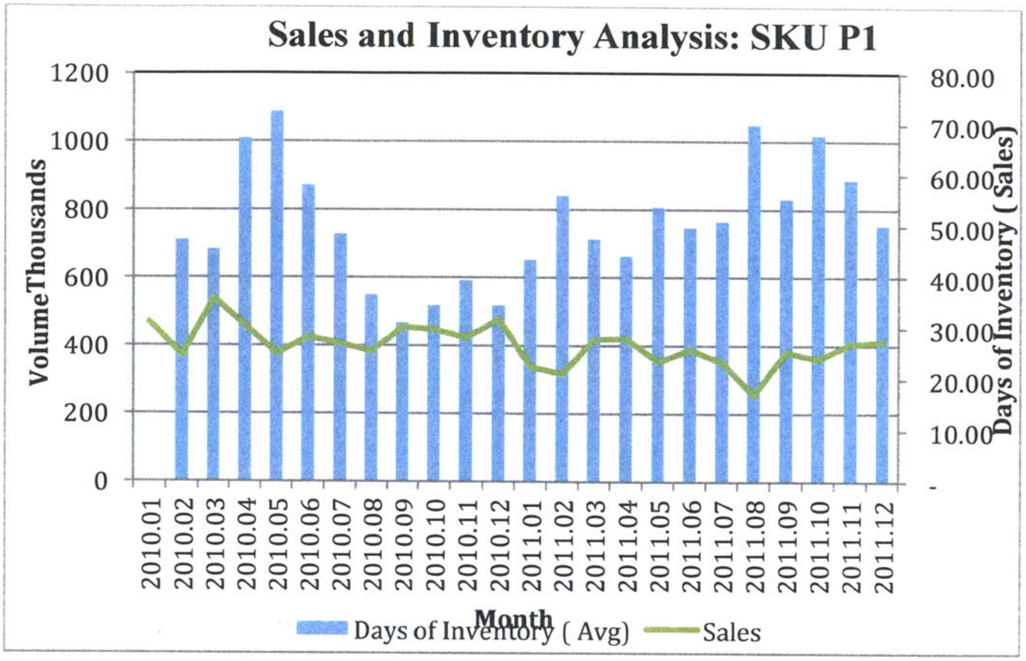

Figure 4.7 Sales and Inventory Analysis for SKU P1

Figure 4.8 shows that the average monthly inventory is much higher than the monthly sales volume for SKU P2.The average inventory pattern exhibited by P2 is similar to that of P1. Again, average inventory has been at about two times the monthly sales level for the last three months for the period of study. The sales is steadier compared to SKU P1 over the last two years.

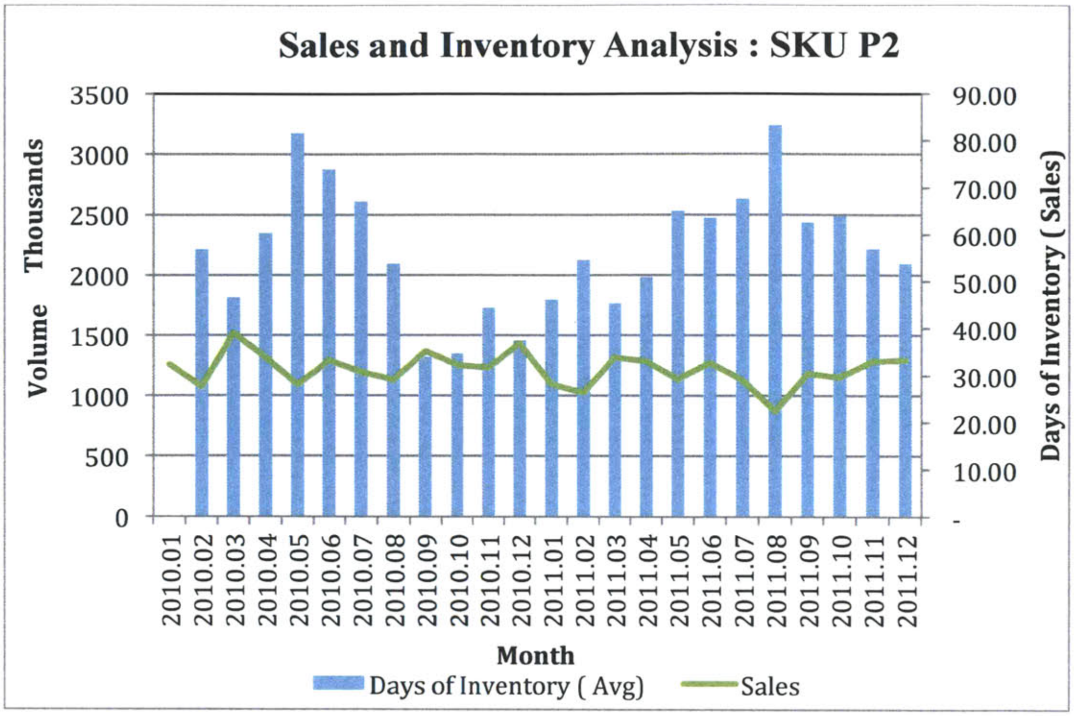

Figure 4.8 Sales and Inventory Analysis for SKU P2

Figure 4.9 shows the average inventory days and sales volumes for SKU P3 for the last two years. The average inventory in relation to sales for SKU P3 is much higher than SKU P1 and P2 because of the higher level of safety stock, owing to longer lead-time of manufacturing in Europe before SKU P3 gets shipped to the distribution center in the US. The sales is steadier compared to SKU P1 over the last two years.

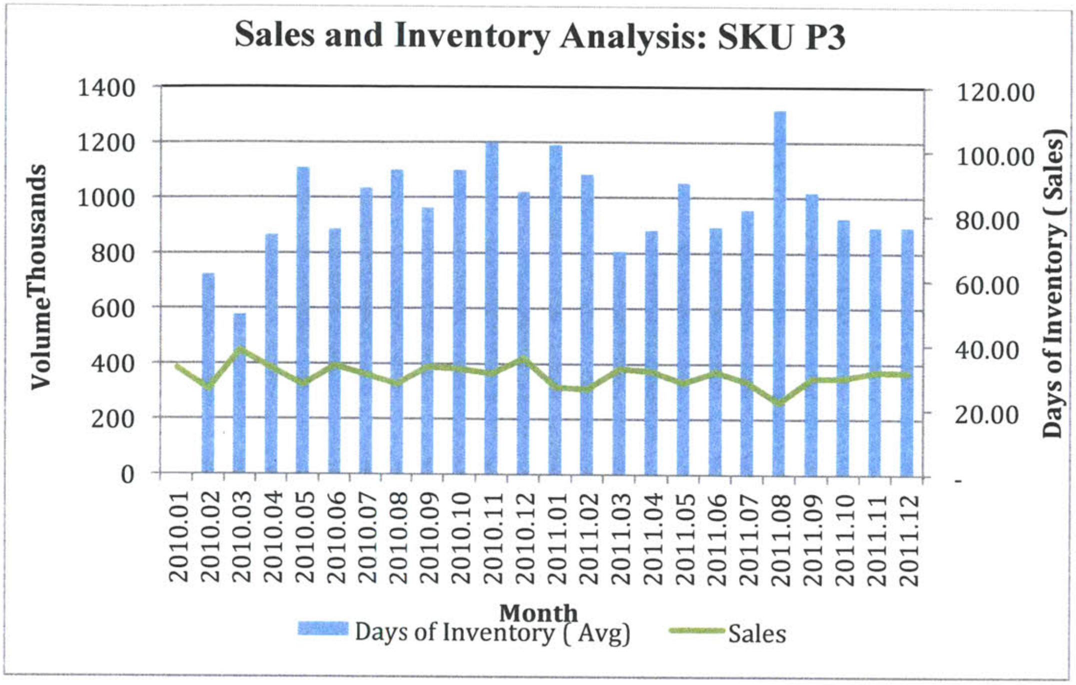

Figure 4.9 Sales and Inventory Analysis for SKU P3

4.1.4 Upstream Value Chain

The manufacturing of Product P comprises two distinct segments. The first part, called primary manufacturing, is the manufacturing of the active pharmaceutical ingredient. For Product P, this is done in Asia. Then the ingredients are shipped to the US for secondary manufacturing, which involves blending these active pharmaceutical ingredients and packaging the finished product.

The manufacturing plan is based on the monthly volume made at the beginning of the planning cycle. The manufacturing schedules are drawn up at the secondary manufacturing and packaging plant. The schedules for manufacturing are fixed and repeat at regular intervals.

In the case of this product, as soon as SKU P1 and SKU P2 are manufactured, they are shipped to RDC, which is the primary warehouse for these SKUs in the US. SKU P3 is manufactured in the UK and shipped to KDC, which is designated as the primary warehouse for this SKU.

Table 4.8 shows the various sub-processes in the manufacturing of product P and the lead-time associated with each of these sub processes. The bottleneck in the process is at the packaging QA (Quality Assurance) approval time and needs to be improved in order to improve the total lead-time.

Total Cycle Time = 32.9 days

Table 4.8 Manufacturing Sub-process at Secondary Manufacturing Plant

Blend Processing Time	• 1.7 days
Blend QA Approval Time	• 1.9 days
Blend wait to Fill Time	• 6.3 days
Fill Processing Time	• 1.4 days
Fill QA Approval Time	• 3.7 days
Fill Wait to Pack Time	• 5.2 days
Packaging Process Time	• 3.5 days
Packaging QA Approval Time	• 9.2 days

4.2 Data Analysis for Product G

Product G, as discussed in previous chapters, is a generic product of the company A that recently went off patent. We have analyzed the demand forecast, order pattern and sales patterns for all five SKUs of product G. The five SKUs of this product contributes to about 1% of sales revenue to the company, and the study of this product will help in analyzing the patterns of other similar products of the company, which make up a significant portion of the total products.

Since the Product G recently went off patent, we study the comparison of demand forecast and order pattern of five SKUs, then look at the sales pattern during the off-patent year and the inventories held at the Company A's facilities.

4.2.1 Demand Forecast and Order Pattern

The FORECAST_UNITS in the figures below represents the forecast of that particular SKU for the period January 2011 till January 2012 while CONSUMPTION_QTY represents the actual quantity of the SKU ordered to the DCs.

(a) SKU G1

Of the five SKUs of Product G, the closest match to the demand forecast was observed for G1. A sharp consumption decline was observed for this SKU as well. This product SKU is forecasted to further decline in coming year.

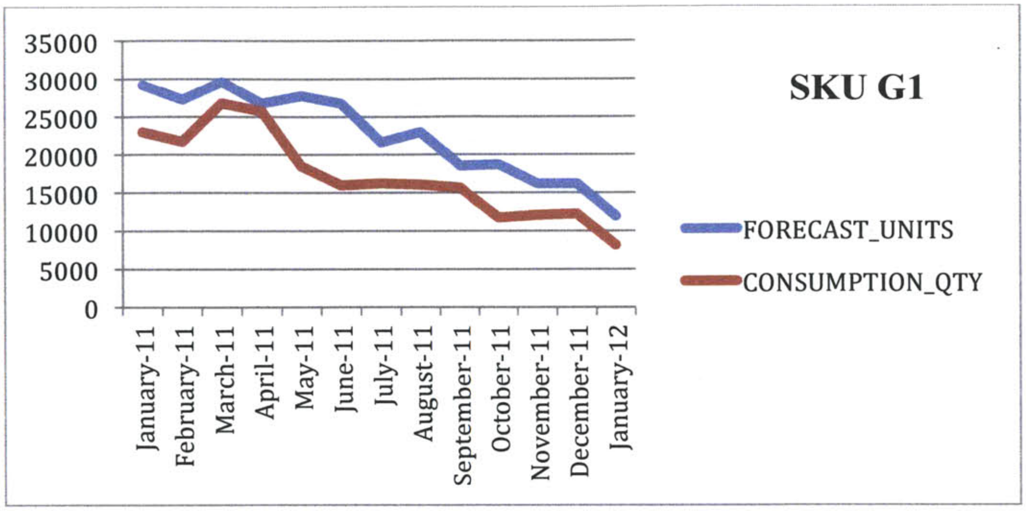

Figure 4.10 Demand Forecast and Order Pattern for SKU G1

(b) SKU G2

The product SKU G2 has a very low demand compared to G1, G3 and G4. However they all share a similar declining trend in demand post off patent.

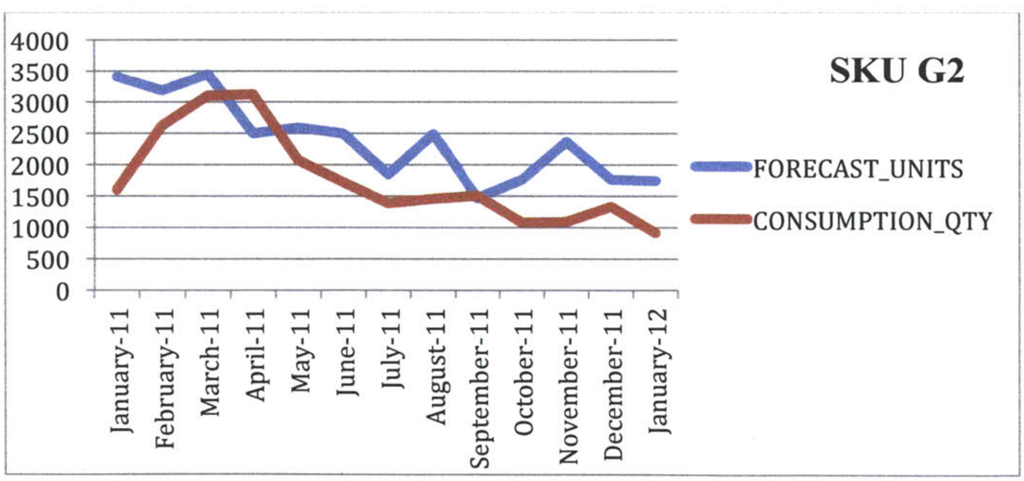

Figure 4.11 Demand Forecast and Order Pattern for SKU G2

(c) SKU G3

The product SKU G3 is the highest selling SKU in terms of volume of Product G. A similar decline in the consumption quantity is observed for this SKU.

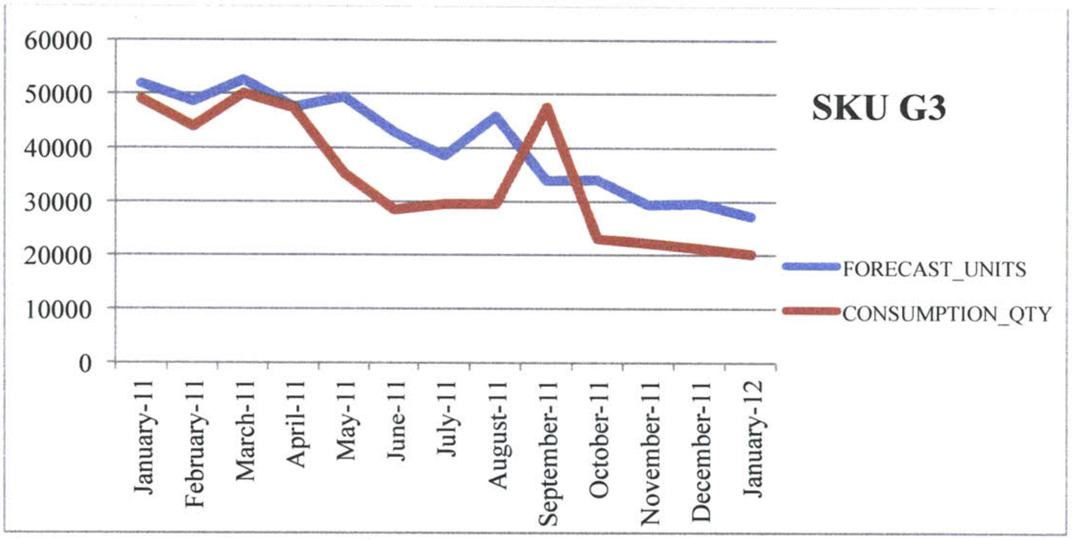

Figure 4.12 Demand Forecast and Order Pattern for SKU G3

(d) SKU G4

The product G4 has a similar pattern of demand and order consumption as G2 and also shares the decline in order quantity and demand as the other SKUs.

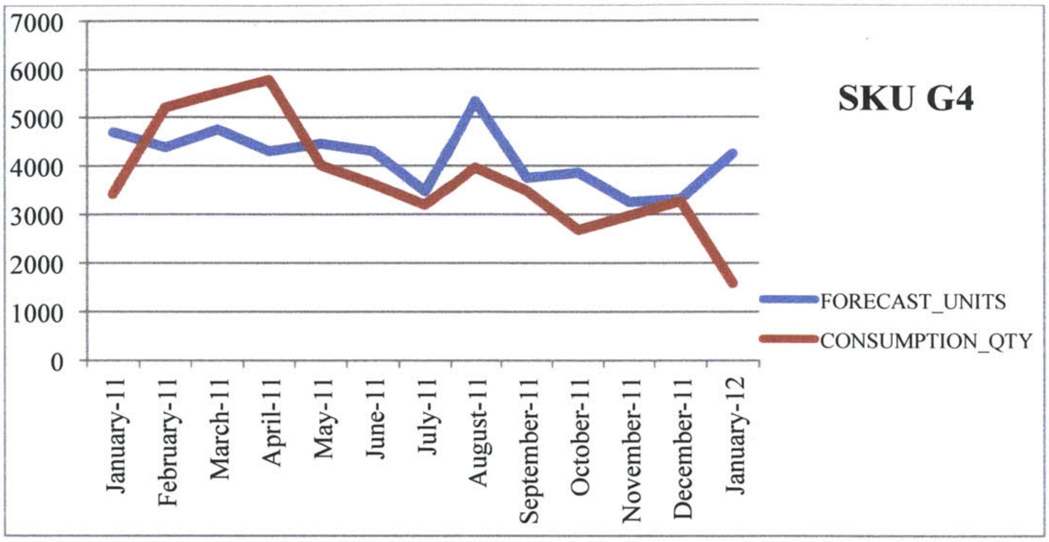

Figure 4.13 Demand Forecast and Order Pattern for SKU G4

(e) SKU G5

Product G5 is the lowest in demand product in the product G family. It shows a very sharp decline in the order consumption post off patent.

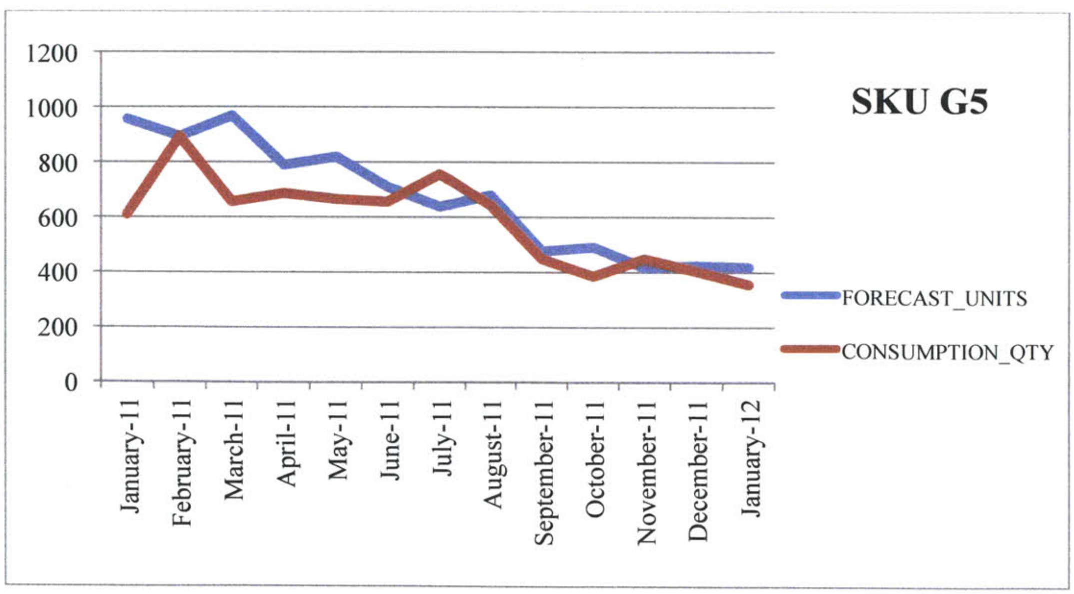

Figure 4.14 Demand Forecast and Order Pattern for SKU G5

4.2.2 Sales Pattern

We studied the sales pattern for all five SKUs of product G for the past two years and found a significant decline in sales triggering early 2010. This correlates with the product going off patent in the beginning of 2010 and the product's substitute entering the generic pharmaceutical market.

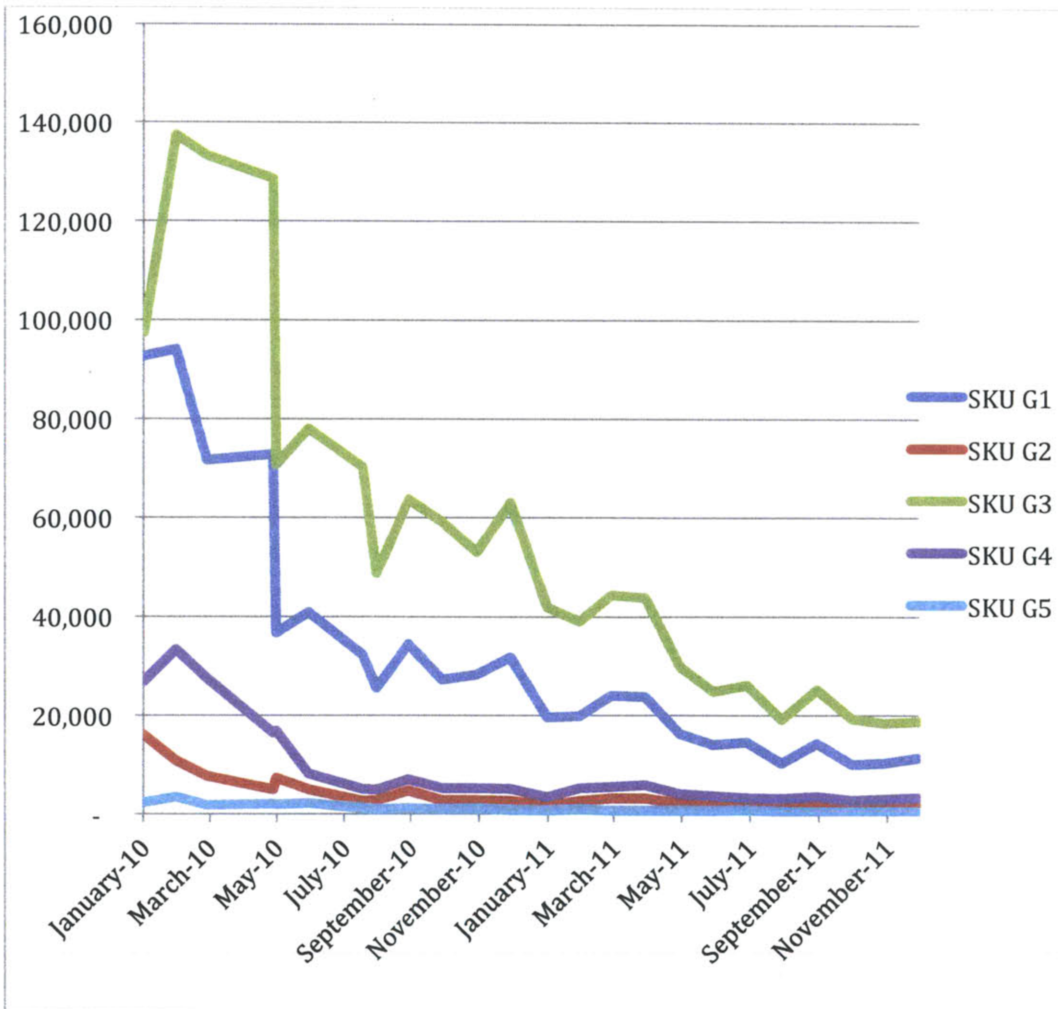

Figure 4.15 Sales Pattern of Product G in 2010 and 2011

4.2.3 Inventory Patterns at DCs

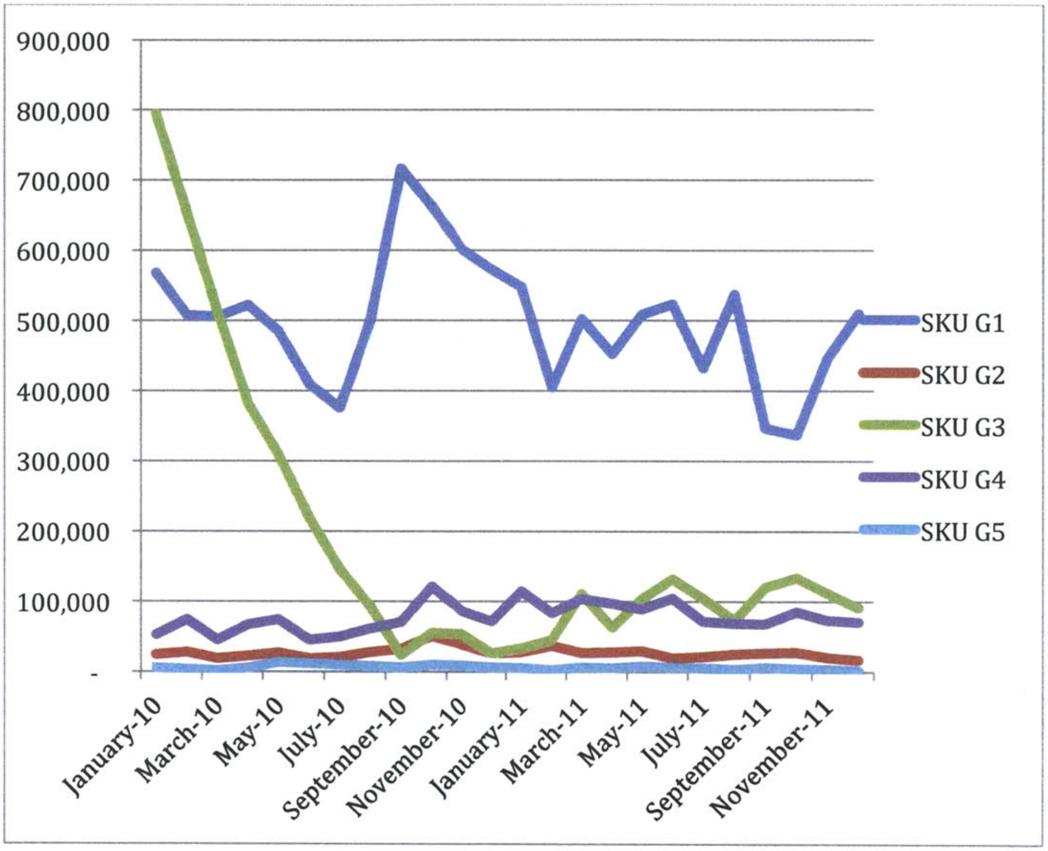

Figure 4.16 Inventory Analysis of Product G in 2010 and 2011

As observed from the above Figure 4.16, the inventory levels for few SKUs are maintained at a higher quantity even after the product going off patent.

Figure 4.17 shows that SKU G3, the highest selling SKU of Product G, has a much higher inventory level even when the sales pattern for this SKU has declined sharply.

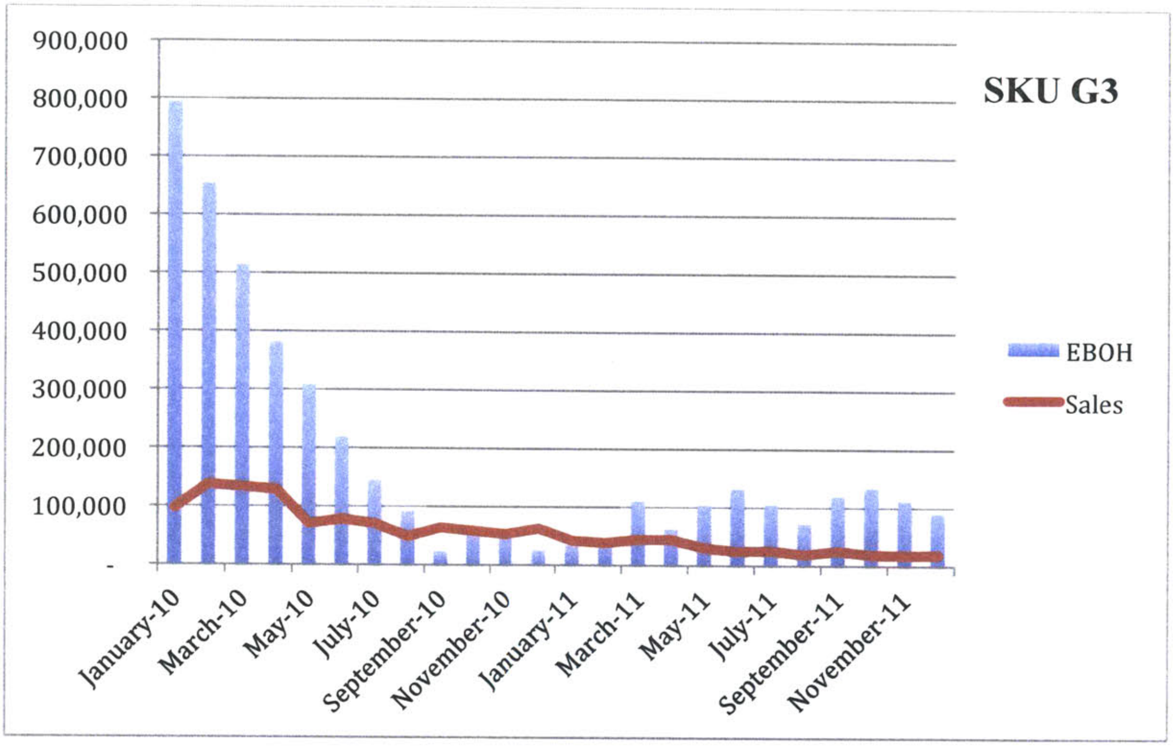

Figure 4.17 Sales and Inventory Analysis of SKU G3 in 2010 and 2011

4.2.4 Upstream Value Chain

Product G is primarily manufactured in India and UK while the packaging is done in a secondary manufacturing US plant referred as SMS in the earlier chapters. The raw materials are procured via 3rd party sources.

Table 4.9 shows the various sub-processes in the manufacturing of product G and the lead-time associated with each of these sub processes. It also includes the pre-manufacturing lead times and material waiting times.

As can be observed from the table, the maximum time spent post primary manufacturing stage is at packaging wait time labeled as Pack Wait in the table and needs to be improved in order to improve the total lead time for the process.

Total Cycle Time = 56 days

Table 4.9 Manufacturing Sub-process at Secondary Manufacturing Plant

Sub-process	Duration
Manufacturing	14 days
Manufacturing QA Approval	9 days
Pack Wait	30 days
Packaging	1 day
Final Release	1 day
Wait to Ship	1 day

4.3 Planning Tool Recommendations versus On-hand Inventory

As discussed earlier, Company A uses tool S to plan the safety stocks at the warehouses. This tool has an inbuilt safety stock equation and EOQ that guides Company A in planning its inventory at the distribution centers. However, we observe that there is a gap between planning and execution. Inventory Analysis in Section 4.1 and 4.2 gives us an insight on how much inventory does Company A hold at its distribution centers.

Table 4.10 summarizes the difference between the inventory recommendation by the planning tool S and inventory current held by Company A at its two distribution center in US for Product P and G.

Table 4.10 Difference between Recommended and Actual On-hand Inventory

Product	SKU	Tool S Recommended Safety Stock (SS)	EOQ (Q)	Max Stock (SS + Q)	Average Stock (SS + Q/2)	Average On-hand Monthly Inventory	Average On-hand Monthly Inventory/ Average Stock Recommended by Tool S	Average On-hand Monthly Inventory/ Maximum Stock Recommended by Tool S	Difference between Max Recommended and On-hand Inventory
P	P1	24	7	31	28	58	2.1	1.9	26
	P2	20	7	27	24	58	2.5	2.1	31
	P3	34	1	36	35	77	2.2	2.1	41
G	G1	54	30	84	69	150	2.2	1.8	66
	G2	59	30	89	74	391	5.3	4.4	302
	G3	53	30	83	68	188	2.8	2.3	105
	G4	45	30	75	60	138	2.3	1.8	63
	G5	37	90	127	82	243	3.0	1.9	116

As observed from Table 4.10, Company A holds significantly high amount of inventory for both the products at its DCs. For Product P, it holds in actual more than twice as much as maximum recommended by planning tool S. For Product G, this ratio ranges from 1.8 to as much as 4.4. With sales declining, as observed in Section 4.2.2 for Product G, holding an excess amount of inventory lowers the inventory turn for the company.

4.4 Financial Analysis

We performed a GMROI (Gross Margin Return On Investment) analysis for the pharmaceutical supply chain involving pharmaceutical companies, wholesalers and retailers. Our study included leading pharmaceutical companies, big wholesalers and important retailers and pharmacies in the industry.

Figure 4.18 shows the financial performance of the players along the value chain by comparing the inventory turns and gross margins for the last 5 years. It can be observed that the pharmaceutical companies form a cluster at the right bottom, indicating high gross margins, but very low inventory turns. On the other extreme are the wholesalers, with low gross margins, but high inventory turns of 8 to14. And the retailers are lies in middle holding about 2 months of inventory and making higher margins than wholesalers. An isoquant is drawn to see where the GMROI, the gross margin return on inventory are equal. It can be observed that retailers and pharmaceutical companies are on the same isoquant, but the wholesalers fall below the isoquant - indicating a lower GMROI than both retailers and pharmaceuticals.

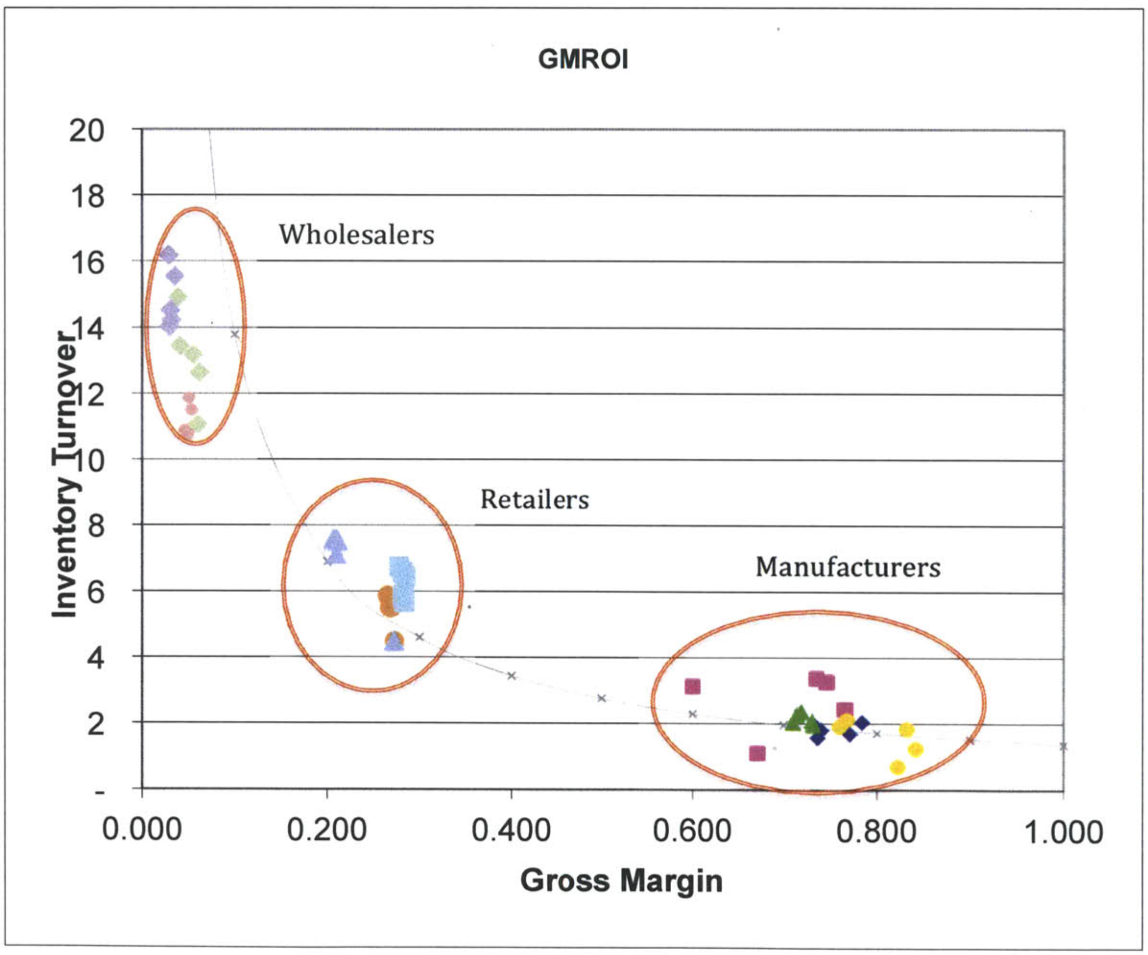

Figure 4.18 GMROI Analysis of Pharmaceuticals, Wholesalers and Retailers

*Source: Hoovers Financial Database

The basic purpose of the analysis is to find out incentives of the different players within the pharmaceutical supply chain to hold higher inventory buffers. Currently wholesalers appear to be undercompensated for the amount of inventory they hold. It looks like the wholesalers would not have incentive to hold higher amount of inventories, if they do not receive a higher compensation to do so.

Also, it can be noted that retailers are on the isoquant that manufacturers are on and suggests that they both receive compensation that makes their GMROI the same.

5 Proposed Model

The starting point to the proposed model for calculating safety stock was the current model. The intent of the current model was to incorporate two different risks into calculation of safety stock - the risk associated with demand variability, i.e. forecast inaccuracy, and the risk associated with supply reliability.

5.1 Current Model in Practice

In this section we describe the current inventory practices and policies of our sponsor company for the baseline distribution model. We do so by investigating the various factors involved roles in the inventory calculations for this multi-echelon supply chain.

The safety stock at the sponsor company is defined using the following formulation:

$$SS = k * \sqrt{\left(\frac{AS}{12} * f - \frac{AS}{12}\right)^2 * \frac{LT}{4*7}} + k * \sqrt{\left(\frac{AS}{12} * SR - \frac{AS}{12}\right)^2 * \frac{LT}{4*7}}$$

Rearranging,

$$SS = k * \sqrt{\frac{LT}{28}} * \left(\sqrt{\left(\frac{AS}{12} * f - \frac{AS}{12}\right)^2} + \sqrt{\left(\frac{AS}{12} * SR - \frac{AS}{12}\right)^2}\right) \quad (6)$$

where SS = safety stock maintained at the facility

AS = annual sales of the product in number of SKUs

k = safety stock factor

f = forecast accuracy (%)

LT = lead time in days, and

SR = supplier reliability (%)

As discussed earlier, the safety stock calculated using the above equation is used in assessing the inventories to hold at the DCs in alignment with the DRP (Distribution Requirement Planning) system.

We first analyzed the inventories for past two years for the two products and formed a baseline using the results. We then use the equation (6) in the tool to calculate the recommended safety stocks and compared this calculated safety stock against the baseline model. This gives an understanding of the current baseline model as well as scope of further reduction in inventories.

5.2 Revised Model

We propose an updated new model that improves the time period in the existing model as well as incorporates the two variances discussed above correctly.

In traditional literature, safety stock is thought of as a compensation for demand variability and we have seen equations like:

$$SS = k * \sigma * \sqrt{L} \qquad (7)$$

where σ is the standard deviation of demand over lead time, k is the safety factor and L is the fixed lead time or the time elapsed between order and receipt at a facility.

There are equations in literature that account for lead-time variability; the fact that the order to receipt time does vary by order. Since the variability of lead-time interacts with variability of demand, the equation that combines the variability is the following

$$SS = k * \sqrt{L * \sigma_D^2 + D^2 * \sigma_L^2} \qquad (8)$$

L = lead time

D = demand over lead time

σ_D = standard deviation of demand over lead time

σ_L = standard deviation of lead time

On careful observation of Equation (6), it can be noticed that there are two standard deviations in the formula, the first one for forecast accuracy and the second one for supply reliability.

Forecast accuracy is measured for individual SKUs on a monthly basis. The standard deviation of forecast accuracy used in the above equation is based on six month's data. As discussed in Chapter 4, supply reliability at Company A is currently set to 80% for all the SKUs and is not measured.

5.2.1 Correction for Number of Days

The equation assumes the number of days in the planning period to be 28, based on a 4 weeks a month. But, all the other parameters are set to monthly basis. For example, monthly sales are calculated as Annual Sales / 12, thereby implying a 30.4 days a month. Similarly, forecast accuracy is calculated on a monthly basis. Hence the number of days in a month assumption has to be corrected to 30.4 days. In the following equation, the number of days in a planning period is approximated to 30 days omitting the decimal for the sake of simplicity of use in calculations. Thus our equation becomes:

$$SS = k * \sqrt{\frac{LT}{30}} * \left(\sqrt{\left(\frac{AS}{12} * f - \frac{AS}{12}\right)^2} + \sqrt{\left(\frac{AS}{12} * SR - \frac{AS}{12}\right)^2} \right) \qquad (9)$$

5.2.2 Correction for Variances

X_D = Demand during lead time

X_S = Demand during lead time

$X_G = X_D - X_S$ = Gap between demand and supply during lead time

The variation of this gap is caused by two different sources. They are variation in demand and variation in supply. Variation in demand is the same as the variation between forecast and actual demand.

Total variation of $X_G = \sigma_g^2$

$$\sigma_g^2 = \sigma_f^2 + \sigma_s^2 + 2\,\mathrm{Cov}(S,D) \qquad (10)$$

Generally, the process driving demand and the process driving supply are thought of to be independent.

When X_D and X_S are independent, Cov(S,D) = 0;

Hence,

$$\sigma_g^2 = \sigma_f^2 + \sigma_s^2 \qquad (11)$$

Effective standard deviation $= \sigma_g = (\sigma_f^2 + \sigma_s^2)^{1/2}$ (12)

Using this logic in the equation for safety stock,

$$\sigma_f = \sqrt{\left(\frac{AS}{12} * f - \frac{AS}{12}\right)^2} \quad (13)$$

and $$\sigma_s = \sqrt{\left(\frac{AS}{12} * SR - \frac{AS}{12}\right)^2} \quad (14)$$

Effective standard deviation of the two variations = $(\sigma_f^2 + \sigma_s^2)^{½}$ (15)

Hence the safety stock equation modifies to

$$SS = k * \sqrt{\frac{LT}{30}} * \sqrt{\left(\frac{AS}{12} * f - \frac{AS}{12}\right)^2 + \left(\frac{AS}{12} * SR - \frac{AS}{12}\right)^2} \quad (16)$$

$$SS = k * \frac{AS}{12} * \sqrt{(f - 1))^2 + (SR - 1)^2} * \sqrt{\frac{LT}{30}} \quad (17)$$

The above equation adds up the variability occurring in the demand and supply processes correctly and is a correct formulation of the equation.

In most cases, the variation in demand and supply are thought of to be independent and hence, the covariance between demand and supply is assumed zero. But if there is any positive correlation between variation in demand and variation in supply, the covariance could be a positive number between 0 and 1 and hence, the safety stock required would be higher than the suggested number. If the correlation were negative, the covariance would be a negative number between 0 and -1, thereby reducing the safety stock required even further than recommended number.

5.3 Model Justification

Consider an inventory stock I (t) at time t. Between time t= t and t = t+L, there are two processes that change the value of I(t). The first is the addition to stock through production, a random process, which produces a random amount $\tilde{P}$ (t, t+L) in the time period. Then there is the demand that takes stock out of the inventory. This too is a random process that takes away $\tilde{I}$ (t, t+L) in the time period.

I (t) = Inventory at time period t

$\tilde{I}$ (t + L) = Inventory at time period t+L : a random variable

$\tilde{P}$ (t, t+L) = Production between time t and t+L : a random variable

$\tilde{D}$ (t, t+L) = Demand from time t to t+L : a random variable

Hence, the $\tilde{I}$ (t, t+L) will be equal to

$$\tilde{I}(t+L) = I(t) + \tilde{P}(t,t+L) - \tilde{D}(t,t+L)$$

I (t) is a fixed quantity and hence its variability is zero. Therefore, the variability of $\tilde{I}$ (t, t+L) is the sum of variabilities of $\tilde{P}$ (t, t+L) and $\tilde{D}$ (t,t+L).

$$Var\left(\tilde{I}(t+L)\right) = Var\left(\tilde{P}(t,t+L)\right) + Var\left(\tilde{D}(t,t+L)\right)$$

$$= \sigma_f^{\,2} + \sigma_s^{\,2}$$

5.4 Comparison with Current Model

The table below, Table 5.1 and 5.2 are the comparison of the safety stock recommendation by the current model at Company A and the proposed model for Product P and Product G for all their SKUs.

For Product P SKU P2, which is the largest SKU in the product portfolio of the company, for the same input parameters, we see that they hold 19.2% more inventory than they need to theoretically, which means 797,002 units (19.8 days of inventory) instead of 643,629 units (16.0 days of inventory).

For Product P SKU P1, we see a difference in recommended safety stock of 27.2%. Similarly, for SKU P3, we see a difference of 20.5%.

Table 5.1 Comparison of Model for Product P

SKU	Annual Sales	Monthly Sales	Safety factor	Supply Reliability	Forecast accuracy	Lead time	Calculated Safety stock by current model	SS Days of Inventory (Current Model)	Calculated Safety stock by proposed model	SS Days of Inventory (Proposed Model)	Change in Safety stock
	AS	AS/12	k	SR	FA	L	SS	DOI	SS	DOI	
SKU P2	14,654,676	1,221,223	2.57	0.80	0.95	30	797,002	19.80	643,629	15.99	-19.2%
SKU P1	4,364,818	363,735	2.57	0.80	0.91	30	282,909	23.59	205,940	17.17	-27.2%
SKU P3	4,281,806	356,817	2.57	0.80	0.95	86	403,172	34.27	320,411	27.24	-20.5%

Table 5.2 shows the comparison of safety stock recommended by the proposed model with the current model in practice at Company A for all the five SKUs of the off-patent Product G.

An average difference of 30% lower in safety stock units is observed in using the new proposed model for the same set of input parameters.

Table 5.2 Comparison of Model for Product G

SKU DESCRIPTION	Annual Sales (AS)	Monthly Demand (AS/12)	Service Level	SR (%)	FA (%)	LEAD-TIME (Days)	k	Calculated SS (Current Model)	DOI (Current Model)	Calculated SS (Proposed Model)	DOI (Proposed Model)	Change in Safety Stock
SKU G1	146,801	12,233	99.0%	80.0%	67.4%	60	2.32	21841	54	15341	38	29.76%
SKU G2	23,456	1,955	99.0%	80.0%	63.0%	60	2.32	3782	59	2696	42	28.72%
SKU G3	295,493	24,624	99.0%	80.0%	68.5%	60	2.32	43030	53	30115	37	30.01%
SKU G4	46,452	3,871	99.0%	80.0%	76.5%	60	2.32	5713	45	3915	31	31.47%
SKU G5	5,121	427	95.0%	80.0%	69.1%	60	1.64	522	37	365	26	30.13%

As can be seen from Table 5.1 and Table 5.2, this new model has a profound impact on the safety stock levels and the cost it can save for the organization. The reduction is observed to be more for Product G as compared to Product P.

5.5 Sensitivity Analysis

One of the questions we raised as a part of base lining is why parameters were set to the values they are set to. For instance, why is supplier reliability set to 80% for all SKUs? While we identify this as an area of further investigation in the future, we limit our discussion to sensitivity analysis, showing the sensitivity of safety stock to different input parameters.

5.5.1 Sensitivity Analysis of Product P

We performed the sensitive analysis using SKU P2, the highest selling SKU of Product P for all the input parameters.

Supply Reliability: Varying supply reliability from 80% to 100% showed that the safety stock is highly sensitive to supply reliability as can be observed in Table 5.3. At 100% supply reliability the safety stock required is just 22% of what is required at 80%. Similarly, if the supply reliability goes down by 10% from 80% to 70%, required safety stock goes up by 48%.

Table 5.3 Sensitivity of SKU P2 to Supply Reliability

Annual Sales	Monthly Sales	Safety Factor	Supply Reliability	Forecast Accuracy	Lead Time	Calculated SS (Proposed Model)	SS Days of Inventory (Proposed Model)	Change in Safety stock
AS	AS/12	k	SR	FA	L	SS	DOI	
14,654,676	1,221,223	2.57	0.7	0.95	30	952,250	23.7	**48.0%**
14,654,676	1,221,223	2.57	0.75	0.95	30	797,429	19.8	**23.9%**
14,654,676	1,221,223	2.57	0.80	0.95	30.00	643,629	16.0	**0.0%**
14,654,676	1,221,223	2.57	0.85	0.95	30	491,808	12.2	**-23.6%**
14,654,676	1,221,223	2.57	0.9	0.95	30	344,594	8.6	**-46.5%**
14,654,676	1,221,223	2.57	0.95	0.95	30	211,817	5.3	**-67.1%**
14,654,676	1,221,223	2.57	0.99	0.95	30	145,689	3.6	**-77.4%**
14,654,676	1,221,223	2.57	1	0.95	30	142,268	3.5	**-77.9%**

Forecast Accuracy: Since forecast accuracy is fairly high for this SKU and it is difficult to achieve a higher number, we have tested sensitivity in a narrow range. Table 5.4 shows that a 5% reduction in forecast accuracy leads to a 9% increase in safety stock and a 2% increase in forecast accuracy leads to 1% reduction in safety stock.

Table 5.4 Sensitivity of SKU P2 to Forecast Accuracy

Annual Sales	Monthly Sales	Safety factor	Supply Reliability	Forecast accuracy	Lead time	Calculated SS (Proposed Model)	SS Days of Inventory (Proposed Model)	Change in Safety Stock
AS	AS/12	k	SR	FA	L	SS	DOI	
14,654,676	1,221,223	2.57	0.8	0.85	30	784,636	19.5	22%
14,654,676	1,221,223	2.57	0.8	0.90	30	701,800	17.4	9%
14,654,676	1,221,223	2.57	0.8	0.93	30	665,045	16.5	3%
14,654,676	**1,221,223**	**2.57**	**0.80**	**0.95**	**30**	**643,629**	**16.0**	**0%**
14,654,676	1,221,223	2.57	0.8	0.96	30	640,140	15.9	-1%
14,654,676	1,221,223	2.57	0.8	0.97	30	634,731	15.8	-1%

Lead Time: Lead time is another important factor. Given that we have about 4 weeks of lead time, a reduction of 2 weeks results in 32% reduction in safety stock, whereas an increase of 2 weeks, results in 18% increase in safety stock. So, sensitivity is different on two sides.

Table 5.5 Sensitivity of SKU P2 to Lead Time

Annual Sales	Monthly Sales	Safety Factor	Supply Reliability	Forecast Accuracy	Lead Time	Calculated SS (Proposed Model)	SS Days of Inventory (Proposed Model)	Change in Safety stock
AS	AS/12	k	SR	FA	L	SS	DOI	
14,654,676	1,221,223	2.57	0.7	0.95	30	952,250	23.7	48.0%
14,654,676	1,221,223	2.57	0.75	0.95	30	797,429	19.8	23.9%
14,654,676	**1,221,223**	**2.57**	**0.80**	**0.95**	**30.00**	**643,629**	**16.0**	**0.0%**
14,654,676	1,221,223	2.57	0.85	0.95	30	491,808	12.2	-23.6%
14,654,676	1,221,223	2.57	0.9	0.95	30	344,594	8.6	-46.5%
14,654,676	1,221,223	2.57	0.95	0.95	30	211,817	5.3	-67.1%
14,654,676	1,221,223	2.57	0.99	0.95	30	145,689	3.6	-77.4%
14,654,676	1,221,223	2.57	1	0.95	30	142,268	3.5	-77.9%

Service Level: Safety factor or the service level is another parameter that safety stock is very sensitive to. Since this SKU is a class A item and hence the safety factor is set to 99.5%. With such a high safety factor, any small increase leads to a high increase in safety stock. A 0.4% increase leads to required safety stock being 9% higher. A reduction to 90% safety factor leads to a decrease of safety stock by 50%.

Table 5.6 Sensitivity of SKU P2 to Service Level

Annual Sales	Monthly Sales	Service Level	Safety factor	Supply Reliability	Forecast accuracy	Lead time	Calculated SS (Proposed Model)	SS Days of Inventory (Proposed Model)	Change in Safety stock
AS	AS/12		k	SR	FA	L	SS	DOI	
14,654,676	1,221,223	99.90%	3.09	0.80	0.95	30	773,916	19.2	**20%**
14,654,676	1,221,223	99.75%	2.81	0.80	0.95	30	702,992	17.5	**9%**
14,654,676	**1,221,223**	99.50%	**2.57**	**0.80**	**0.95**	**30**	**643,629**	**16.0**	**0.0%**
14,654,676	1,221,223	99.00%	2.33	0.80	0.95	30	582,609	14.5	**-9%**
14,654,676	1,221,223	98.50%	2.17	0.80	0.95	30	543,476	13.5	**-16%**
14,654,676	1,221,223	98.00%	2.05	0.80	0.95	30	514,339	12.8	**-20%**
14,654,676	1,221,223	97.50%	1.96	0.80	0.95	30	490,852	12.2	**-24%**
14,654,676	1,221,223	95.00%	1.64	0.80	0.95	30	411,936	10.2	**-36%**
14,654,676	1,221,223	90.00%	1.28	0.80	0.95	30	320,951	8.0	**-50%**

5.5.2 Sensitivity Analysis of Product G

Similar to Product P, we performed the sensitive analysis using SKU G3, the highest selling SKU of Product G for all the input parameters.

Supply Reliability: Table 5.7 shows the sensitivity of safety stock to variation in supply reliability parameter. A 10-point increase in supply reliability lowers the safety stock requirements by 12%. Similarly, a 10 point decrease in supply reliability factor increases the safety stock requirement by 16%.

Table 5.7 Sensitivity of SKU G3 to Supply Reliability

Annual Sales (AS)	Monthly Demand (AS/12)	Service Level	SR (%)	FA (%)	LEAD-TIME (Days)	k	Calculated SS (Proposed Model)	DOI (Proposed Model)	Change in Safety Stock
295,493	24,624	99.0%	70.0%	68.5%	60	2.32	35118	43	16.61%
295,493	24,624	99.0%	75.0%	68.5%	60	2.32	32462	40	7.79%
295,493	24,624	99.0%	80.0%	68.5%	60	2.32	30115	37	0.00%
295,493	24,624	99.0%	85.0%	68.5%	60	2.32	28154	35	-6.51%
295,493	24,624	99.0%	90.0%	68.5%	60	2.32	26666	33	-11.45%
295,493	24,624	99.0%	95.0%	68.5%	60	2.32	25732	32	-14.55%

Forecast Accuracy: Safety Stock is relatively more sensitive to forecast accuracy than supply reliability for Product G. Any improvement in the accuracy of forecasting can lower the inventory needed to hold. A 10% increase in forecast accuracy leads to about 15% reduction in safety stock as can be seen in Table 5.8. Also, any further decrease in forecast accuracy can cause increase in safety stock by substantial quantity.

Table 5.8 Sensitivity of SKU G3 to Forecast Accuracy

Annual Sales (AS)	Monthly Demand (AS/12)	Service Level	SR (%)	FA (%)	LEAD-TIME (Days)	k	Calculated SS (Proposed Model)	DOI (Proposed Model)	Change in Safety Stock
295,493	24,624	99.0%	80.0%	55.0%	60	2.32	39785	49	32.11%
295,493	24,624	99.0%	80.0%	68.5%	60	2.32	30115	37	0.00%
295,493	24,624	99.0%	80.0%	75.0%	60	2.32	25866	32	-14.11%
295,493	24,624	99.0%	80.0%	80.0%	60	2.32	22851	28	-24.12%
295,493	24,624	99.0%	80.0%	85.0%	60	2.32	20198	25	-32.93%

Lead Time: Lead-time for Product G is twice that of Product P. Reduction in lead-time by two weeks can result in reduction of safety stock by 14% and increase in lead-time by 10 days cause an increase in safety stock by 8%. Table 5.9 shows the different variations in lead-time and the sensitivity of safety stock to these variations.

Table 5.9 Sensitivity of SKU G3 to Lead Time

Annual Sales (AS)	Monthly Demand (AS/12)	Service Level	SR (%)	FA (%)	LEAD-TIME (Days)	k	Calculated SS (Proposed Model)	DOI (Proposed Model)	Change in Safety Stock
295,493	24,624	99.0%	80.0%	68.5%	70	2.32	32528	40	**8.01%**
295,493	24,624	99.0%	80.0%	68.5%	60	2.32	30115	37	**0.00%**
295,493	24,624	99.0%	80.0%	68.5%	45	2.32	26080	32	**-13.40%**
295,493	24,624	99.0%	80.0%	68.5%	30	2.32	21294	26	**-29.29%**
295,493	24,624	99.0%	80.0%	68.5%	15	2.32	15057	19	**-50.00%**

Service Level: The safety factor of four SKUs of Product G is set to 99% while the fifth SKU has a safety factor of 95%. With such a high safety factor, any small increase leads to a high increase in safety stock. Table 5.10 shows that a 0.5% increase in service level leads to required safety stock being 10% higher. A reduction to 90% safety factor leads to a decrease of safety stock by 45%.

Table 5.10 Sensitivity of SKU G3 to Service Level

Annual Sales (AS)	Monthly Demand (AS/12)	Service Level	SR (%)	FA (%)	LEAD-TIME (Days)	k	Calculated SS (Proposed Model)	DOI (Proposed Model)	Change in Safety Stock
295,493	24,624	99.5%	80.0%	68.5%	60	2.57	33360	41	**10.78%**
295,493	24,624	99.0%	80.0%	68.5%	60	2.32	30115	37	**0.00%**
295,493	24,624	95.0%	80.0%	68.5%	60	1.64	21351	26	**-29.10%**
295,493	24,624	90.0%	80.0%	68.5%	60	1.28	16635	21	**-44.76%**
295,493	24,624	85.0%	80.0%	68.5%	60	1.04	13453	17	**-55.33%**
295,493	24,624	80.0%	80.0%	68.5%	60	0.84	10925	13	**-63.72%**

Figure 5.1 and 5.2 summarizes the sensitivity analysis for Product P and G. The horizontal axis represents the increase and decrease in the parameter values while the

vertical axis represent the change in safety stock in response to the change in the parameters.

For Product P, supply reliability is the most important factor to consider. Other factors like forecast accuracy, lead-time and safety factor also play an important role. However, there is not much scope in changing these factors.

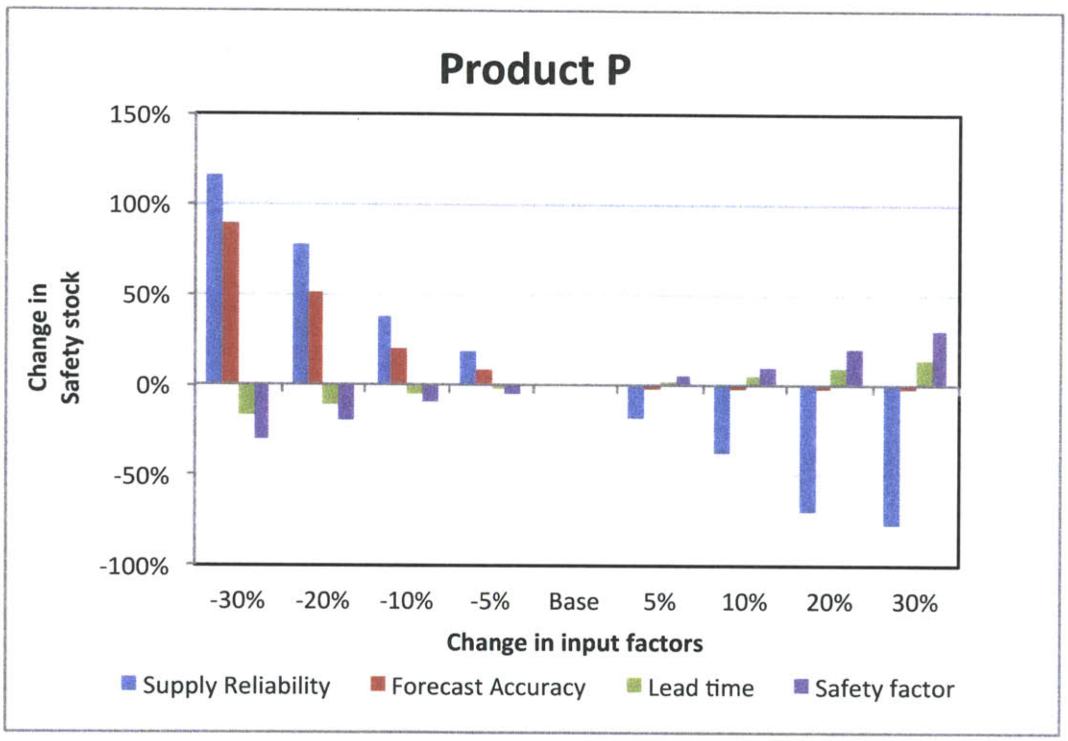

Figure 5.1 Sensitivity Analysis for Product P

On the other hand, for Product G, it would be very beneficial if the forecast accuracy were increased.

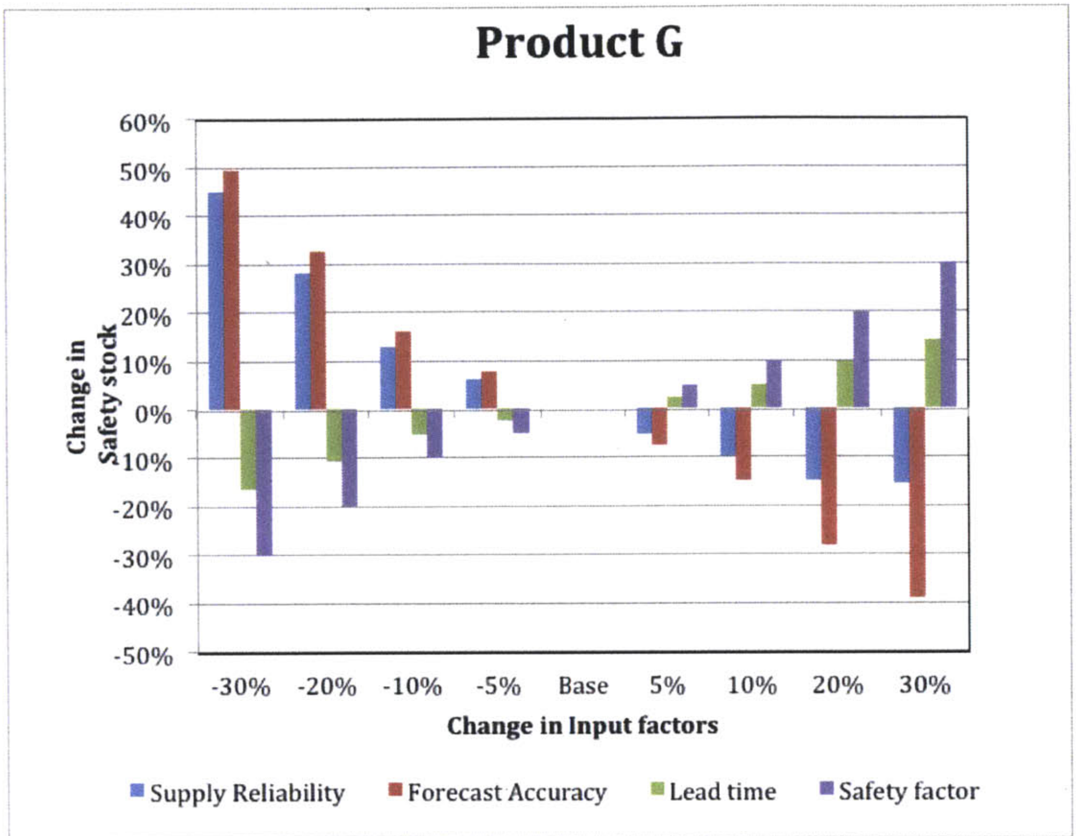

Figure 5.2 Sensitivity Analysis for Product G

6 Conclusions

We studied the supply chain of our sponsor company and proposed a model that can help them reduce the inventories as well as the working capital. Initially we focused on gathering data and organizational information. A review of the inventory and supplier reliability literature shaped our understanding of the safety stock equation used with variable parameters across industries. We then used this understanding to develop our model. In this chapter, we present our conclusions and key insights, drawn from the development and use of existing and proposed model. We conclude by providing key applicable recommendations for making the distribution system more inventory-efficient in a multi-echelon network. We also outline future research to extend our model further as well as extending to other product lines and network.

6.1 Key Insights

As we have noted in the previous two chapters, the safety stock levels of the finished goods inventory maintained in the distribution centers is higher than what the planning tool recommends. Hence, there is a clear scope for reducing the safety stock inventory. Apart from this, we have also shown that the currently used planning tool uses a safety stock calculating equation that is not theoretically sound. We have developed the corrected version of the equation with the same set of parameters, as in the original Equation (6). We have also improved the equation by correcting the number of days per month used in the planning equation (refer Equation (16)). We have shown that the proposed equation delivers benefits in terms of reduced safety stock, which implies reduced working capital investment. Currently, estimated reduction in safety stock investment is approximately $ 10 Million for just two products. If the proposed planning tool is extended to all the products across the organization, the benefits will be substantially high.

6.2 Recommendations

Based on the insights, we offer the following three recommendations to our sponsor company:

i) **New planning equation:** Implement the new planning equation for all products and SKUs: We have seen that the proposed equation, if implemented, would bring about a significant reduction in the safety stock carried across distribution facilities.

ii) **Cycle time analysis for upstream processes**: Through our analysis of inventory days and the finished goods inventory levels, we believe that there are potential opportunities to reduce cycle time of the upstream activities and thereby reduce inventory days. Hence, we recommend carrying out the cycle time analysis of upstream processes.

iii) **Orders pattern analysis for all products**: To better understand the variability in demand, we recommend that order pattern analysis be carried out for all products at the distribution centers. This will enhance the understanding of levels of inventory held at different parts of the supply chain.

We conclude by commenting on the importance of setting the right set of values for input parameters as well as looking through the end to end supply chain in order to optimize the overall objectives. Our research has shown that there is a greater scope of reducing the inventories by setting the correct values of operational parameters having multiple trade-offs and aligning the processes with the objectives.

6.3 Future Research

We have identified certain areas for further investigation and we believe that this exercise will benefit our sponsor company in its quest to design the most optimal inventory policies for all its products. They are listed below:

Identifying right set of input factors for safety stock calculations: As seen from the previous chapter, we have done sensitivity analysis for safety stock with respect to all the input factors. We have seen that Safety stock is pretty sensitive w.r.t input factors. Identifying the right set of input factors is important to meet the strategic inventory objectives as well as to optimize the inventory levels. Hence, we believe that more research needs to be done with respect to the optimal set of input parameters. The other factor that needs to be borne in mind is that the company requires the wholesaler's inventory to go down for the next few years and this decision has repercussions on the inventory our company needs to carry.

Understanding downstream sales patterns: Understanding of downstream sales patterns (both wholesalers and retailers) is an important input for modeling and different possible distribution models and understanding their impact. We recommend our sponsor company to collect as much sales information about downstream partners' sales pattern all the way to end consumer.

Alternate distribution models with quantitative modeling: If we are able to gather downstream sales pattern data, modeling different distribution models, which was one of the objectives of this thesis, could be accomplished. The assessment of the working capital required for these different models could be accomplished.

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