Multi-Echelon Inventory Optimization For an Oil Services Company

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Abstract

In the oilfield services industry, healthy margins and the criticality of product availability have often over shadowed the need for operational efficiency. Although those factors have not changed, the emergence of stronger industry competition and challenging economic climates have prompted ABC company to explore efficiency gains via supply chain optimization. This thesis examines and assesses opportunities for ABC Company to employ statistical inventory models, understand a variety of factors that influence inventory levels and costs, and improve its network structure. As many inventory models are not designed to accommodate SKUs that have very low rates of consumption, we also propose a methodology that will provide operational guidance and cost implications to address these types of SKUs.

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Chapter 1- Introduction

1.1 – Company Introduction

The company in this study (hereafter called "ABC Company") is a global oilfield services provider with a business unit (hereafter called the "BU") that centers around the complete life of an oil or gas well in the North American market. In the BU, they serve many customers who have developments in all the major basins of natural gas and oil in North America and the Gulf of Mexico. Their customers operate at a very high rate (dollars of revenue per hour) and suffer significant financial setbacks when their production goes offline. ABC's business model is a combination of new business and services to repair existing products in the field. If the customer's needs are not able to be met, ABC predicts the customer will likely turn elsewhere for product fulfillment as there are many oil field service competitors in the same locale. In these cases not only does ABC lose the immediate sale, but they may lose the customer for a longer term. Because of this sensitivity, ABC is looking to operate at a high service level to meet these needs and avoid stock outs at all opportunities while still being sensitive to cost.

1.2 – The BU Network and Top Level Supply Chain Map

The BU provides products and services to its consumers via four DCs that service and test parts (hereafter called Service Centers or "SC") as illustrated in Figure 1.1. Product inventory flows from production sites to a central DC. The regional DCs then order inventory from the central DC and receive weekly replenishment orders to fulfill the demands of its consumers.

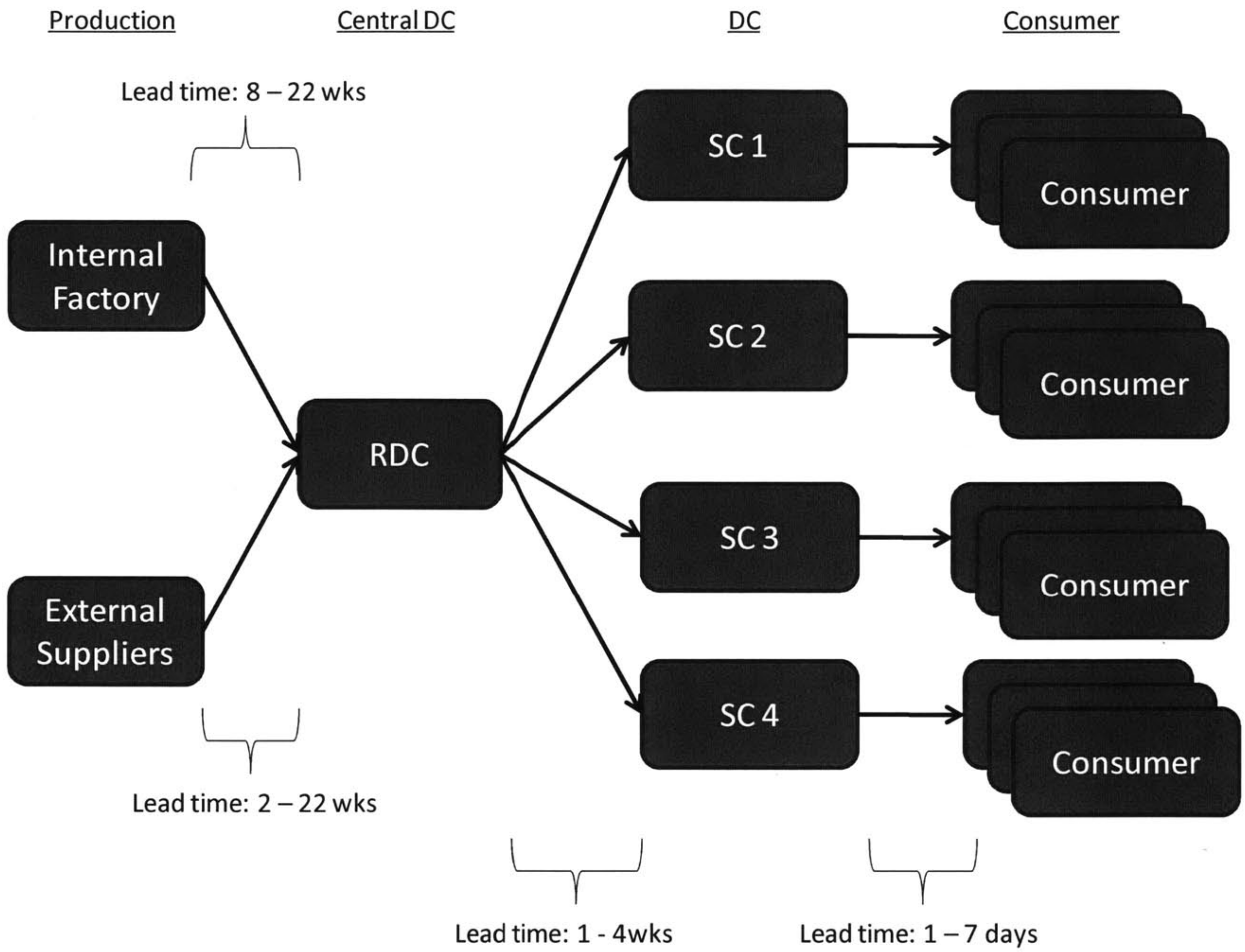


Figure 1.1 – The BU Supply Chain Network

It should be noted that lead time from production to the central DC and from the central DC to the regional DCs is highly variable and subject to the characteristics noted in Table 1.1.

Table 1.1 – Lead time factors – Production to Central DC

Factor	Description
Make or buy	Is the product produced internally or purchased externally?
Inventory or make to order?	Is the product an item typically held in inventory or made to order?
Production location	Is the product produced in Asia or in the United States?
Transit	Shipped via ocean freight, air, or truck? (Mixed modes are also common)

As the demand for parts and products vary significantly, the challenge of avoiding stock outs while constrained by prohibitive inventory costs has been a chronic problem. The large number of SKUs that need to be available is also posing a challenge for ABC's spare parts network as some parts are physically very large and expensive (such as 10,000 foot cable reels), while others are small and less costly (such as screws and washers). ABC also does not have any forecasting tools or product specifications available that may identify when parts may need to be replaced.

While uncertain about demand, ABC has simultaneously experienced significant fluctuations in lead time for production. Many of the SKUs needed in the spare parts network are produced in Asia and lead times have peaked at 22 weeks despite historical norms of 8 to 12 weeks. These fluctuations in replenishment, coupled with an unknown demand, have led to increased transportation costs in the form of last minute product transfers known as "hot shots."

1.3 – Project Overview and Motivation

As a result of the challenges described above, ABC is struggling with identifying the levels to which inventory should be stored and what the reorder points, on a per location basis, should be. ABC is also looking to be more flexible to the needs of its customer base as it looks towards the future, but is wary of the burden of additional costs. ABC's SKU base and normal business functions also put its inventory into a hybrid role. There are many SKUs which are used as spare parts for repair as well as inputs into the production of new finished goods. As such, the applicability of traditional spare parts inventory management strategies are unlikely to be optimal solutions.

The purpose of this thesis is to help ABC identify its desired customer service levels (CSL) and recommend a strategy for their parts inventory. In addition, this thesis delivers a model that reflects total relevant cost to provide guidance as variables (demand, lead time, holding costs, etc.) fluctuate. Our analysis is intended to improve the network structure for parts distribution and segment ABC's inventory to optimize and align their inventory deployment with desired service levels. In addition to the segmentation of fast moving inventory parts, our research also sheds light on the inventory and working capital implications of alternative stocking strategies for slow moving parts.

Chapter 2 - Literature Review

Historically, sales have dominated revenue strategy and operations have dictated cost strategy. Inventory management was often viewed as a necessary business function (similar to accounting and finance) where it was a necessary function, but not a core part of the corporate strategy. With the advent of the Information Technology age and increasing trend of globalization, inventory management has evolved from being a necessary business function to often being considered part of the core strategy of a business.

With an increasingly strong trend of globalization over the past 15 years, the needs of customers and companies have moved well beyond local economies. Today's customers want accessibility to products more quickly than ever before and are often more interested in fulfilling a need now than waiting for a slower but more cost efficient fulfillment. Companies have been forced to change their own strategies as customer loyalty continues to erode as a barrier to market entry. This change has resulted in increasing competition and the availability of competing products.

Companies like Wal-Mart and Dell have excelled in supply chain innovation and have shown how an efficient supply chain can provide a strong competitive advantage. Wal-Mart transformed its supply chain and became the largest retailer in the world by utilizing efficient inventory management techniques (Simchi-Levi D., 2003). In the late 1990s and early 2000s, Dell used an innovative strategy of build to order and a revolutionary inventory reducing lean supply chain to rise in the PC industry while leapfrogging market share leaders HP, Compaq, and IBM (Holzner, 2005).

Notable successes in the business world are few when it comes to inventory management as a core factor of success. Though inventory management has been studied and theorized in academia for a considerable time, its application in industry has been far from universal or comprehensive. The difficulty of implementing, choosing, and updating an inventory management strategy require a depth of knowledge and considerable time that often drives companies to deviate from a formal strategy to the less formal strategy. This literature review will offer a brief highlight of inventory management basics, review of five inventory management strategies, assess each strategy's strengths as solutions in various environments without presenting deeply complicated mathematics, and an analysis on their qualitative and quantitative properties as we discuss how to best apply these models to modern day challenges.

2.1 – Inventory Management Basics

Items held in inventory are categorized as raw materials, work in progress (WIP), or finished goods. Inventory can be held at a variety of places within a supply chain that range from suppliers, factories, distribution centers, in-transit, and retail outlets to name a few. Companies need to hold inventory to buffer against uncertainty (example, forecast for speculation of future sales) or time delay (example, time in transit from factory to the consumer) in their business cycles (Silver, 1998). Decisions on inventory are also subject to a dynamic customer demand, replenishment lead times, fulfillment lead times, the number of SKUs kept in inventory, order costs, the costs of holding inventory (including the cost of capital), and a desired customer service level (Graves, 2011). How, then, does a company formulate an inventory strategy?

An inventory strategy is driven by three levels of inventory decisions (Chopra, 2007). First, there are the supply chain strategic decisions such as "what are the potential alternatives to holding inventory" and "how should the product be designed?" Then, there are the deployment decisions. Dell revolutionized this level of decision making as this level addresses questions such as "what SKUs should be held in inventory" or "where and how much of each SKU should we hold in inventory?" (Holzner, 2005). Now that the SKUs and inventory levels and locations have been determined, it brings us to the third level of decision making that addresses questions surrounding reorder and replenishment. Here, decisions are made on how often inventory positions are reviewed, how frequently reorders are performed, and how much inventory should be ordered.

2.1.1 – Inventory Classifications

Although inventory holding calculations are made at the SKU level, the sheer size of a SKU base often makes this an impractical and tedious effort. To better cope with a large SKU base, companies often create groups and determine an inventory strategy for that group. Individual SKUs are then assigned to one of the groups and are subject to that group's inventory policy.

In a commonly used model, inventory items typically follow an A-B-C classification (Silver, 1998) where A items are the most prioritized items. When looking at inventory totals, A items typically represent 80% of the value and 20% of the SKUs, B items 15% of value and 30% of SKUs, and C items 5% of value and 50% of SKUs. A items deserve the most managerial attention and review. Their importance to the company also means that there is an underlying expectation that there will be exceptions in their handling. B items are typically moderate in impact to the business and companies can leverage some automation in the handling of stock levels as they require less managerial review. C items have a minor impact on a company's functions and are the ideal classification to apply an inventory model and enable significant automation.

It's extremely important to note that the term "value" is a subjective criterion and are arbitrary classifications. Some examples of "value" are:

- The cost of goods sold.
- The sales (or retail) price.
- The relative importance, regardless of sales price or cost, of the SKU to the corporate mission or strategy.

Although A-B-C segmentation might help improve the understanding of a firm's SKUs, it is not usually an efficient inventory policy on its own. Since A-B-C segmentation ignores lead time and variability, it is unlikely to yield optimal results.

Instead, we advocate SKU segmentation as a necessary prerequisite for the optimal operation of an inventory strategy. The SKU segmentation should follow the company's product strategy and corporate priorities to account for factors (including but not limited to) lead time, physical size, the criticality of product availability, consumption and cost.

2.1.2 – Safety Stock

In most inventory models, the inventory for one SKU is characterized in an equation by the following, total system inventory = safety stock + cycle stock (inventory on hand + inventory in-transit). Safety stock (denoted as ss hereafter) is calculated by using the following equation.

$$ss = k\,\sigma \tag{2.1}$$

Above, ss equals the safety factor, based on the probability of not stocking-out during a replenishment period (denoted as *k* hereafter), times the standard deviation of errors of the forecasts. For periodic systems where there is a lead time and a review period, Equation 2.1 may be modified below.

$$ss = k\sigma\sqrt{L + R} \tag{2.2}$$

Further expanded, ss equals k times the standard deviation of errors of the forecasts times the square root of the sum of the replenishment lead time (denoted as *L* hereafter) plus the length of review period (denoted as R hereafter).

If the forecast errors are unknown, an alternative equation is used to find σ. If expected lead time (denoted as E(L) hereafter) and expected demand (denoted as E(D) for this section only) are independent variables that each have its own standard deviation, σ is calculated by:

$$\sigma = \sqrt{(E(L)\sigma_D^2 + (E(D)^2)\sigma_L^2} \tag{2.3}$$

Table 2.1 - Safety Stock Variables

Variable	Description	Units
ss	Safety stock	Units
k	Safety factor, based on the probability of not stocking-out during a replenishment period	NA
σ	Standard deviation of errors of forecasts over a replenishment lead time	Units
σ_D	Standard deviation of demand	Units
σ_L	Standard deviation of lead time	Days
R	Amount of time for review of inventory	Days
L	Lead time for order replenishment	Days
E(D)	Expected Demand (this section only)	Units/Time Period
E(L)	Expected Lead time	Days

2.1.3 – Reorder Point

Some inventory models include a reorder point which serves as a trigger to submit a replenishment order. It is calculated by equation 2.4:

$$\mathbf{s = x_L + k\sigma} \qquad \textbf{(2.4)}$$

2.1.4 – Cycle Stock

Since it's not always practical to order one new unit every time a unit is sold, products are typically ordered in batches. Moving forward with batch orders gives way to the use of cycle stock where cycle stock equals inventory on hand (denoted as *IOH* hereafter) + inventory on order.

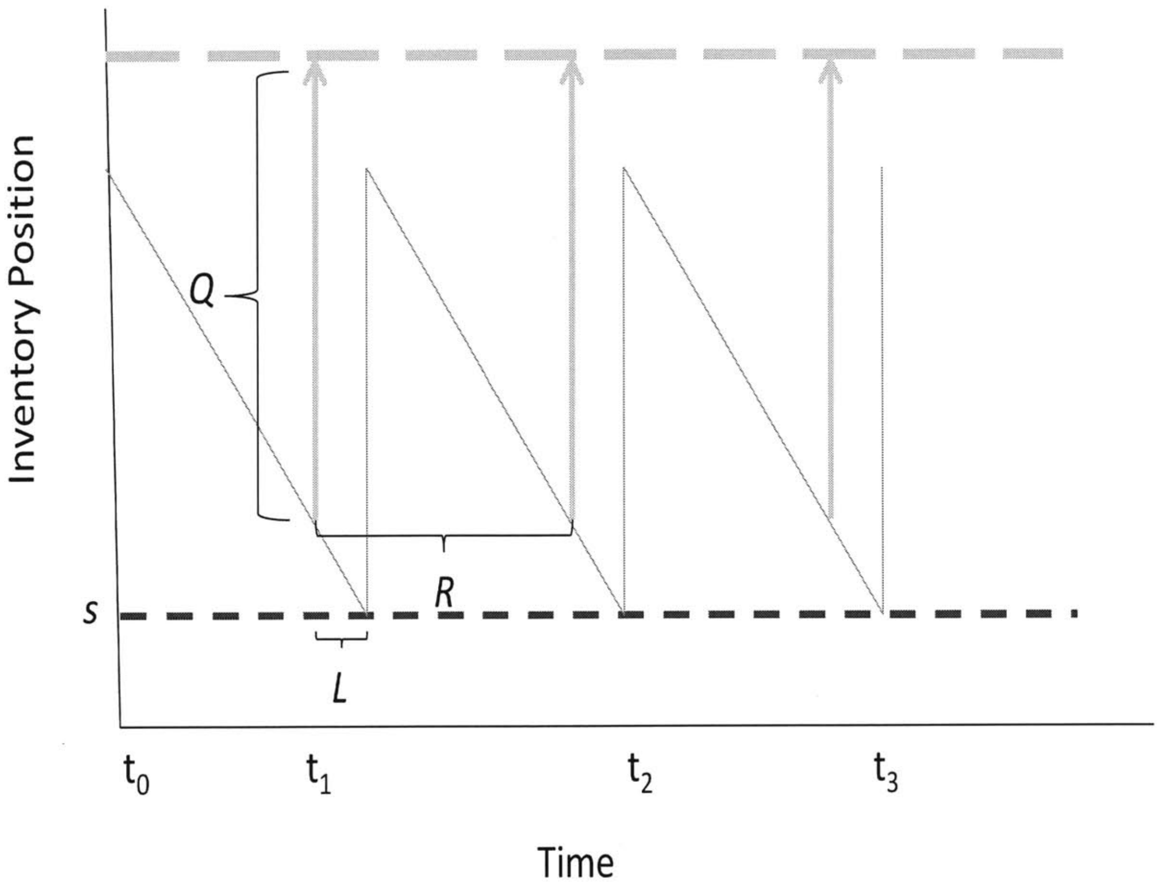


Figure 2.1 – Cycle Stock

In Figure 2.1, the saw tooth shaped line indicates inventory on hand, while the vertical line indicates the amount ordered, Q. At time t_0, total IOH is equal to top of the saw tooth line. IOH is reduced by demand (denoted as *D* hereafter) and after *R* period of time, Q is ordered at time, t_1. Because there is a lead time associated with replenishment, it's necessary to forecast the demand over the lead time (denoted as x_L hereafter). Total cycle stock inventory is now equal to IOH + Q. After L has passed, the replenishment order is received and IOH rises.

Table 2.2 - Cycle Stock Variables

Variable	Description	Units
Q	Quantity of units ordered	Units
x_L	Forecast demand over the lead time	Units / Time
s	Reorder point	Units

2.1.5 – Economic Order Quantity

The economic order quantity (denoted as *EOQ* hereafter) is an important building block of inventory systems. It takes into account the basic cost per order (denoted as *A* hereafter), cost per unit (denoted as *v* hereafter), and inventory carrying costs (denoted as *r* hereafter) to minimize inventory related costs.

$$EOQ = \sqrt{\frac{2AD}{vr}} \tag{2.5}$$

Table 2.3 – EOQ Variables

Variable	Description	Units
A	Order cost	$ / order
D	Average demand	Units / year
v	Purchase cost	$ / unit
r	Holding cost	$ / $ held / year

2.2 – Inventory Models

With a few of the basics now covered, it is time to move to a discussion about inventory models. While there are numerous models to pick amongst, this literature review will cover the five models which make the most sense for ABC Company.

2.2.1 – Continuous Review in an Order Point, Order Quantity System (s, Q)

The (s,Q) is a system where the R is zero. In this model, a fixed quantity, Q, is ordered whenever the inventory position drops to or below *s*. Though the on-hand inventory is the trigger in a (s, Q) system, it's critical to discern that the inventory position includes on-order stock that has not yet been received. Figure 2.2 illustrates this model further.

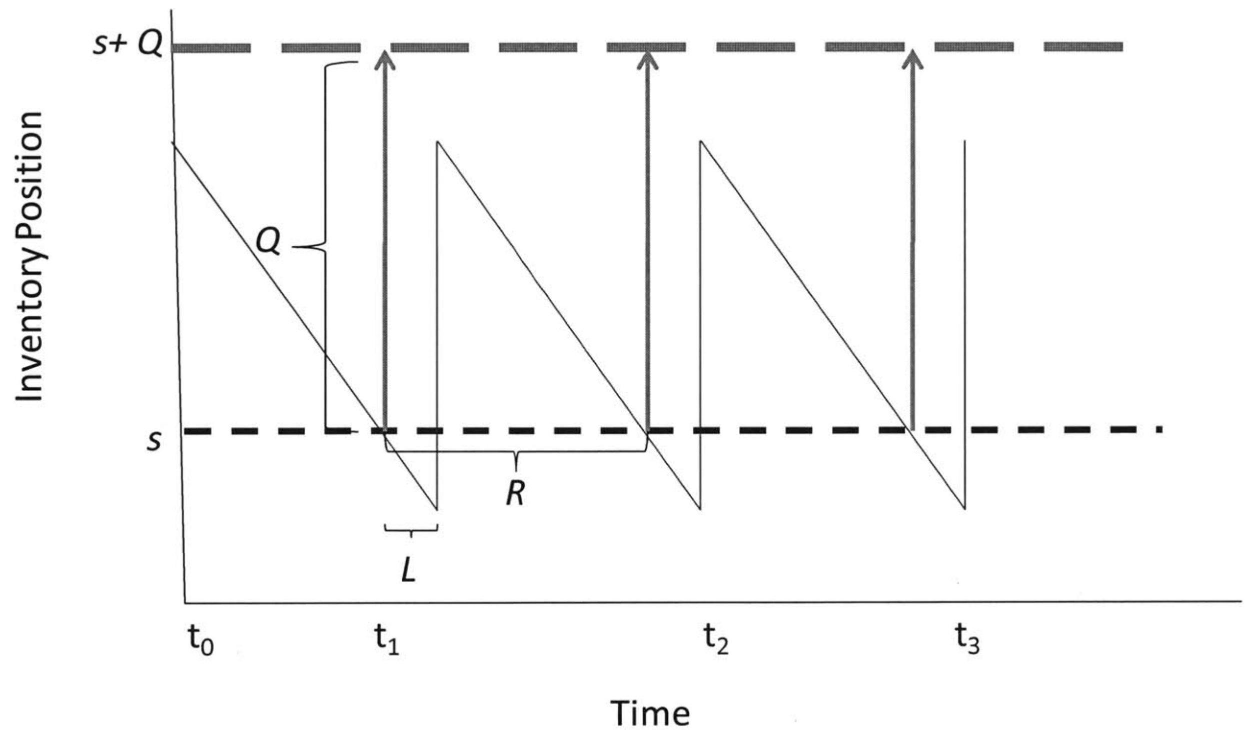


Figure 2.2 – (s, Q)

At time t_1, inventory reaches s units. This triggers the ordering process where a fixed quantity of Q units are ordered and total inventory in the system equals s + Q. At time t_1+ L, after waiting for the lead time for order fulfillment, inventory rises when Q units have been received.

The (s, Q) system is commonly referred to as a "two-bin" system (Silver, 1998). The first bin contains inventory above *s* and is the first bin to have inventory removed when fulfilling orders. The second bin is the inventory below *s* and is used to fulfill orders when the reorder point has been triggered. Once the replenishment order is received, it fills the second bin first and all remaining units are moved to the first bin.

2.2.2 – Continuous Review in an Order Point, Order Up To System (s, S)

The (s, S) system is very similar to the (s, Q) system above. They both assume a continuous system where R = 0 and a trigger point of s. The main difference is that the framework of the (s, S) system indicates that when the inventory on hand reaches s, the number of units in the replenishment order should raise total inventory to the predetermined order-up-to level, S, the quantity ordered is the order-up-to level minus your current inventory on hand. To represent this in the form of an equation,

$$\mathbf{Q = S - s} \qquad \mathbf{(2.6)}$$

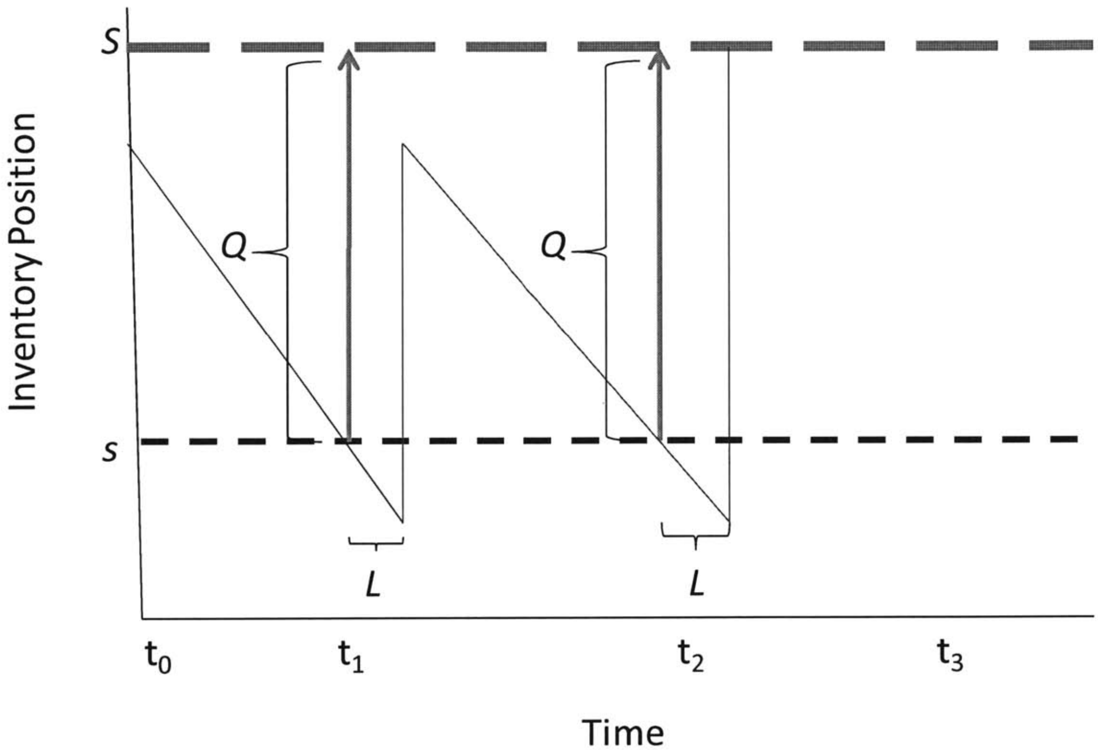


Figure 2.3 – (s, S)

Notice that replenishment orders are placed when IOH drops to or below s and is not subject to any specific review period. In Figure 2.3, at t_1 IOH drops to s and Q units are ordered and a second order is placed before t_2. This model is frequently referred to as a "min / max" system because inventory typically remains between the minimum value of s and a maximum value of S (Caplice, 2010).

2.2.3 – Continuous Review in One for One System (S-1, S)

The (S-1, S) system is a derivative of the (s, S) policy and designed to handle a special case of inventory items that fall beyond the efficacy of traditional inventory systems. It assumes a normal, discrete demand and constant lead time and its application has been studied and applied to expensive, slow moving inventories where order costs are negligible and holding costs are linear per unit per unit time. More specifically, this system is often applied to inventories whose demand is infrequent, inventory quantities are too small for batched ordering, and holding costs are less than shortage costs (Schultz, 1990).

As its name suggests, a replenishment order is triggered when IOH falls below S. Here, the replenishment order is equal to the magnitude of demand and can be characterized by Q = D. As the total inventory quantities and total inventory costs in a system are often very sensitive to changes in inventory levels of expensive items, the strategy behind the management of these items becomes an integral part of a comprehensive, flexible and efficient inventory model.

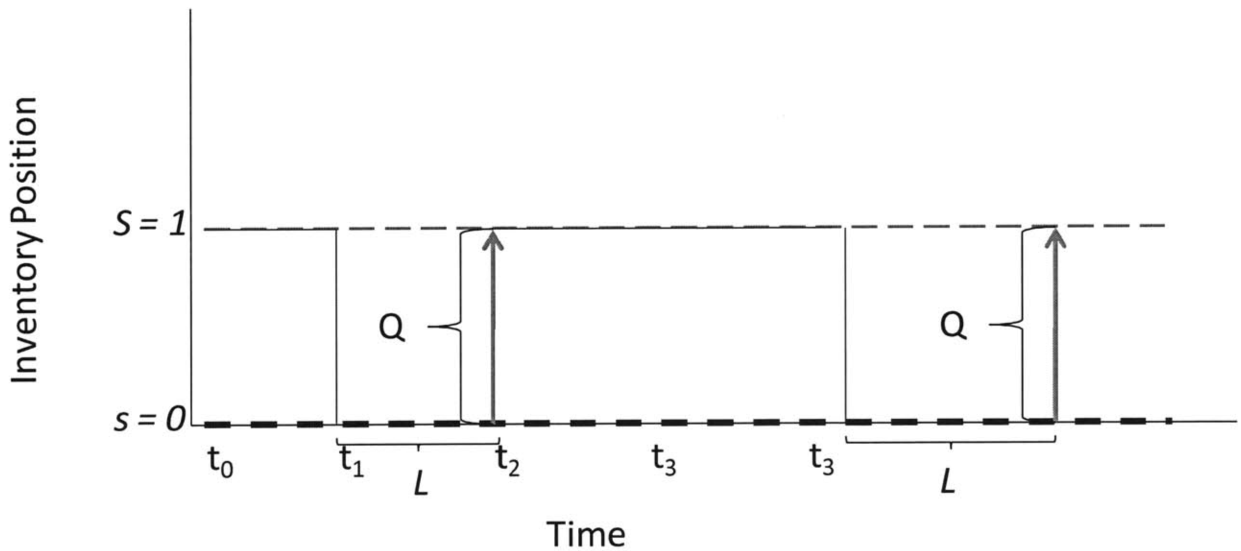


Figure 2.4 – (S-1, S)

2.2.4 – Periodic Review in an Order Up To Level System (R, S)

The (R,S) system is commonly referred to as a replenishment cycle system and is widely used in practice (Silver, 1998). In the two continuous systems discussed earlier, the controlling factor was the trigger point, s. In a periodic review system, the controlling factor is not an inventory level. Instead, it is a period of time, R.

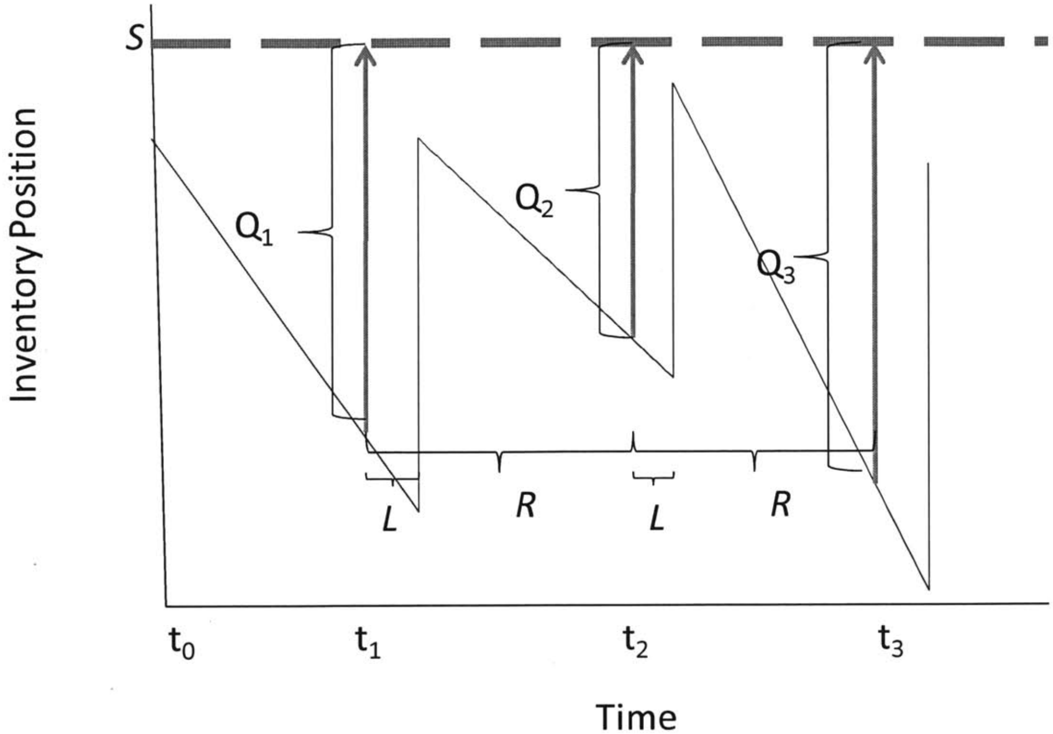


Figure 2.5 - (R, S)

In the (R, S) system, inventory is reviewed every R periods. Inventory replenishment orders are then calculated based on inventory on hand and the order-up-to level. Figure 2.5 illustrates that rule as it's clear that $Q_1 \neq Q_2 \neq Q_3$.

This model is frequently used in environments where no computers are present as inventory managers are essentially able to set and order up to the maximum inventory level, S, and not worry about calculating the inventory replenishment order, Q, until the R period has passed (Caplice, 2010).

2.2.5 – Periodic Review in an Order Point, Order Up To Level System (R, s, S)

The (R, s, S) system is a combination or hybrid approach that combines the (s, S) continuous review system and the (R, S) periodic review system. Here, inventory is reviewed every R periods. If the inventory on hand is above s, then no action is taken. If the inventory is at or below s, then a replenishment order of Q is placed.

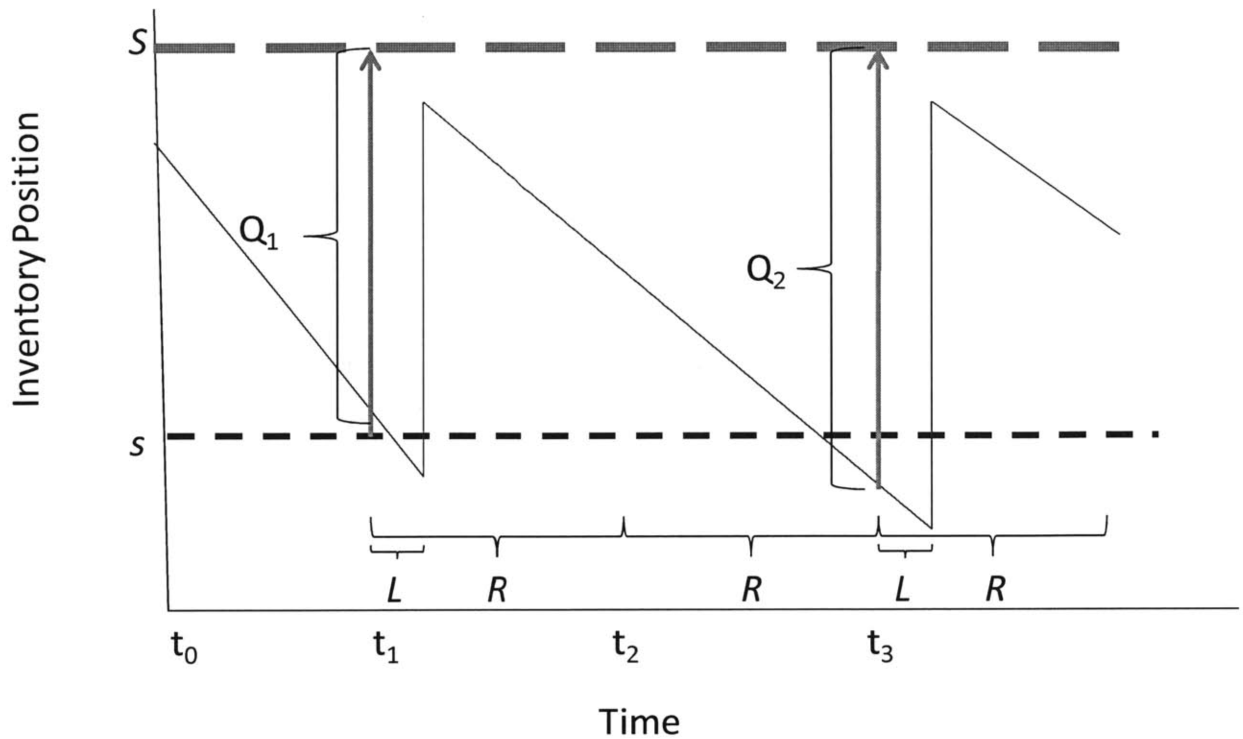


Figure 2.6 – (R, s, S)

Figure 2.6 depicts inventory for three periods. At t_1, Q_1 units are ordered. At t_2, since IOH has yet to reach or fall below *s*, zero units are ordered. A new order is not placed until t_3 where Q_2 units are ordered.

Many authorities and authors on inventory management have written that under general conditions, the best (R, s, S) system allows for lower total of replenishment, carrying, and shortage values than any other system (Silver, 1998). However, the burden required to find the optimum values in this system is heavier than those found in other systems (Caplice, 2010) (Simchi-Levi D., 2003) (Graves, 2011).

2.3 – Total Cost

Finding the total cost (denoted as *TC* hereafter) is one analytic way to understand and compare different inventory models. It is the sum of purchase costs plus order costs plus holding costs plus costs of a stock out and is calculated by the following equation:

$$TC = vD + A\left(\frac{D}{Q}\right) + vr\left(\frac{Q}{2} + k\sigma\right) + \mathrm{C_{ST}} * \mathrm{P[ST]} \qquad \textbf{(2.7)}$$

Here, C_{ST} is the cost of a stock out type and P[ST] is the probability of that stock out type. Using total costs can provide guidance for strategic decision making as it may be strongly influenced by the cost of a stock out (Caplice, 2010).

2.4 –Total Relevant Cost

Total relevant cost (denoted as *TRC* hereafter) is equal to "the sum of those costs per unit of time which can be influenced by the order quantity, Q" (Silver, 1998). More generically, it's the sum of the order costs plus the holding costs plus the costs of a stock out. Mathematically, it's TC minus the order costs.

$$TRC = A\left(\frac{D}{Q}\right) + vr\left(\frac{Q}{2} + k\sigma\right) + C_{ST} * P[ST] \qquad \textbf{(2.8)}$$

Again, C_{ST} is the cost of a stock out type and P[ST] is the probability of that stock out type.

2.5 - Single-Echelon Systems

In a single echelon system, there is one level of stocking points that service the final consumer. In this model, each service center operates as an independent stocking point for its consumers and is affected by fluctuations in demand.

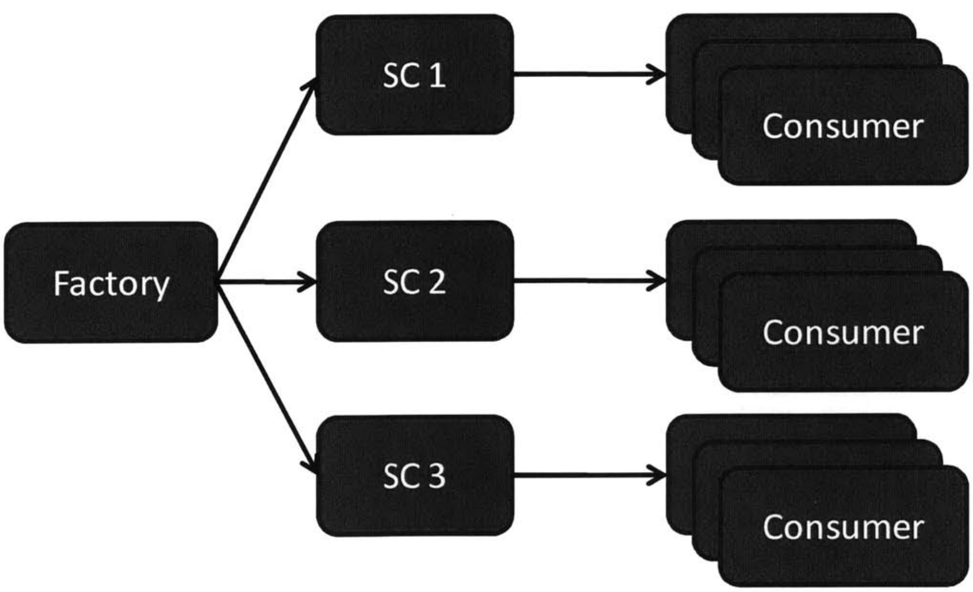


Figure 2.7 – Single Echelon Diagram

The inventory strategy in a single-echelon model is dependent on a variety of possible factors including the desired customer service level, ordering costs, and holding costs. Developing a strategy is further complicated by external constraints such as ordering constraints, lead time variability, and demand variability.

2.6 – Multi-Echelon Systems

Now consider a case where there is another echelon between the factory and the SC as seen in Figure 2.8.

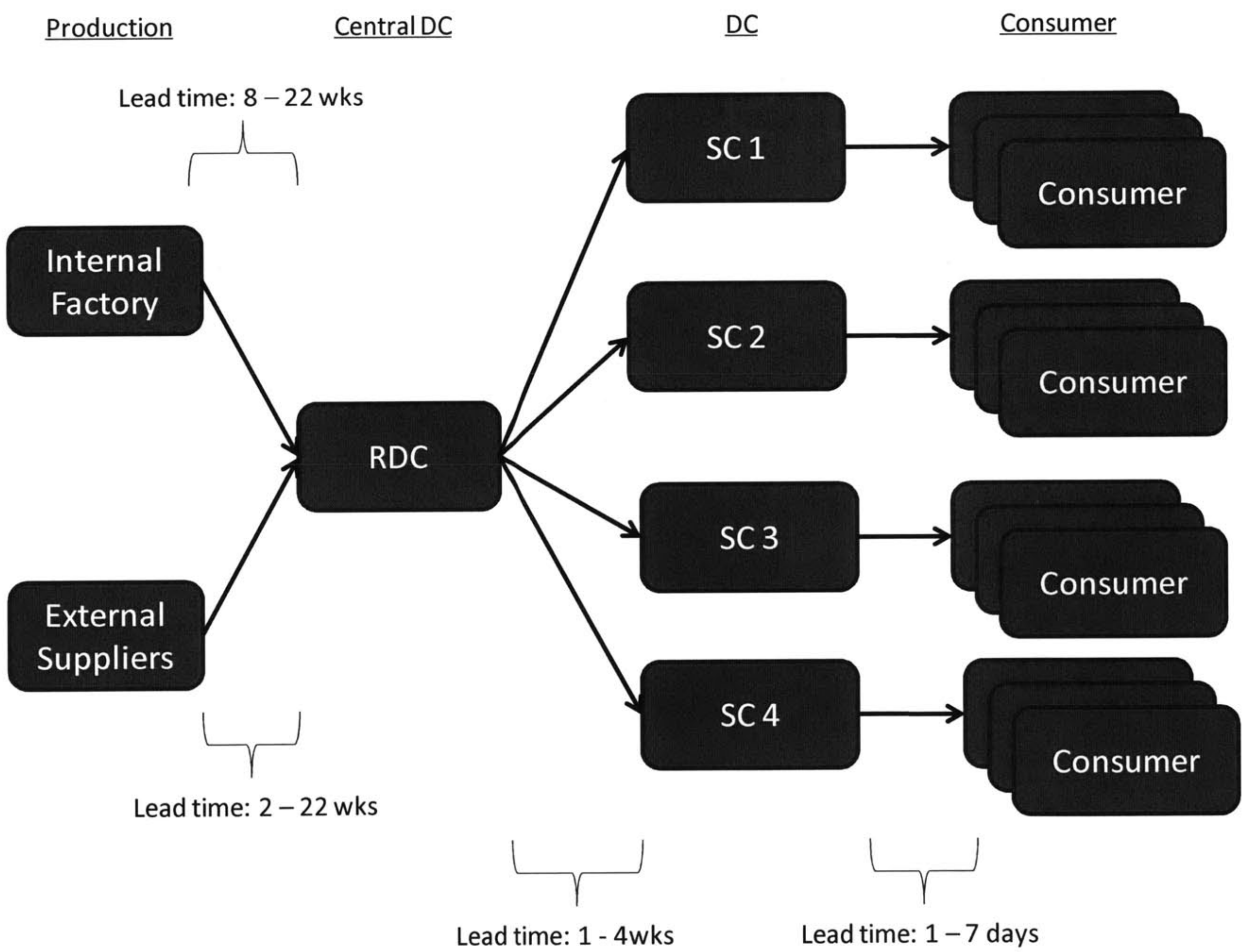


Figure 2.8 – Multi-Echelon Diagram

RDCs are often used in situations where lead time from the factory is long, lead time from the factory is highly variable, there are holding cost advantages, or the system is subject to volatile demand variability.

As was the case in the single echelon model, the SCs are on the front lines of fulfillment and are, therefore, vulnerable to the variability of consumer demand. When demand is highly variable, SCs are forced to stock larger quantities of inventory (based on a defined CSL) to meet consumer demand. By adding an intermediary stocking point, RDC serves as a demand risk pool for the SCs and is able to balance some of that variation with the demand from other SCs. To calculate the standard deviation of an RDC, the following equation is used:

$$\sigma_{RDC} = \frac{\sqrt{\sigma_a^2+\sigma_b^2+\sigma_c^2+\cdots\sigma_n^2}}{n} \qquad \textbf{(2.9)}$$

In circumstances where the lead time from the factory to the next level of the echelon is long or highly variable and the lead time from the RDC to the SCs is less than the lead time from the factory to the RDC, the RDC serves as an inventory consolidation point. This allows the SCs to maintain less safety stock and hold inventory positions closer to its cycle stock requirements.

In sections 2.2.1 we discussed inventory classifications and in 2.2.3 we discussed an alternative strategy to segment expensive, slow movers from the standard inventory classifications. By combining those two strategies with a multi-echelon system, they leverage the use of the law of large numbers and allow the expensive, slow movers to be centralized in the RDC. The resulting impact is that many of the service centers will no longer hold the expensive, slow movers and the total system inventory for those SKUs will decrease.

Chapter 3 - Methodology

3.1 – Model Network and Data

The goal of the thesis was to create a model to optimize ABC's current inventory requirements and provide a min / max level on a per SKU per location level. After analyzing the current network, as illustrated in Figure 3.1, it was decided that an optimal inventory policy required a "fast moving" regional distribution center. This would ensure that the service centers are replenished in short periods of time. The RDC would also allow slow movers to be held up stream. The model reflected these factors via a multi-echelon network as per Figure 3.2.

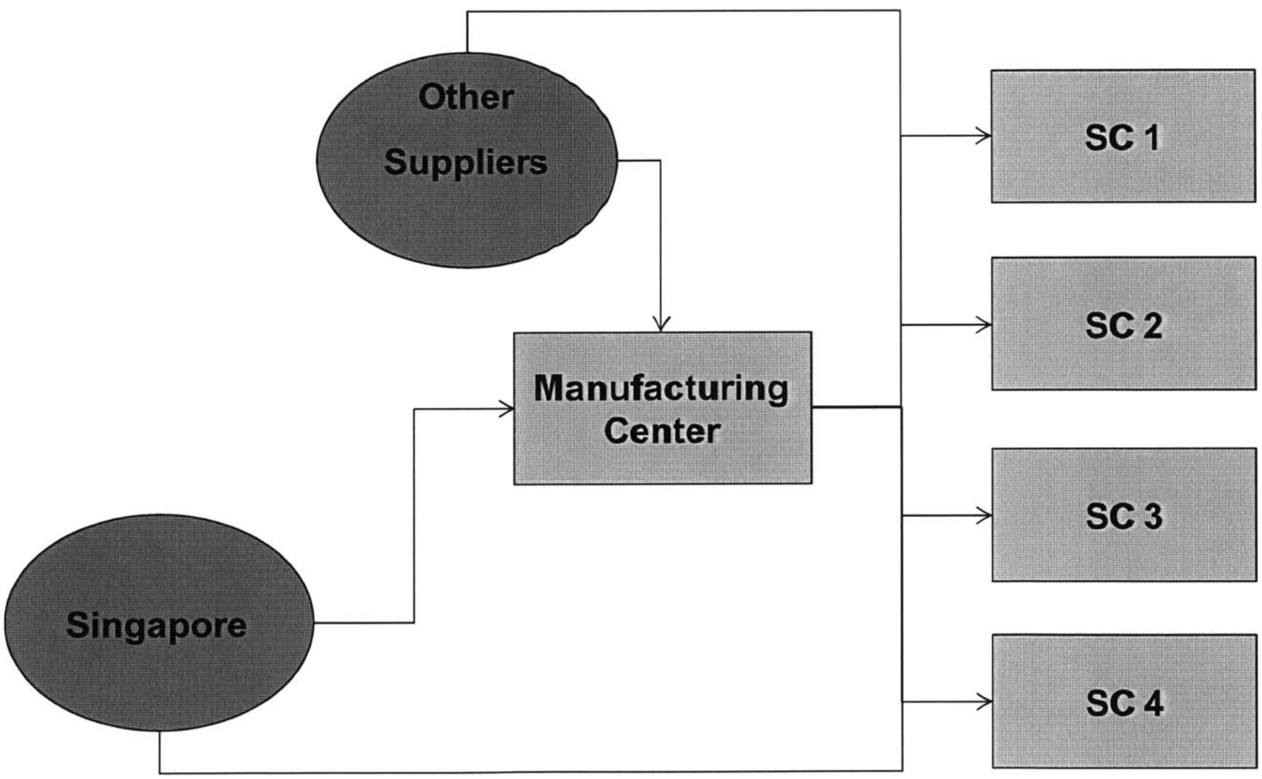


Figure 3.1 – Current Network

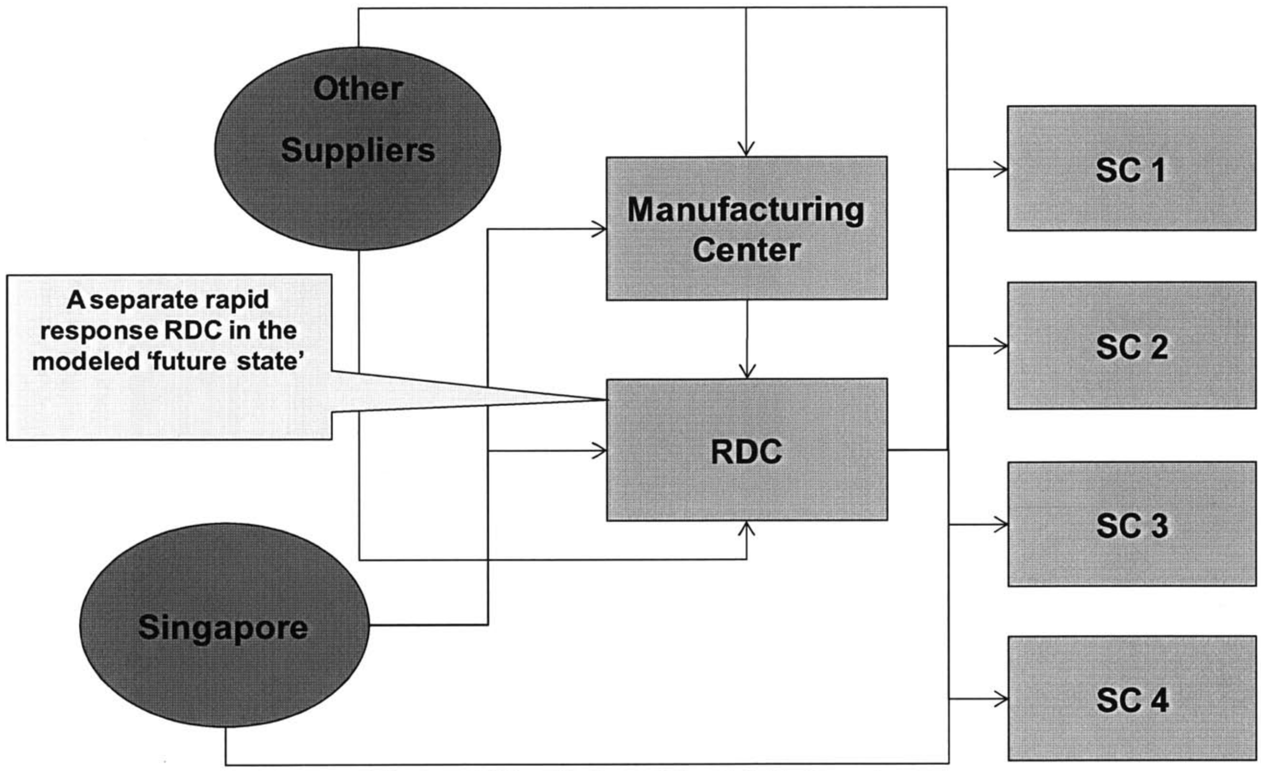


Figure 3.2 – Future Model Network

A number of key inputs were required to build the model. These included:

1) Six months of SKU level usage data for each SC.
2) SKU master table with SKU groupings and values.
3) SKU categorization by supply chain characteristics.
4) Missing SKU costs replacement table.
5) Assumptions for lead times, order costs, service levels and holding cost percentage.

The output from the model broke the results into SC output and RDC output. Each of these files contained average inventory amounts and min / max levels on a SKU level.

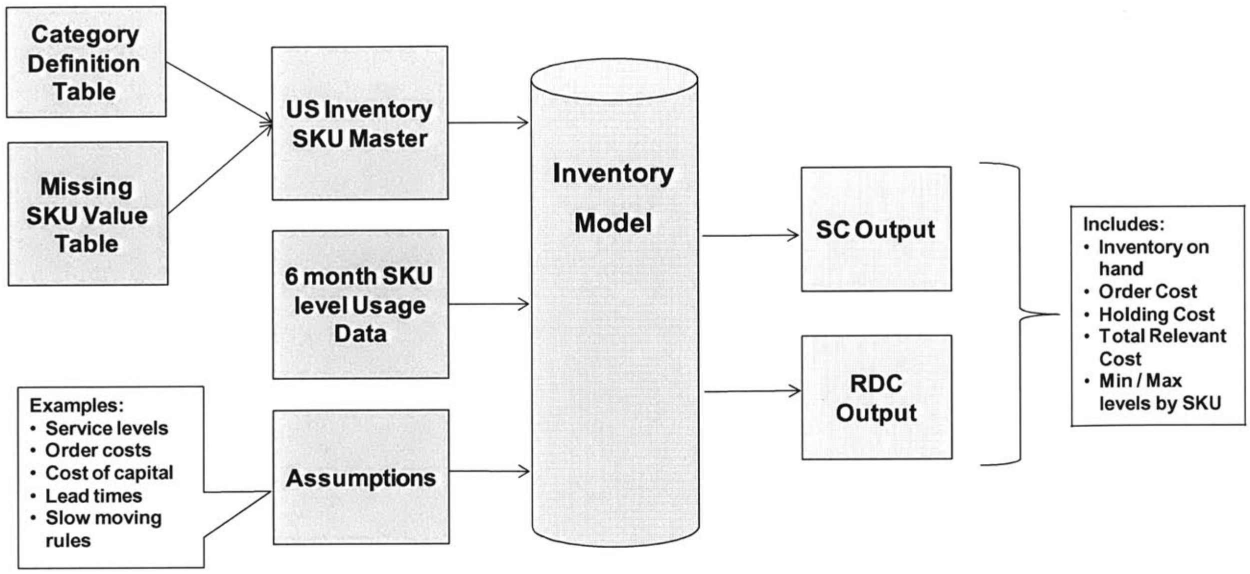


Figure 3.3 – Model Data

Figure 3.3 shows the data inputs into the inventory model and the outputs split by SC and RDC locations.

Early on in the project, we identified that the SKUs had to be organized into supply chain groupings to allow for model manipulation. We then cut the SKUs into twelve different categories (from 0 to 11) according to demand velocity, value and manufacturing requirements. With the aid of ABC, over 4,500 SKUs from the SKU master file were categorized.

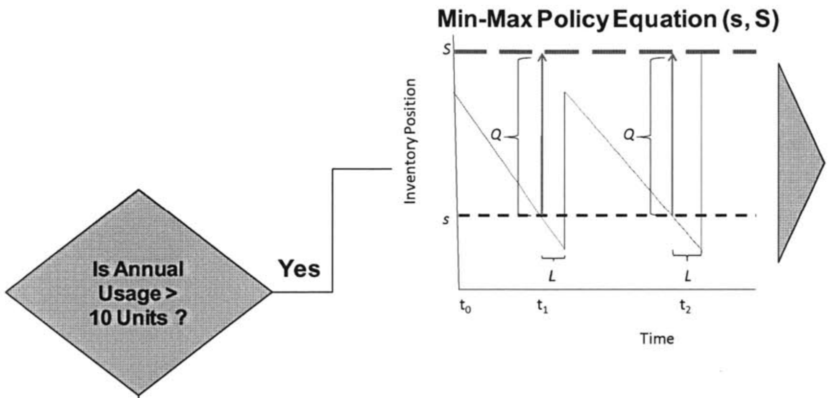
Table 3.1 – SKU Categorization
(Note that specific product names have been changed)

Category	Demand	Value	Make / Purchase	Description
0	NA	NA	NA	One-offs, obsoletes
1	S	L	Purchase	Small low cost parts
2	S	H	Purchase	VSDs, transformer, SCBAs, WH, HHS, by-pass, BIW, soft start, switchboard, VSD spares
3	S	H	Make	Orange series, small parts, for non standard equipment kit, adapters, seal section , pumps, TC
4	F	L	Purchase	High running parts (typically purchased) such as O-rings, snap rings, fasteners, thrust washers, spacers, clamp, marker
5	F	L	Make	Shipping caps, terminal covers tubes, lead guard, 2 piece rings, compression tubes
6	F	H	Purchase / Make	Purchased: fluids. Make: Kits, rotors, MLE, intake, motor, seal section, pumps, TC
7	F	H	Make	Impeller / diffuser, heads, bases, bodies, couplings
8	F	H	Make	Stators, shafts, housings
9	F	H	Make	Cable
10	F	H	Make	Sensor, gauges, blue, magenta
11	F	H	Make	Orange

Table 3.1 gives the twelve categorizations and their attributes. The demand velocity is defined as either slow (S) or fast (F), the value is defined as low (L) or high (H) and finally whether the SKU is purchase (Purchase) or manufactured (Make).

3.2 – Model Calculation

The model only performed inventory calculations where there was sufficient data. For those SKUs that had consumption of greater than ten units per annum, the inventory calculations of an (s, S) system were used in accordance with the equations of Silver, Pike and Peterson (Silver, 1998).



$$ss = k\,\sigma$$

$$\sigma = \sqrt{(E(L)\sigma_D^2 + (E(D)^2)\sigma_L^2}$$

$$TRC = Order\ Cost + Holding\ Cost$$

$$TRC = A\left(\frac{D}{Q}\right) + vr\left(\frac{Q}{2} + k\sigma_L\right)$$

Low Consumption Table (Example)

12 month Consumption	6 month Consumption	Average Units Hold at SC 12 months
0 to 0	0 to 0	0
1 to 3	0.5 to 1.5	0
4 to 7	2 to 3.5	1
8 to 10	4 to 5	2

Figure 3.3 – Model Calculation Decision Rules

Figure 3.3 shows the decision tree for the model's inventory optimization. If consumption was greater than ten units per year, the (s, S) process was executed (Caplice, 2010).

However, if there was less than or equal to ten units of consumption per year, we concluded that a set of rules from a low consumption table needed to be created and consulted for an actionable plan. The details of each of these processes are outlined next.

3.2.1 – Model Calculation – SKUs with > 10 units of Annual Consumption

For SKUs with greater than ten units of consumption the following steps were followed:

1) Calculate weekly standard deviation in consumption.
    - From site visits and analysis it was established that daily standard deviation could not be relied on accurately in the data as there may have been up to two or three days lag before consumption data was entered in the system.
2) Use weekly standard deviations and then convert back to a daily value.
3) Calculate the safety stock from demand variability and supply variability using $Safety\ Stock = k\sqrt{\sigma_D^2 E(L) + \sigma_L^2 E(D)^2}$, where:

Table 3.2 – Safety Stock Variables

Variable	Description	Units
k	Safety factor, based on the probability of not stocking-out during a replenishment period (k is equal to the inverse normal of the desired service level)	NA
σ_D	Daily standard deviation of demand	Units
σ_L	Daily standard deviation of lead time	Days
E(L)	Lead time for order replenishment	Days
E(D)	Average daily demand	Units / day

4) Solve the economic order quantity using $EOQ = \sqrt{\frac{2AD}{vr}}$, where:

Table 3.3 – EOQ Variables

Variable	Description	Units
A	Order cost	$ / order
D	Average annual demand	Units / year
v	Purchase cost	$ / unit
r	Holding cost	$ / $ held / year

5) Find the reorder point, i.e. the min level using $s = x_L + k\sigma$, where:

Table 3.4 – Re-order Point Variables

Variable	Description	Units
s	Re-order point (min)	Units
x_L	Demand over lead time	Units
k	Safety factor, based on the probability of not stocking-out during a replenishment period	NA
σ	Standard deviation of errors of forecasts over a replenishment lead time	Units

6) Solve for the max level using $S = EOQ + s$, where:

Table 3.5 – Order up to Level Variables

Variable	Description	Units
S	Order up to level (max)	Units
EOQ	Economic Order Quantity	Units
s	Re-order point (min)	Units
Q	Order quantity	Units

7) Calculate the average inventory on hand by taking the average of the EOQ and adding the safety stock $Avg\ IOH = \frac{EOQ}{2} + Safety\ Stock$
8) Calculate the total relevant cost (TRC) using

$$TRC = Order\ Cost + Holding\ Cost$$

$$TRC = A\left(\frac{D}{Q}\right) + \ vr(\frac{Q}{2} + k\sigma_L)$$

3.2.2 – Model Calculation - SKUs with ≤ 10 Units of Annual Consumption

Three separate classes of SKUs were defined in the slow consumption group for both the RDC and the SC. We introduced a new sub-classification to better model inventory levels and cost for these SKUs. First, an Alpha class was defined for SKUs with lead times of over 100 days. Second, a Beta class for SKUs with lead times of less than 100 days and finally a Chi class for cables.

3.3 – Model Inputs

The model required a number of key inputs as shown in Table 3.6. Each of these inputs was presented in a separate tab in the model whereby ABC could alter these variables to conduct scenario analysis.

Table 3.6 – Model Input Overview

Input Name	Input Description
Customer Service Level (CSL)	Customer service level, based on the probability of not stocking-out during a replenishment period
Order Cost (A)	The cost of placing an order per SKU
Holding Cost (r)	The cost of capital + non-capital (warehousing, insurance etc)
Alpha Slow Moving	A set of rules for SKUs with consumption < 10 per annum and lead times > 100 days
Beta Slow Moving	A set of rules for SKUs with consumption < 10 per annum and lead times < 100 days
Chi Slow Moving	A set of rules for Cables with consumption < 10 reels per annum
Lead Time to RDC	The lead time into the distribution center
Lead Time to SC	The lead time from the distribution center to the SC
Reel Conversion	An average length of cable per reel

Table 3.7 – Cycle Service Level (CSL), Order Cost (A) and Holding Cost (r)

CSL	Order Costs - SC (A)	Order Costs - RDC (A)	Holding Cost (r)	Number of SKUs Using this Model
95%	$1.50	$16.00	20%	1,379

Table 3.7 shows the model inputs for CSL, order cost and holding cost. For all categories, 0 to 11, the cycle service was taken as 95%. Based on calculations of costs per lines and number of FTEs in the order process at the SC and the RDC, a cost per line of $1.50 in the SC and $16.00 in the RDC was used. The order cost per SKU was calculated by breaking the costs into the pick cost, for dispatch and put-away, and the cost for data entry. For the holding cost, a rate of 20% was used as per ABC's recommendation.

The model inputs for slow moving item tables were discussed with and agreed upon with the help of inventory planners from ABC.

Table 3.8 - Alpha Class (Long Lead Time)

Location	Consumption Break	Average Inventory to Hold	Number of SKUs Using this Model
SC	0 to 0	0	0
	1 to 3	0	164
	4 to 7	1	131
	8 to 10	2	67
RDC	0 to 0	0	0
	1 to 3	1	670
	4 to 7	1	432
	8 to 10	2	186

Table 3.9 - Beta Class (Short Lead Time)

Location	Consumption Break	Average Inventory to Hold	Number of SKUs Using this Model
SC	0 to 0	0	0
	1 to 3	0	982
	4 to 7	1	789
	8 to 10	2	416
RDC	0 to 0	0	0
	1 to 3	0	141
	4 to 7	1	162
	8 to 10	2	70

The difference between Alpha (Table 3.8) and Beta (Table 3.9) classes is in the consumption break category 1 to 3. One unit is held for the Alpha class in the RDC but not in the Beta class RDC.

Table 3.10 - Chi Class (Reels of Cable)

Location	Consumption Break	Average Inventory to Hold (Reels)	Number of SKUs Using this Model
SC	0 to 0	0	0
	0 to 1	1	41
	2 to 6	1	7
	7 to 10	2	3

From Table 3.10, the reels of cables are treated slightly differently in that for a lower level of consumption, the minimum number of reels at the SC is one.

Table 3.11 - Lead Time and Lead Time Variability into the RDC

Category	Lead Time (days)	Lead Time Variability (days)
0	14	3
1	14	3
2	84	14
3	112	14
4	14	3
5	112	14
6	112	14
7	112	14
8	112	14
9	NA	NA
10	112	14
11	112	14

Table 3.11 shows the lead times and the variability in lead time into the distribution center. These figures represent an expected future state – currently lead times are up to 22 weeks. Furthermore, category 9 has no values as no cables are held at the RDC.

Table 3.12 - Lead Time and Lead Time Variability into the SC

Category	Lead Time (days)	Lead Time Variability (days)
0	5.5	0
1	5.5	0
2	84	14
3	5.5	0
4	5.5	0
5	5.5	0
6	5.5	0
7	112	14
8	5.5	0
9	84	14
10	5.5	0
11	5.5	0

In Table 3.12, it was assumed that the rapid response distribution center would service the SCs in a predictable manner. This means that the lead time variability is 0 for categories serviced directly from the RDC. In order to calculate the average lead time from the RDC to the SC, it was assumed that a weekly truck would be sent out to the SC. If the SC ordered at the last minute, there would be a two day lead time. If the SC center missed the cut off period, then the SC center would have to wait up to nine days for the next truck to arrive. Therefore, for categories served directly from the SC, 5.5 days was taken as the lead time, the average between two and nine days.

3.4 – Assumptions

A number of key assumptions were made in the inventory model.

- Six months of consumption data was taken from the SC (May 2010 to October 2010) and was annualized in the model.
- The RDC was assumed to be a separate efficient entity from the current manufacturing facility, whose volumes were aggregated from SC consumption.
- A continuous review policy (s, S) model was used to model SKUs with a consumption of > 10 units per year.
- For SKUs, with consumptions of ≤10 units per year, average inventory holding was entered separately through slow moving tables. The min / max levels for these SKUs were then back calculated using principles of a (S-1, S) system.
- Lead times from RDC to SC was based on the average between the minimum lead time of 2 days and the maximum of 9 days, i.e. 5.5 days.
- Lead time variability from RDC to SC was assumed to be negligible.
- For SKUs with unknown unit costs, the average of the combination of category and type was used. This list of 263 SKUs was then checked with ABC for major deviations.

Chapter 4

Analysis and Results

The methodology outlined in Chapter 3 was used to run the model. Optimal inventory holding and min / max levels by SKU were calculated. Some results have been disguised to protect ABC's confidentiality. It should be noted that the assumptions behind the model assume that ABC is running optimally. It is believed that ABC is currently not running at this optimal level. For example, lead times into the RDC and SC can fall and a degree of variability in demand can be smoothed. Hence, ABC is not on any efficiency frontier where there is a tradeoff between service and inventory holding. ABC will reduce inventory as well as increase service levels as they move closer to the assumptions used in the model.

The analysis will focus on five sections:

- Key variables used in the model and their effect on inventory on hand
- Scenario models for the effect on inventory under different conditions
- Sensitivity of the 'fast movers' used in the statistical inventory model
- Sensitivity of the 'slow movers'
- Further analysis

4.1 – Key Variables

There are a number of key variables that were used in the model. The effect that they have on inventory on hand are summarized in Table 4.1.

Table 4.1 - Model Variables and the Effect on Inventory

Model Variable	Effect on Inventory	Insights
Customer Service Level	↑	• An increase in the customer service level increases safety stock and therefore increases inventory.
Order cost per line and holding cost	↓↑	• The order cost and the holding cost influences the economic order quantity (EOQ) in the proportions of $\sqrt{\frac{\text{Order Cost}}{\text{Holding Cost}}}$ • The EOQ strikes a balance between the holding costs and the order cost.
Lead time	↑	• An increase in the lead time into the RDC and out of the RDC increases inventory. • Inventory needs to be held to cover the lead time into the facility after the order has been placed.
Lead time variability	↑	• The lead time variability increases the safety stock required. • This uncertainty is buffered through greater levels of inventory.
Demand variability	↑	• Demand variability also increases the safety stock required.
Slow moving	↑	• The slow consumption values are critical in defining inventory holding of slow moving parts, defined as < 10 units of consumption per annum. • A slight increase in one of these values will have a large effect on the inventory on hand.
Vendor Managed Inventory (VMI) of Surface Equipment	↓	• Outsourcing Surface Equipment using VMI techniques will significantly reduce inventory held at the RDC.

From Table 4.1, it is clear that there are a number of levers that can be adjusted that have different effects on the inventory model.

4.2 – Scenarios

A set of scenarios were analyzed to see the effect of relaxing some assumptions in the model. A baseline and six scenarios were examined according to Table 4.2.

Table 4.2 – Scenario and Descriptions

Scenario #	Description
Baseline	The current level of inventory that exists in the network
1	A run of the model with the initial assumptions given in chapter 3
2	Remove surface equipment from RDC via Vendor Managed Inventory (VMI)
3	Remove all items in the RDC with usage < 3 units per year
4	Reduce lead time into the RDC by 20%
5	Reduce demand variability from RDC to SC by 20%
6	Scenario 1,2,3 combined

The first five scenarios in Table 4.2 assume only one change at a time. In scenario six however, multiple scenarios are combined. The results from this analysis are given in Figure 4.1.

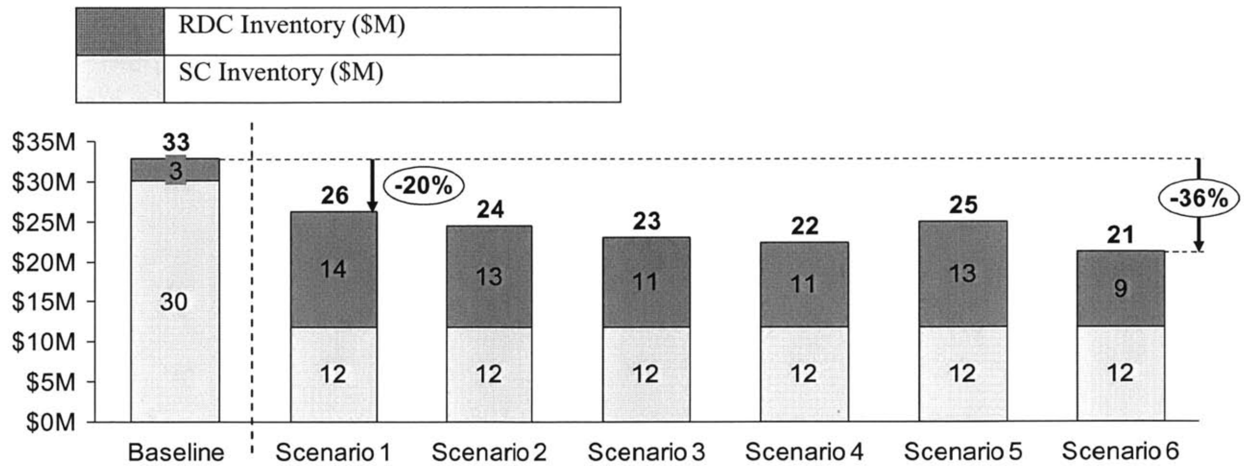


Figure 4.1 – Scenario Comparison and Inventory Value ($M)

It is clear from Figure 4.1 that the savings from using a rigorous inventory model range from 20% to 36% from the scenarios analyzed.

4.2.1 – Scenario 1 Comparison to the Baseline at the SC

Scenario 1, the initial model, was compared to the current state inventory levels at both the SC and the RDC. The SC were compared first.

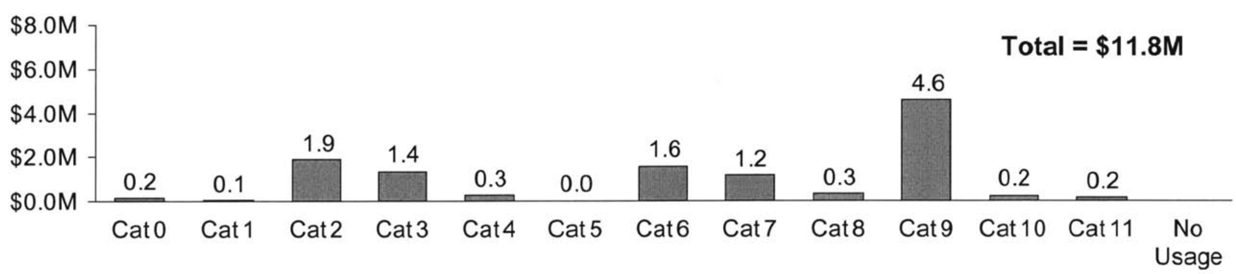


Figure 4.2 – Scenario 1 – All SC Inventory by SKU Category

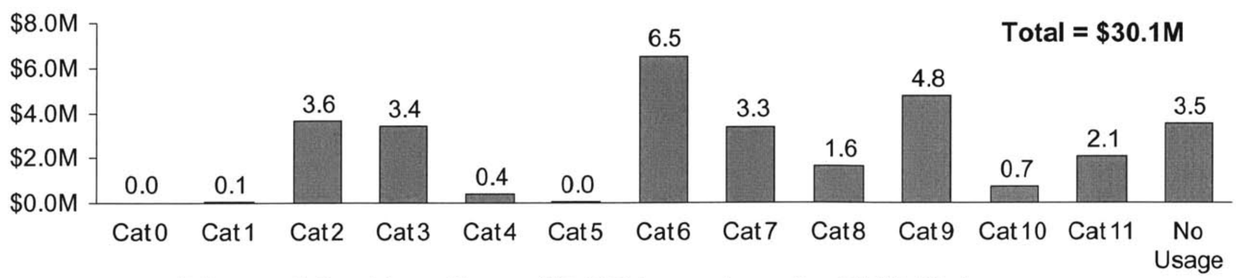


Figure 4.3 – Baseline – All SC Inventory by SKU Category

The above figures show that categories 2 (surface equipment), 3 (slow moving pumps) and 6 (fast moving motors) have a significant reduction in inventory. The baseline shows a category of 'no usage' as the data did not have any consumption of these SKUs during the time interval analyzed.

4.2.2 – Scenario 1 Comparison to the Baseline at the RDC

From Figures 4.4 and 4.5, there are significant increases in the modeled situation. The reasons for this two-fold. First, the current RDC prioritizes manufacturing responsibilities over efficient distribution. Second, due to the manufacturing process there is a significant amount of 'other' inventory from raw materials and work in progress (WIP).

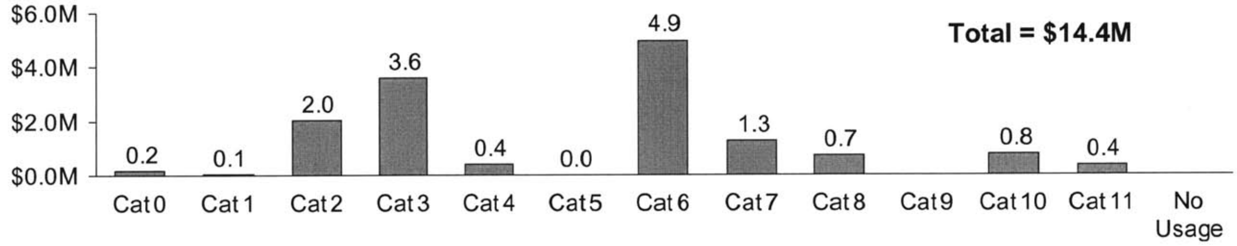


Figure 4.4 – Scenario 1 RDC Inventory by SKU Category

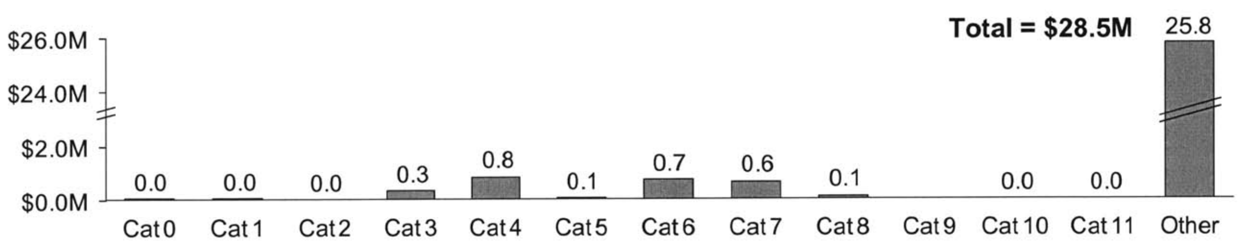


Figure 4.5 – Baseline RDC Inventory by SKU Category

4.3 – Sensitivity of the Fast Movers in the Statistical Inventory Model

Sensitivities were examined for the fast moving SKUs that utilized the continuous review statistical inventory model. An analysis on key metrics such as customer service level, lead time and demand variability were conducted.

4.3.1 – Customer Service Level Sensitivity on a SKU level

Before any global analysis was examined, we looked at the effect of customer service level (CSL) on the safety stock, min (reorder point) and the max (order up to level) for a single SKU #1234. To protect the ABC's confidentiality the real SKU number has been masked.

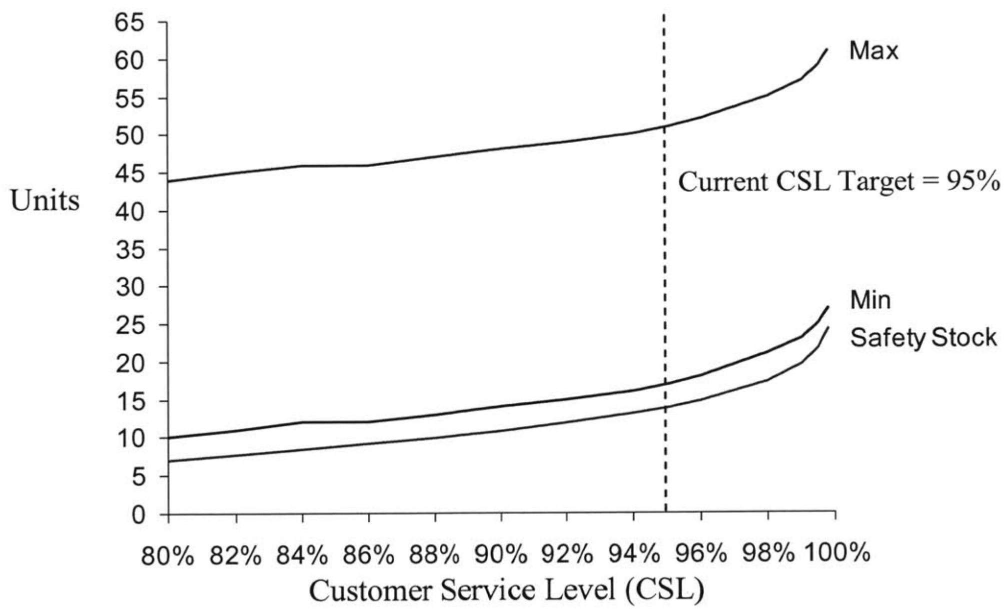


Figure 4.6 – Inventory Levels v CSL for a Single SKU #1234

Figure 4.6 shows the non-linear effect of a higher CSL from the continuous review policy as used in the inventory model. As one approaches the higher end of customer service, as given on the x-axis above, the amount of safety stock, the reorder point and the max level both rise sharply. This example highlights the tradeoff between service and inventory.

4.3.2 – Sensitivity of Inventory Based on Lead Time to the RDC v Demand Variability

For the first global analysis, a sensitivity of the value of inventory on hand was examined with changes in two variables. These variables were lead time to the RDC and demand variability from the RDC to the SC.

Change in Lead Time to the RDC (%)

Change in Demand Variability from RDC to SC (%)	0%	-5%	-10%	-15%	-20%	-25%	-30%
0%	0%	-1%	-1%	-14%	-15%	-16%	-16%
-5%	-1%	-2%	-2%	-15%	-16%	-17%	-17%
-10%	-2%	-3%	-4%	-16%	-17%	-18%	-18%
-15%	-4%	-4%	-5%	-18%	-18%	-19%	-19%
-20%	-5%	-5%	-6%	-19%	-19%	-20%	-20%
-25%	-6%	-7%	-7%	-20%	-20%	-21%	-22%
-30%	-7%	-8%	-8%	-21%	-22%	-22%	-22%

Figure 4.7 – Inventory Sensitivity for Lead Time to the RDC v Reduction in Demand Variability

In Figure 4.7, the shaded cell '0%' within the data region is the current state of inventory on hand where there are no changes to the assumptions of lead time or demand variability. As one goes across Figure 4.7, the change in lead time to the RDC decreases from 0% to -30%. Similarly, as one goes down Figure 4.7, the change in demand variability decreases from 0% to -30%. One can see from this figure that the change in lead time to the RDC has a greater effect than the demand variability between the RDC and SC. Hence, a 20% reduction in lead time alone causes a 15% reduction in inventory, while a 20% reduction in demand variability has a lower value at 5% inventory reduction.

There is a step function in the reduction in lead time to the RDC from the 10% mark to the 15% mark. This is because Alpha value SKUs (with a lead time of greater than 100 days) are forced into the Beta range (lead time of less than 100 days), which have less stringent inventory assumptions.

4.3.3 – Sensitivity of Inventory Based on Customer Service Level v Demand Variability

For the second global analysis, a sensitivity of the value of inventory on hand was examined with changes in two variables. These variables were customer service level (CSL) and the demand variability from the RDC to the SC.

Change in Demand Variability from RDC to SC (%) \ CSL (%)	80%	85%	90%	95%	98%	99%
0%	-21%	-16%	-9%	0%	10%	17%
-5%	-21%	-16%	-10%	-1%	8%	15%
-10%	-21%	-17%	-11%	-2%	6%	13%
-15%	-22%	-18%	-12%	-4%	5%	12%
-20%	-23%	-19%	-13%	-5%	3%	9%
-25%	-24%	-20%	-14%	-6%	2%	8%
-30%	-24%	-20%	-15%	-7%	1%	6%

Figure 4.8 – Inventory Sensitivity for CSL v Reduction in Demand Variability

In Figure 4.8, the shaded '0%' cell within the data region is the current state of inventory on hand where there are no changes to the assumptions of customer service level or demand variability. One can see that customer service level has a greater impact on inventory than a reduction in demand variability. For example, reducing CSL alone from 95% to 80%, inventory drops by 21%. However, if demand variability is reduced by 30% while keeping CSL at 95%, inventory reduces by 7%. The effect of increasing CSL and reducing demand variability offset themselves. If CSL is increased to 98%, a reduction in demand variability of 30% would bring inventory marginally above the original levels with a 1% increase.

4.3.4 – Sensitivity of Inventory Based on Customer Service Level v Lead Time to the RDC

For the third global analysis, a sensitivity of the value of inventory on hand was examined with changes in two variables. These variables were customer service level (CSL) and lead time to the RDC.

CSL (%)

Reduction in Lead Time to the RDC (%)	80%	85%	90%	95%	98%	99%
0%	-21%	-16%	-9%	0%	10%	17%
-5%	-21%	-16%	-10%	-1%	9%	16%
-10%	-21%	-16%	-10%	-1%	8%	15%
-15%	-34%	-29%	-23%	-14%	-5%	2%
-20%	-34%	-30%	-24%	-15%	-6%	1%
-25%	-34%	-30%	-24%	-16%	-7%	0%
-30%	-35%	-31%	-25%	-16%	-8%	-1%

Figure 4.9 – Inventory Sensitivity for CSL v Lead Time to the RDC

Once again in Figure 4.9, the shaded '0%' cell within the data region is the current state of inventory on hand where there are no changes to the assumptions of customer service level or lead time to the RDC. One can see that customer service level has a greater impact on inventory than a reduction in lead time to the RDC, but a slightly higher effect than demand variability reduction as previously shown in Figure 4.8. For example, reducing CSL alone from 95% to 80%, inventory drops by 21%. However, if lead time to the RDC is reduced by 30% and CSL is kept at 95%, inventory reduces by 16%. The effect of increasing CSL and reducing lead time offset themselves. If CSL is increased to 99%, a reduction in lead time of 25% would bring inventory back to original levels.

4.4 – Sensitivity of the Slow Moving SKUs

A key part of this research was to enable the model to deal with slow moving SKUs. We will discuss this concept further in the next section.

4.4.1 – Slow Moving SKUs – Alpha

Table 4.3 shows the effect on inventory holding from the addition of one unit of inventory to each of the consumptions breaks in the alpha category (>100 days lead time). Categories 1 to 3 in the RDC have the greatest marginal effect on inventory holding at $3.21M for one additional unit of inventory held.

Table 4.3 – Marginal Increase in Units of Inventory Held

Location	12 month Consumption	Scenario 1 (units)	Scenario 1 plus one additional unit (units)	Marginal Increase in Inventory ($M)
SC	1 to 3	0	1	$0.20
SC	4 to 7	1	2	$0.06
SC	8 to 10	2	3	$0.01
RDC	1 to 3	1	2	$3.21
RDC	4 to 7	1	2	$1.61
RDC	8 to 10	2	3	$0.26

One can see the importance of these parameters from Table 4.4 and Figure 4.10 for SKUs with a lead time of more than 100 days. In each sensitivity in Table 4.4, the figures that have been changed from the initial assumptions are shaded. Scenario 1 represents the initial case where the standard assumptions of chapter 3 are used. Sensitivity A relaxes some of these assumptions in the lower breaks of 1 to 3 and 4 to 7, yielding an inventory reduction of 19%. All following scenarios increase the amount of slow moving inventory held. In Sensitivity E, this leads to a 45% increase in the inventory over Scenario 1.

Table 4.4 – Alternative Stocking Scenarios – Alpha and Inventory on Hand ($M)

Location	12 month Consumption	Scenario 1	Sensitivity A	Sensitivity B	Sensitivity C	Sensitivity D	Sensitivity E
SC	0 to 0	0	0	0	0	0	0
SC	1 to 3	0	0	1	1	2	2
SC	4 to 7	1	0	2	2	2	5
SC	8 to 10	2	2	2	4	4	8
RDC	0 to 0	0	0	0	0	0	0
RDC	1 to 3	1	0	1	1	2	2
RDC	4 to 7	1	0	2	2	2	5
RDC	8 to 10	2	2	2	4	4	8
Total Inventory ($M)		**$26.21**	**$21.33**	**$28.08**	**$28.62**	**$32.04**	**$38.13**

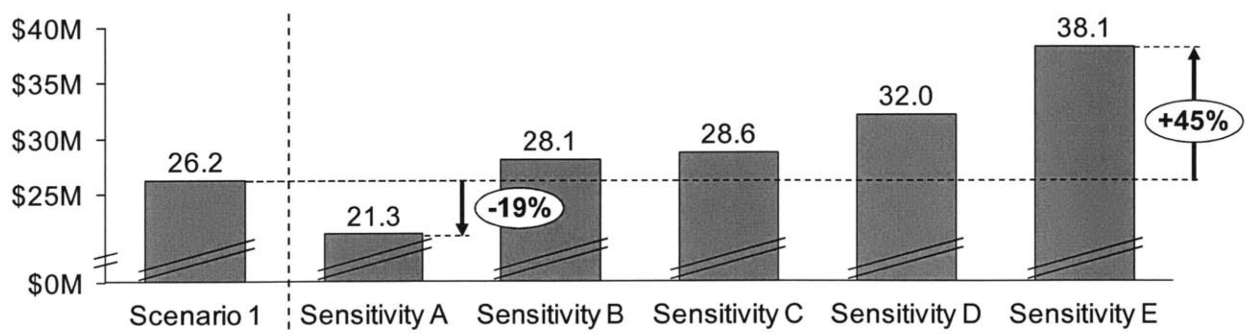


Figure 4.10 – Alternative Stocking Scenarios – Alpha and Inventory on Hand

4.4.2 – Slow Moving SKUs – Beta

Table 4.5 shows the effect on inventory holding from the addition of one unit of inventory to each of the consumptions breaks in the beta category (<100 days lead time.) Categories 1 to 3 category in the SC have the greatest marginal effect on inventory holding at $4.57M for one additional unit of inventory held.

Table 4.5 – Marginal Increase in Units of Inventory Held

Location	12 month Consumption	Scenario 1 (units)	Scenario 1 plus one additional unit (units)	Marginal Value Increase in Inventory ($M)
SC	1 to 3	0	1	$4.57
SC	4 to 7	1	2	$2.37
SC	8 to 10	2	3	$0.64
RDC	1 to 3	0	1	$0.88
RDC	4 to 7	1	2	$0.59
RDC	8 to 10	2	3	$0.31

From Table 4.6 and Figure 4.11, one can see the importance of these parameters for SKUs with a lead time of less than 100 days. Again, in each sensitivity in Table 4.6, the figures that have been changed from the initial assumptions are shaded. Scenario 1 represents the initial case where the standard assumptions of chapter 3 are used. Sensitivity A relaxes some of these assumptions in the lower breaks of 1 to 3 and 4 to 7, yielding an inventory reduction of 11%. All following sensitivities increase the amount of slow moving inventory held. In Sensitivity E, this leads to a 110% increase in the inventory over Scenario 1.

Table 4.6 – Alternative Stocking Scenarios – Beta and Inventory on Hand ($M)

Location	12 month Consumption	Scenario 1	Sensitivity A	Sensitivity B	Sensitivity C	Sensitivity D	Sensitivity E
SC	0 to 0	0	0	0	0	0	0
SC	1 to 3	0	0	1	1	2	2
SC	4 to 7	1	0	2	2	2	5
SC	8 to 10	2	2	2	4	4	8
RDC	0 to 0	0	0	0	0	0	0
RDC	1 to 3	0	0	1	1	2	2
RDC	4 to 7	1	0	2	2	2	5
RDC	8 to 10	2	2	2	4	4	8
Total Inventory ($M)		**$26.21**	**$23.25**	**$30.78**	**$34.61**	**$42.13**	**$55.14**

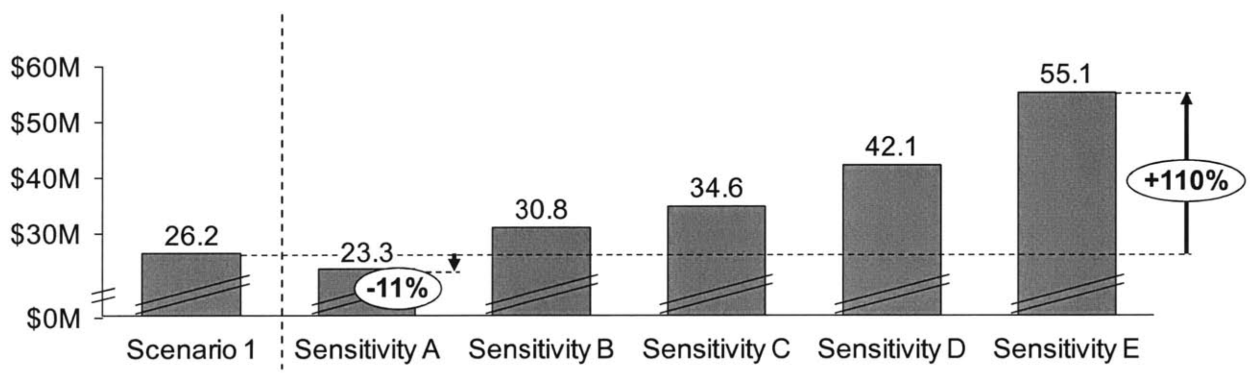


Figure 4.11 – Alternative Stocking Scenarios – Beta and Inventory on Hand

4.4.3 – Slow Moving SKUs – Chi

Table 4.7 shows the effect on inventory holding from the addition of one unit of inventory to each of the consumptions breaks in the chi category (reels of cable). One can see that the 0 to 1 category in the SC has the greatest marginal effect on inventory holding at $2.0M for one additional unit of inventory held.

Table 4.7 – Marginal Increase in Units of Inventory Held

Location	12 month Consumption	Scenario 1 (units)	Scenario 1 plus one additional unit (units)	Marginal Value Increase in Inventory ($M)
SC	0 to 1	1	2	$2.00
SC	2 to 6	1	2	$1.22
SC	7 to 10	2	3	$0.09

In the Chi slow moving category, one can see from Table 4.8 and Figure 4.12 the sensitivity in altering the level of inventory for reels cables. Scenario 1 is once again the initial scenario from chapter 3. In Sensitivity A, the assumption of carrying inventory in the 0 to 1 reels was relaxed, leading to an 8% reduction in inventory. This reduction was due to the large number of incomplete reels of cable that were used during the year. Sensitivity B and C add further restrictions on inventory, with Sensitivity C resulting in a 16% increase in inventory over Scenario 1.

Table 4.8 – Alternate Stocking Scenarios – Chi and Inventory on Hand ($M)

12 month Consumption	Scenario 1	Sensitivity A	Sensitivity B	Sensitivity C
0 to 0	0	0	0	0
0 to 1	1	0	1	1
2 to 6	1	1	2	4
7 to 10	2	2	2	8
Inventory ($M)	**$26.21**	**$24.21**	**$27.43**	**$30.41**

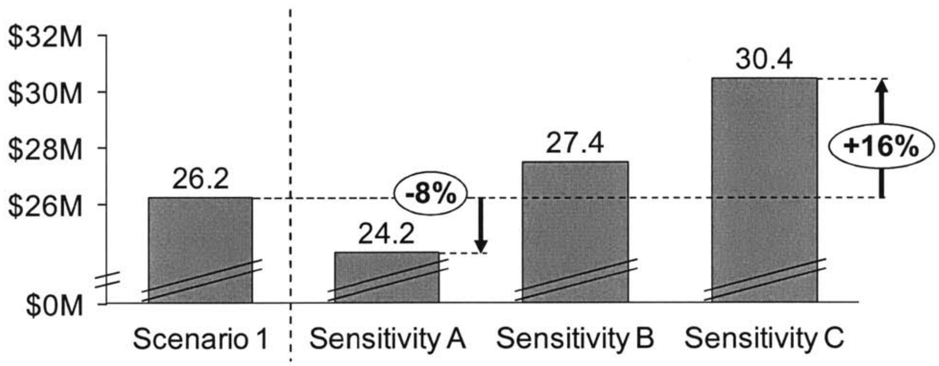


Figure 4.12 – Alternative Stocking Scenarios – Chi and Inventory on Hand

4.5 – Further Analysis

An area of analysis which would drive further benefits is repair kits. A repair kit is defined as a group of SKUs that are used to fix a common issue with a pump system. An initial investigation was done in this thesis. However, the total value of the kits given from ABC was too low to pursue further.

An analysis of common failure modes and common parts that are associated with those failures would detail what should be used in a repair kit. These repair kits could be assembled at the RDC and sent out to the SC. The benefits from kitting firstly include greater picking efficiencies at the RDC. It is far more effective for a store-man to make up several kits at once than wait for the orders of individual components and send them out to SC each time a repair is needed. Second, kitting enables lower lead times to the SC centers which creates greater customer service. Kitting is an area of opportunity that has the potential to add further efficiencies and savings into ABC's supply chain.

Chapter 5 - Recommendations

5.1 – Set Up an Efficient RDC

In section 2.6, we discussed the benefits of multi-echelon systems. As our model and results suggest, we believe ABC has much to gain with the addition of an efficient RDC. More specifically, the RDC will serve as a demand and inventory pool for the SC while also serving as a buffer for slow moving items (see section 4.4).

5.2 – Employ Statistical Inventory Models

Our analysis suggests that ABC has not adopted or implemented universal inventory policies within its supply chain. Although we have suggested the application of a (s, S) model in our analysis, it is integral for ABC to find and implement the best inventory models for its business environment.

5.3 – Segment the SKU Base

ABC's large SKU base and fungible parts (components, spare parts, and finished goods) make for a unique environment. In order for the statistical inventory models to reach maximum effectiveness, ABC needs to segment its SKU base. As used in our methodology in Chapter 3, our first level of segmentation separated the SKU base into those that had greater than 10 units of consumption per year and those with 10 or less consumption per year. Our secondary level of segmentation looked at the SKUs with 10 or less consumption per year and factored in lead times. Furthermore, there may be unique items that need to be classified and handled differently (such as our Chi class) due to unique product characteristics.

While we have begun with these initial levels of segmentation, ABC should continue to refine its product strategy and corporate priorities to account for factors (including but not limited to) physical size, the criticality of product availability, lead time, consumption, and cost.

5.4 – Maintain Strong Data Integrity

The effectiveness of any model or inventory strategy will only be as good as its data. It's absolutely imperative that ABC ensure that their demand, replenishment, and inventory data streams are sufficient to power their inventory models and strategies. Furthermore, ABC should set an annual or semi-annual review period in which they review SKU segmentation assignments.

5.5 – Explore External Supplier Replenishment Options

ABC should consider exploring vendor managed inventory (VMI) for surface equipment and cables product groups. In a vendor managed scenario, ABC determines the inventory min / max values for specific SKUs and the manufacturer monitors and replenishes inventory levels. The benefits of this system include a stronger relationship between ABC and the vendor. Furthermore, the VMI relationship provides better visibility into ABC's usage of the SKUs which allows the vendor to more efficiently plan production.

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