Analysis of Postponement Strategies in Supply Chain

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Abstract

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Inventory is an important part of supply chain management as it directly impacts both cost and service. As demand is more or less uncertain and it takes time to manufacture and deliver the goods, some amount of inventory is required somewhere in the chain to provide the required service to the end customer. Increasing supply chain inventories increases customer service and consequently revenue, but it comes at a higher cost. The aim of supply chain inventory management is to optimize the inventories and to shift the current customer service curve outward through improved inventory strategies and redesigning the supply chain. This thesis is aimed at studying the effectiveness of various factors in the supply chain environment with and without postponement strategies. Analysis of these factors enables a better understanding of the supply chains and will help to design these systems more effectively. Simulation models are developed using Arena and are used to capture the system dynamics with probability distribution which provides valuable insight into which variables are the most important and how variables interact. It also helps to capture the uncertainty and stochastic nature of the model. Two-level Fractional Factorial Experimental designs are used to study and analyze the performance of service level and inventory levels and to determine which variables are the most influential.

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Chapter One

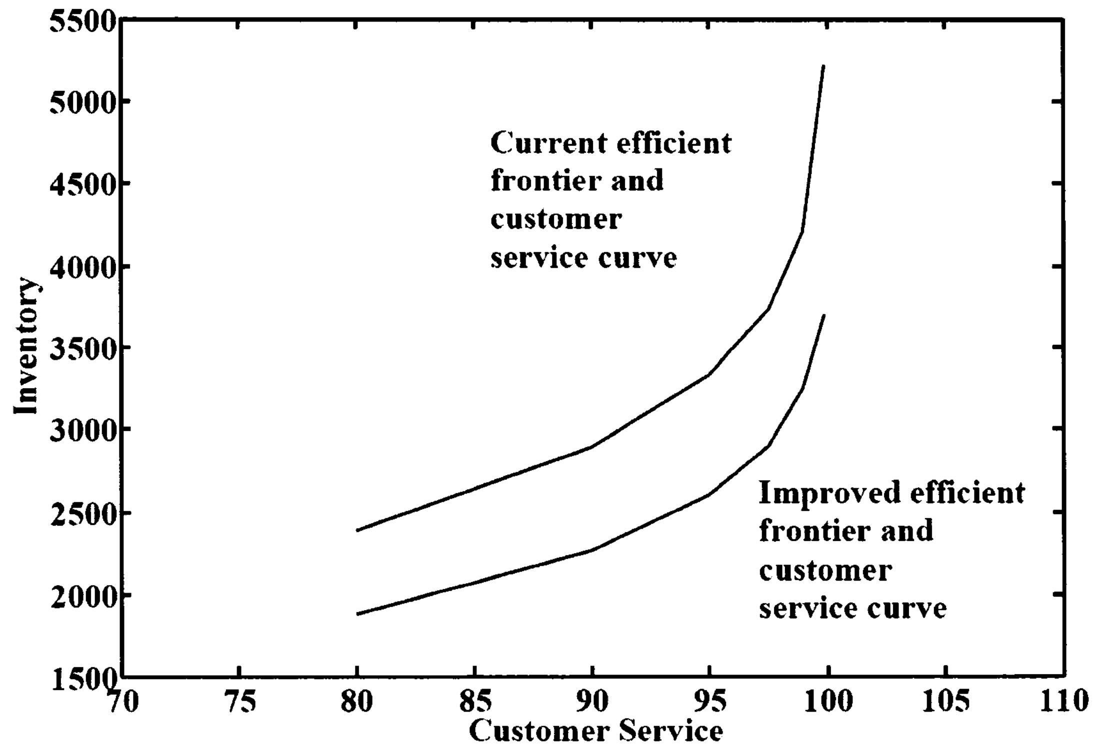
Introduction to Postponement

1.1 Introduction

Over the past 10 years, there has been a growing consciousness in industry towards the importance of effective Supply Chain Management (SCM). A recent study found that when a company announces a supply chain malfunction, its stock price immediately tumbles 7.5% and losses average 18.5% over a one-year period (Singhal and Hendricks, 2002). The term supply chain has become a standard part of the business vocabulary. There are as many definitions for the term as articles or books on the topic. The general idea, however, is integration. Excellent performance can be achieved by taking an integrated view of all the activities required to convert raw materials into finished goods. The result of poor integration is inventory. Inventories are required to buffer the uncertainties and inefficiencies. Therefore, inventory has become a crucial part of supply chain management.

There is a huge prospect for business, if the inventories are managed properly throughout the supply chain. In 2001 the total value of inventories in the United States was close to $1.5 trillion (Neale et al., 2003). This was due to the fact that aggregate inventory-to-sales ratios have tumbled significantly since the early 1990s. There has been an increased focus on supply chain management, supported by new information technologies, for the decline in relative inventory levels. Even with this decline, the prospects are huge. The success of companies like Dell and Wal-Mart in the management of supply chain inventories is well known. There are also recent inventories blunders of companies like Nike and Cisco.

Figure 1.1: The Efficient Frontier and Inventory Improvement Goal



Inventory is an important part of supply chain management as it directly impacts both cost and service. As demand is more or less uncertain and it takes time to manufacture and deliver the goods, some amount of inventory is required somewhere in the chain to provide the required service to the end customer. Increasing supply chain inventories increases customer service and consequently revenue, but it comes at a higher cost. The aim of supply chain inventory management is both to move the supply chain onto the efficient frontier (Figure 1.1) by optimizing the inventories and to shift the current customer service curve outward through improved inventory strategies and redesigning the supply chain. For a given customer service level, the efficient frontier gets the minimum amount of inventory required to achieve that level of service.

1.2 The Importance of Inventory

The efficient frontier demonstrates the tradeoff between inventory and service. There are certain factors associated with inventory.

- **Cost**

The Inventory costs are hard to calculate. Unlike other costs that are direct expenses, inventory-driven costs are mostly indirect. Because they are hard to isolate and calculate, inventory–driven costs are often ignored when making important supply chain decisions. This must be avoided because inventory costs are very real and can be very significant. Inventory driven costs in the supply chain include the following; traditional carrying costs, opportunity cost, devaluation, obsolescence, rework, price protection, and returns. The inventory costs resulting from devaluation, obsolescence, and rework have taken on greater significance in the last few years as the rate of technology change has increased and product lifecycles have fallen. Devaluation occurs when product held in inventory loses value over time. Inventory in the personal computer (PC) industry loses 1% to as much as 4% of its value each week (Taylor 2001). In the programmable logic industry, obsolescence costs are on the order of 5-10% of the gross inventory value (Brown et al., 2002). A manufacturer of computer printer components found that obsolescence and rework combined to increase its inventory driven cost rate from 24% to 40% (Lee and Billington, 1992).

- **Service**

Inventories throughout the supply chain influence the availability of products, how quickly they are supplied, and at what cost. Service is almost always related to the ability to satisfy a customer demand within a certain time. The location and amount of inventories determines a supply chain's ability to provide short customer response times and reliably meet a high percentage of what is often very uncertain demand. The consequences of poor service include lost sales and, in some cases, financial penalties imposed by supply chain partners. If the product is not available when a customer wants it, the supply chain may loose that sale. Proctor & Gamble estimates that it loses the sale of its product 29% of the time when a retailer is out-of-stock. The particular retailer loses that sale 41% of time (Albright, 2002). A lost sale of a Hewlett-Packard inkjet printer results in lost profit margin on the printer, lost profit margin on future supplies for that printer (such as ink cartridges and paper), and a hit to HP's efforts to build brand loyalty that could impact future product sales. For a typical inkjet printer (which costs HP about $ 150 to build), the lost margins on the supplies over the life of the printer (about $40) actually exceed the lost margin on the printer (about $35) (Johnson and Anderson, 2000). Imation, a leading provider of removable storage products including diskettes and recordable CDs, found its retail partners such as Best Buy and Staples starting to charge penalties for late delivers. In many cases these penalties far exceeded Imation's margin on the entire delivery. By improving their inventory strategy across the supply chain, Imation was able to increase service by 25-30 points and eliminate millions of dollars in penalties (Optiant Inc., 2002).

1.3 Postponement in Supply Chain

The Manufacturing world is facing the challenge of delivering what the customers want, when they want, while meeting the financial need to keep inventory levels down. Whether it is Dell's strategy of build-to-order or meeting the inflexible standards of 99.99% service levels from retailers like Wal-Mart, postponement has gained importance as an inventory management strategy. Postponement also known as delayed differentiation is an "adaptive supply chain strategy that enables companies to dramatically reduce inventory while improving customer service" (Muzumdar et al., 2003). The concept is to delay the point of commitment of work-in-process inventory into a final product and, thereby, gain control of efficient asset utilization in a dynamic and uncertain environment.

Nowadays, consumers are demanding higher levels of customization, yet are not willing to pay extra or wait longer. Product proliferation is a common challenge for firms providing customized products. Component commonality, postponement can be used to cope with this challenge. In this thesis, we study the effectiveness of these strategies. Component commonality is one of the most popular supply chain strategies to tackle the challenges such as difficulties in estimating demand, controlling inventory, and providing high service levels for customers. It promotes using a common component to substitute a number of unique components in various products so that safety stocks can be reduced due to risk pooling.

To understand when and where postponement can augment the overall business performance, it is necessary to focus on the cost versus service level equation. Once it was impossible for manufactures to achieve excellence in both categories. But postponement provides a base to achieve the difficult quest: holding the right inventory, at the right place, in the right form. To reduce the possibility of lost sales, traditionally companies have kept high inventory levels or invested in demand forecasting. But companies are recognizing that it is inefficient to increase finished goods inventory, especially in market where consumers are demanding higher levels of customization and where product life is short.

- **Product Variety and Mass Customization**

There is a development in industry towards increased product variety and shorter lead times and therefore companies are trying hard for mass customization (Pine 1993; Swaminathan 2001). Companies are trying to shift from mass production to mass customization. Firms are put under pressure to meet the customer demand for increased product variety and shorter lead times. This results in customization-responsiveness squeeze (McCutcheon et al., 1994). Such an environment can have a negative effect on the company's performance. The increased demand for variety leads to more forecast errors. Lee and Billington (1994) report forecast errors of 400% for high technology products, which can lead to an increase in the inventory level. In electronics and computers, technology advancement has reduced the product life cycles. This results in holding obsolete finished goods inventory. For example, in printer and PC business, the annual holding cost of inventory may approach 50% of the product cost (Johnson and Anderson, 2000).

Mass customization can be achieved by postponing the configuration of generic components into a wide variety of end products. In postponement a product is processed till it remains generic and the customization is delayed until demand is realized. A generic product offers more flexibility when demand is uncertain since it can be transformed into any final product. Instead of keeping high finished goods inventory or suffer stock outs which can result in lost sales or interrupt plant production schedules, the customization of the product can be delayed until customer orders arrive. Postponement concept of delaying the point of product differentiation has been found to be an effective strategy in product variety. Postponement delays product differentiation at a point closer to the customer. This involves designing and developing generic products that can be customized once the actual demand is known. It also involves the implementation of precise inventory approach to position inventory farther away from the customer while satisfying the service levels and reducing the inventory costs. Postponement lessens the forecasting horizon and thereby solves the uncertainty of end product demand (Whang and Lee, 1998). Also better inventory performance can be achieved by redesigning a product or its supply chain. In this thesis we study the inventory-service level tradeoff and the impact of various factors on service level, which are discussed in more detail in Chapter 3. A recent study by Oracle Corporation, Cap Gemini Ernst and Young

(Muzumdar et al., 2003) found that over 75% of respondents executing postponement got significant benefits and 91% of respondents observed significant improvements in customer satisfaction and inventory costs.

The cost for increased demand for product variety and shorter lead times can be intimidating, but companies cannot neglect the customer demand. In 1980s most machine tool companies in U.S. lost market share to a Japanese competitor due to lack to offer variety in a cost effective way. As companies expand globally, the increase in product variety is unavoidable and this can result in product differentiation in terms of government regulations and local language requirements. For example, Hewlett-Packard was faced with the complexities of differentiating the product by local languages for end product packaging and instruction manuals (Venkatesh and Swaminathan, 2003).

1.4 Examples of Postponement

A recent study by Oracle Corporation, Cap Gemini Ernst and Young (Muzumdar et al., 2003) also found the majority of companies that have implemented postponement strategies are realizing significant improvements in customer satisfaction, inventory costs and more accurate demand forecasting. The success of Hewlett-Packard and Benetton using postponement is well known. Lee and Billington (1993) describe postponement efforts in the distribution of Hewlett-Packard DeskJet printers. The printer industry being highly competitive, the customers of HP's computer peripherals (dealers) wanted to carry as little inventory as possible; yet wanted high level of availability to end-users. The distribution process was re-engineered to implement postponement. This effectively moved the point of differentiation to the regions. This was achieved by making changes to the product design. As a result of these changes, there were additional investments due to product redesign and enhancement to distribution center capabilities. However, this additional investment was balanced by the resulting inventory savings due to postponement.

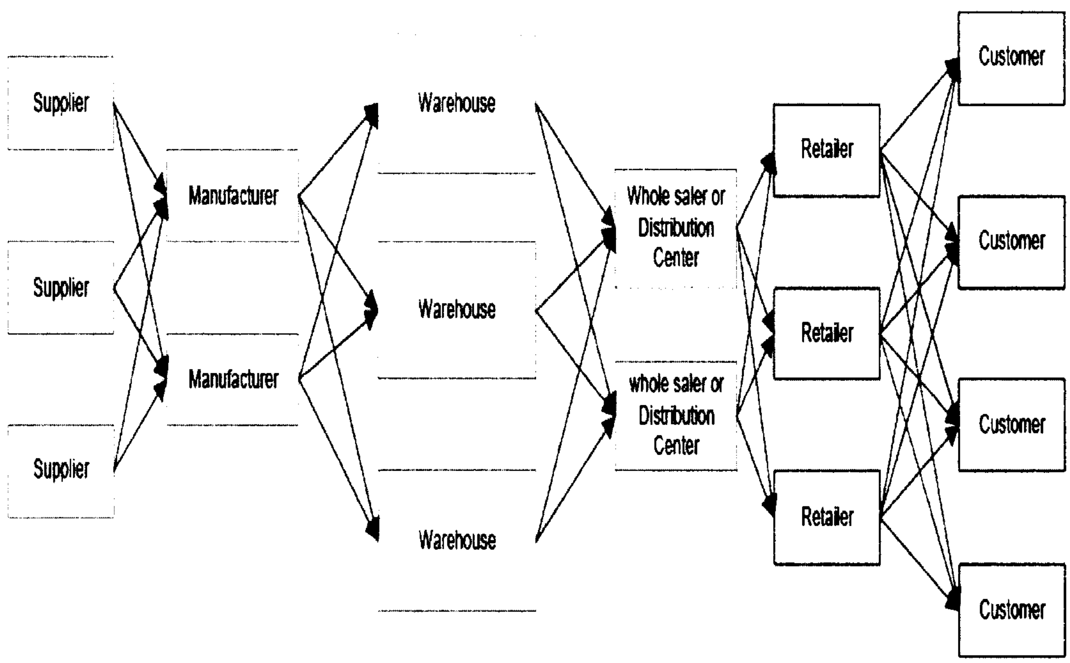
Benetton operated in a highly competitive industry characterized by a fussy customer base demanding an increasing variety of products. In a very short product life cycle, Benetton faced with the mismatch of inventory and customer demand. The desired colors were out of stock and there was excess inventory of unpopular colors. Benetton was able to re-sequence the steps in its sweater manufacturing operation after it decoupled the overall operational process into several modular sub processes. Benetton changed the order of the dyeing and knitting sub processes. Benetton dyed the uncolored sweaters either when it received an order or has a better idea of customers color taste for that particular season. The company effectively postponed the point of product differentiation and substantially reduced obsolete inventory (Feitzinger and Lee, 1997). Toyota is assuring to build a car to customer specifications and deliver it within five days of receiving the order (Simison, 1999). Dell delivers a customized PC within a few days of customer order. Consumer electronics and PCs are customized for different retail channels such as activating a range of features, deactivating built in functionality such as fax. This allows Wal-Mart to sell a different product than Best Buy or Office Depot (Johnson and Anderson, 2000). Cannondale, a premium mountain bike producer offers 22 models. Where as National, a Japanese manufacturer gives its customer a chance to choose from a palette of 104 different colors. Another competitor VooDoo offers 672 models (Ulrich et al., 1998).

In June 1998, Lucent Technologies had the opportunity to win a major contract to supply a y2k complaint network to Saudi Arabia. To win the contract, Lucent would have to be able to deliver the product within three weeks of receiving the details of each sites requirement. Using the existing process, it took 23-25 weeks to deliver after receiving the details. Lucent Technologies utilized postponement (product and process design) in order to take advantage of a significant opportunity. Lucent made changes in the product design so that most modules were generic, and could be sourced from multiple locations. Instead of waiting for months, parts and installers reached the customer within 7-10 days (Davila and Wouters, 2003). The semiconductor firm Xilinx also utilizes product and process postponement. The products are designed to be programmable (product postponement), which allows customers to fully configure the function of the integrated circuit using software. Also they hold some products in generic form (process postponement), which allows them to hold less inventory in finished goods form. Xilinx performs customization steps quickly enough to allow it to build to order (Brown et al., 2000).

1.5 Simulation

In early 1990's the phrase "Supply Chain management" came into operation (Chang and Makatsoris, 2001). It is a process of integrating all the members in the chain, so that goods are produced and delivered at the right place, in right quantities and at the right time, while satisfying the customer and minimizing costs. Figure 1.2 shows a typical supply chain. It begins with suppliers. They provide materials to the manufacturer, which are processed and kept in warehouses. The goods are then send to the distribution centers who ship the goods to retailers. The products are then purchased by the customers. Some industries have different structure of the supply chain network.

Figure 1.2: A Typical Supply Chain (Source: Chang and Makatsoris, 2001)



In today's world managing the supply chain has become a key factor for any successful business. Sometimes the impact of a company's plan on the supply chain is unpredictable before execution. Simulation allows the assessment of the functionalities prior to the implementation of the plan. Therefore, the development of the simulation model for supply chain has become a necessity. Also if such systems were simple enough, it would be possible to use mathematical methods to obtain exact information. There are some real-world systems that are too complex to be solved by analytical methods, and such models must be studied by means of simulation (Law and Kelton, 2000).

Simulation methods and applications imitate real systems via computer. Simulation can be applied in many fields and industries and it is a very popular and powerful method. In simulation there is flexibility to model things as they are. It also allows uncertainty and non-stationarity in modeling. There were many hurdles for the acceptance and usefulness of simulation. Previously, writing computer programs to execute large-scale systems was a difficult task. But nowadays, many software packages have been developed that have features to program a simulation model. Another obstruction was the cost of computer time needed to simulate and collect the necessary amount of simulation output. This difficulty is becoming less severe as most of the analysts are using high speed PCs, which are relatively cheap and simulations can be run overnight to produce large amounts of output data. Given these, simulation is chosen as the main modeling tool in this thesis.

1.6 Research Background

This research concentrates on component commonality and postponement, which is used to analyze the inventory-service level tradeoff. It generalizes earlier results obtained by Graman and Magazine (1998 & 2002). Graman and Magazine (1998 & 2002) studied the benefits of postponement using a single-period inventory model and consider a manufacturing system that produces a single item which is customized into multiple products. For this model, they derived analytical expressions for service measure and also inventory calculations and through a numerical study show the benefits related to inventory reduction by using postponement.

1.7 Contribution of this thesis

- In this thesis, the generic product model developed by Graman et al. (1998 & 2002) is extended to include lead time and weeks of inventory. The original analytical model developed by Graman and Magazine is further analyzed for various parameters using simulation experiments. We study the effectiveness of strategies like component commonality and delayed product differentiation. We also study how customer service level as well as inventory level is affected by various parameters.
- Simulation models are developed and are used to capture the system dynamics with probability distribution which provides valuable insight into which variables are the most important and into how variables interact. It also helps to capture the uncertainty and stochastic nature of the model.
- A complete supply chain model with inclusion of factors such as demand variability, demand correlation, lead time, weeks of inventory and number of products are used to conduct a thorough investigation of the interactions of postponement along with other system parameters. To make the simulation more realistic, negative demands are not allowed in the simulation (truncated to zero). In most cases the negative demands are considered to be zero which makes the

case unrealistic. This is done by using left truncated normal distribution (Johnson and Thomopoulos, 2002).

- Two-level Fractional Factorial Experimental designs are used to study and analyze the performance of service level, inventory levels and to determine which variables are most influential. Additionally we determine how the variables interact among themselves in the supply chain environment with and without postponement strategies.

1.8 Organization of the Thesis

Following the introduction to postponement in chapter 1, in chapter 2 the literature for the recent and earlier work in this is reviewed. Chapter 3 presents the problem definition and modeling of the single-period inventory model. The impact of the single-item, multiple product environments on the inventory-service level tradeoff is examined by varying various parameters. A simulation based study is used to examine the effect. Chapter 4 presents example problems tested on the model and analysis of the results using experimental design. In Chapter 5 conclusion is presented with directions for future research work that can be done in this area.

Chapter Two

Literature Review

Delayed product differentiation is among the most useful strategies to manage the risk associated with product variety and uncertain sales. The product collection offered by a company often consists of families of closely related products which vary from each other in terms of some degree of differentiation features only. For example in the apparel industry, a given style is usually offered in many distinct sizes and colors. In the grocery industry products are typically sold in several package sizes, with a proliferation of differentiating features. Automobile manufactures offer a virtually endless variety of model configurations, while a computer or printer model is distributed with different types of accessories (e.g. power supply modules, manuals written in different languages). Delayed differentiation or postponement attempts to reduce the risks associated with product variety, by taking advantage of the commonality between items and by designing the production and distribution processes so as to delay the point of product differentiation.

The purpose of this literature review is to link the existing related body of knowledge with the characteristics of postponement. We review the literature in component commonality, postponement and delayed differentiation. The rest of this chapter is organized as follows. In section 2.1, we introduce the evolution of postponement and in section 2.2 different postponement strategies are discussed. Section 2.3 deals with packaging postponement which is one of the five types of postponement described by Zinn (1990) and Zinn and Bowersox (1998). In section 2.4 and 2.5, we discuss the techniques for managing product variety such as component commonality and multi-echelon inventory. Section 2.6 deals with delayed product differentiation and we discuss how different authors have utilized delayed product differentiation to study the effectiveness of postponement. In section 2.7 we discuss the issues of supply chain management and the requirements for supply chain simulation modeling.

2.1 Evolution of Postponement

The concept of postponing product differentiation beyond manufacturing has been discussed for over 50 years (Alderson, 1950; Bucklin, 1965). Alderson (1950) appears to be the first who coined the term postponement in marketing literature. Alderson held that "the most general method which can be applied in promoting the efficiency of a marketing system is the postponement of differentiation,...., postpone changes in form and identify to the latest possible point in the marketing flow; postpone change in the inventory location to the latest possible point in time". According to him this approach could reduce the amount of uncertainty related to marketing operations. Bucklin (1965) provide arguments as to how postponement would be difficult in manufacturing environment mainly operating on a make-to-stock basis. He argued that some unit in the chain would have to bear the risks associated with product variety, and postponement only helped in shifting this risk to some other partner in the chain. However, as companies started to shift from the traditional make-to-stock to make-to-order policy, postponement has become an attractive alternative.

However, it was only about fifteen years ago that logistics researchers began to define and study the concept (Zinn et al., 1988). In the past ten years, the demands of managing global product offerings have pushed managers in many industries to consider postponement as a supply chain strategy for mass customization (Feitzinger and Lee, 1997). This has transformed into more interest in studying the benefits of postponement.

2.2 Postponement Strategies

Zinn et al. (1988) describe different types of postponement that could be executed in the supply chain and this includes labeling, packaging, assembly, manufacturing (from postponement) and time postponement. Four different strategies of form postponement which when merged with time postponement make up the five postponement strategies. The different types refer to the different points in the supply chain where postponement customizes semi-finished product into an end product after understanding the customer demand. Labeling postponement refers to a situation where a standard product is stocked and labeled differently depending on the demand. In packaging postponement products are not packaged until final orders are received. Manufacturing and assembly postponement is a situation where additional manufacturing or assembly may be done before shipping the product based on the realized demand. Finally, in time postponement products are not shipped to the retail warehouses but are kept at a central warehouse and are delivered directly to the customers.

Zinn et al. (1988) developed a methodology to assist manager's estimate when postponement is necessary. Normative cost models were developed for five different types of postponement strategies. Each model is simulated across a range of eight product and demand characteristics and then tested with computer simulation. Their results show that there is a cost advantage in postponing the distribution of a substantial number of products. They also provide insights on how the principle of postponement can be applied to improve the productivity of physical distribution system.

Extending the ideas of Zinn et al. (1988), Pagh and Cooper (1998) developed a simple and conceptual model to explain the scope of postponement strategies that could be implemented by companies. Four generic strategies were identified: full speculation, logistics postponement, manufacturing postponement and full postponement. These were presented in the form of a matrix (P/S) as shown in table 2.1.

The full speculation strategy represents complete confidence on forecasting, where the manufacturing operations are performed prior to the product being shipped to the market. Manufacturing postponement represents form based postponement while logistics postponement represents time postponement. The strategy of full postponement represents the highest level of delay in the supply chain. The decision about which strategy to use is essentially a trade off between different levels of customer service and inventory, production and distribution costs.

Table 2.1: The P/S Matrix (source: Pagh et al. 1998)

		Logistics	
		Speculation	**Postponement**
Manufacturing	**Speculation**	The full speculation strategy - low production and distribution costs - high customer service and high inventory costs	The logistics postponement strategy - low production - low/med. Inventory costs and customer service - high distribution costs
	Postponement	The Manufacturing postponement strategy - low distribution costs - mid./high customer service, production costs and inventory costs	The full postponement strategy - low inventory costs and customer service - mid./high production costs - high distribution costs

To some extent, many global companies are currently practicing postponement. The important question is when the strategy is appropriate and when it is not? When should a company position itself on the P/S matrix? There are many variables which can determine the most appropriate level of postponement. These variables are classified into three groups by Pagh and Cooper (1998): market, process and product factors. Market factors are related to customer demand and service level requirements. These parameters include demand fluctuations or variance, correlation in demand across the different products, lead time and service level requirements. Process factors are those manufacturing and distribution processes which include the sequence of operations performed to customize the product, the network of the supply chain, whether the product is made to order or stock as well as how much and at which location inventories (components, subassemblies and finished goods) are stored in supply chain. Product factors include the product design and are related to the degree of standardization that is present in the components and the costs related to standardizing as well as the modularity in the product design.

The ability of a firm to implement a successful postponement strategy depends on how well it can modify the process and product characteristics to the market requirements. The changes related to process design are termed as process postponement, while those related to product design are termed as product postponement.

2.3 Packaging Postponement

Packaging postponement is one of the five types of postponement described by Zinn (1990) and Zinn et al. (1998). Their definition of packaging postponement is based on the assumption that a specific product is marketed in different package sizes. In the status quo option, products are packaged to forecast at the plant and shipped to the warehouse in expectation of sales. When postponement is practiced the item is bulk shipped to the warehouse and packaged when customer orders are received. The number of package sizes is the only variable in their analysis. They found that packaging and time postponement are the most promising types of postponement with respect to distribution cost savings. While product value is the most important variable that justifies form postponement. Howard (1994) describes a distribution system with packaging postponement for computer printer. Printers were bulk packaged, shipped to the final destination country, and finally packaged with language-specific manuals and country-specific accessories. The product was redesigned to support localization. Howard (1994) found that having only generic printers in stock instead of large quantities of each individual version decreased the overall inventory levels significantly. There was a substantial logistical cost savings by allowing the distribution centers to perform both differentiation and packaging.

2.4 Component Commonality

Traditional research on component commonality has been mainly focused on reduction in component inventory due to commonality. Commonality refers to using the same component (or item) in several different products. A number of authors have examined the benefits that results from component commonality. Collier (1981) defines an index to measure the degree of component commonality. He found that higher degree of component commonality is associated with the reduction in manufacturing costs. Baker et al. (1986) investigated the benefits in terms of reduced inventory or increased service due to component commonality. They represent a two product, two-level, single period inventory model to study the effect of commonality. They observed that the number of units in stock is minimized with respect to service level. The demands follow a normally distributed scenario. Due to commonality the total number of units in inventory is reduced and the inventory level of common component is lower than the total inventory of the two components. This is due to the fact that the standard deviation of a sum is less than the sum of the standard deviations when demand being aggregated is independent. This has been termed as risk pooling.

Gerchak et al. (1988) extend Baker et al's (1986) work and under a general demand distribution show that the total material purchase cost is minimized. Eynan and Rosenblatt (1996) extends Baker et al's (1986) work by permitting the price of the common component to surpass the price of the common component that it substitutes and study situations in which commonality is effectively justified. They consider a single-period model that minimizes total component cost subject to an aggregate service level. They consider one basic and a standardized model and show that minimizing the number of components is not necessary optimal. Hiller (1999) considers a multiple-period case, and concludes that benefits of commonality are lessened in the multiple-period case. Results show that the strategy of no commonality and pure commonality is dominated by the strategy of using commonality.

2.5 Multi-Echelon Inventory

Modeling postponement concept is similar to the modeling of a multi-echelon inventory system. In a multi-echelon system lower echelon are descendants of an upper echelon site. This is analogous to a postponement process in which multiple products share a common item. Eppen and Schrage (1981) and Federgruen and Zipkin, (1984 a, 1984 b) provide test heuristic procedures for ordering and allocating inventories within a distributor-retailer system. However, they restrict themselves to a system in which the warehouse holds no inventory. Jackson (1988) continues this work by including policies in which warehouse allocates only a portion of its given initial inventory to n identical retailers. The use of a central distribution center to hold stock and assign it to local distribution centers reduced backorders compared to a system with no central stock. Jonsson and Silver (1986) considered a two-echelon inventory system with one central warehouse and n identical regional warehouses. They found that holding a portion of inventory at a central warehouse and distributing it with the retailers reduces the total backorders. Rogers and Tsubakitani (1991) developed a single-period, single-component, multi-level inventory problem with one supplier of a common component part and n finished-goods items with backorder optimization. Their objective was to minimize the sum of penalties associated with expected backorders at the goods level by selecting the optimal inventory levels for the common component and finished goods subject to a budget constraint for total system holding costs. Graman and Magazine (2002) modeled analytically the relationship of inventory investment to demand variability and target service level. In their model inventory can be stored in an intermediate form. On realization of demand all the finished goods are used first, and then the semi-finished product is used to satisfy the demand. Through a numerical study they show that very little postponement capacity can actually provide all the benefits related to inventory reduction. Each of the multi-echelon models described are cost based models, whereas the approach used by Graman and Magazine (2002) focuses on the inventory service-level tradeoff.

2.6 Delayed Product Differentiation

Processes and products are being redesigned to delay the point of product differentiation by extending the stages of the production process in which a common component/

process is used. This allows performing the required customization at a point closer to the customer. Many authors have focused on the selection of the point at which differentiation should occur. Lee (1996) points out that in order to perform a complete analysis regarding the benefits of postponement due to component standardization, the model should take into consideration the following features:

- Inventory savings from part
- Material costs for common parts
- Additional costs for postponement
- Inventory gains from finished products

Lee (1996) represents simple inventory models to support product and process design for product proliferation environment. He showed that by properly exploiting the opportunities either in the design of the product or in the process, significant benefits can be obtained in terms of inventory and service.

Lee and Tang (1997) developed a model for evaluating the costs and benefits gained by delaying product differentiation. They analyzed some special theoretical cases that enable to characterize the optimal point of product differentiation. In their model, buffer stocks are kept after every stage. The model also includes processing cost, inventory assets, lead time and deals with a situation in which differentiation is achieved by using postponement. Postponement is beneficial if the total of the relevant costs for the proposed last common operation is lower than the cost of the current last common operation. Garg and Tang (1997) developed an analytical inventory model for a product with more than one point of product differentiation. In each model they examined the benefits of delayed differentiation at each point and derived the necessary conditions when one type of delayed differentiation is more beneficial than the other. Their analysis indicates that variability of demand, correlation and the relative magnitude of lead time plays an important role in determining which point of differentiation should be delayed.

Swaminathan and Tayur (1998) modeled the use of semi-finished inventory of computer models (vanilla boxes) as a way of delaying differentiation of product during assembly. Their model found the optimal inventory levels and allocation of vanilla boxes to different products before receiving the customer orders. Their results show that the vanilla process, under reasonable capacity constraints, outperforms the assemble-to-order process, but may not do any better than the make-to-stock, when the demands are stable and have small correlation. But when demands have high negative correlation, the vanilla process performs at least as well as both the assemble-to-order and make-to-stock processes. Garg and Lee (1998) analyzed a divisional supply chain and proposed strategies for increasing inventory turns. Analytical models were developed to assess the cost drivers and various strategic options. They found that postponement was an important factor in several options and showed that postponement may not always be the most cost-effective solution. They identified various factors that influence the level of postponement such as lead times, length of review period, demand variability and level of component commonality.

Whang and Lee (1998) shows how the respective values of postponement from resolution of uncertainty of demands and forecast accuracy can be calculated in a simple build-to-stock model. They found that when the value of forecast improvement is large, the reduction in safety stock increases. During this time the resolution of uncertainty was also small. But as the resolution of uncertainty dominates the value of forecast improvements the reduction in safety stock decreases. They also found that due to postponement, there is a reduction in safety stock at a decreasing rate. Van Mieghem (2004) analyzed a model with two products where each product is assembled from two components. He assumed that both common and product specific components are stocked and drives conditions under which commonality should be adopted. He stated this condition in terms of a maximal commonality threshold cost that depends on the demand forecast only through its correlated demand and financial data. He found that for high commonality cost, neither commonality nor postponement is optimal. A pure commonality strategy where each product is assembled using a common component, however is never optimal unless complexity costs are introduced. Van Mieghem (2004) shows that while the value of the commonality strategy decreases in demand correlation between products, commonality is optimal even when the product demands are perfectly correlated.

Su et al., (2005) concentrated on component commonality, postponement, and/or delayed differentiation. They study the effectiveness of these strategies. First, they evaluate the inventory costs for various percentages of component commonality substitution. Second, they analyze the performance of two postponement strategies and their relationship with product proliferation. They also calculated the cost and benefits of implementing delayed differentiation in a make-to-order environment and provide insights for choosing the point of differentiation.

2.7 Simulation in Supply Chains

In early 1990's MRP-II was extended to cover areas like engineering, finance, human resources, project management etc., hence the term ERP was coined. An ERP system has great deal of planning capability and includes software for manufacturing, order entry; accounts receivables, purchasing etc., but the various materials, capacity and demand constraints are all considered separately in isolation of each other (Chang and Makatsoris, 2001). In mid 90's large number of software packages have emerged that are called supply chain management (SCM) systems or advanced planning and scheduling (APS). The SCM systems take into account most of the factors and constraints that limit the ability to timely deliver the goods. The leading SCM systems consider all the relevant constraints and they perform real-time simulations of adjustments in the constraints. Adding these kinds of capabilities is harder in ERP systems as they are mainly concerned with transaction processing. SCM system can give answers in minutes or seconds, while getting answers from ERP systems may take hours. Many leading ERP suppliers such as Oracle, Sap have been developing advanced planning modules and other components of SCM to resolve the shortcomings of ERP systems. SCM systems provide various advantages such as throughput improvements, cycle time reduction, and inventory cost reductions. Although the ERP and SCM solutions provide lots of benefits, they are too costly to use them for academic research.

The evaluation of operating performance prior to the implementation can be done through discrete event simulations. The simulation models enable companies to perform powerful what-if analyses giving better planning decisions. Comparison of various operational alternatives can be done without interrupting the real system so that policy decisions can be made. Chang and Makatsoris (2001) has discussed the issues of supply chain management and the requirements for supply chain simulation modeling. According to Chang and Makatsoris (2001), a good understanding of overall supply chain and business characteristics is most important. According to them it is essential to set proper performance measures and it is better to focus on the problem area depending on the specific scenario.

For several decades analytical modeling has been used as a tool within supply chain management. But analytical models are not powerful enough to understand complex real-world systems. To understand organizational decision-making, simulation has gained considerable attention and momentum (Swaminathan et al., 1996). Swaminathan et al. (1996) mention the use of modeling and simulation in supply chain with different purposes. The effect of various supply chain strategies on demand amplification can be studied. Modeling and simulation can be used to test the impact of various strategic level decisions on the performance of supply chain. This may for example be the impact of reducing the number of plants or relocating warehouses. Simulation does not give the optimal solution, but allows the user to test different solutions. Simulations can be run with different parameters and the results can be analyzed and compared with heuristic search methods such as simulated annealing, genetic algorithm, etc to arrive at the optimal solution.

Kelton and Barton (2003) have introduced some of the ideas, issues, challenges and solutions to decide how to experiment with simulation modes. According to them careful designing of simulation experiments is necessary. It not only saves time and efforts, but provides efficient ways to estimate the effects of changes in the models input on the output. They discuss the traditional experimental-design methods in the context of simulation experiment.

Chapter Three

Modeling

This chapter will explain, in detail, the basic structure of the system under study. The system is modeled and then analyzed through simulation experiments. Two models are developed, one for the non-postponement scenario and one for the postponement scenario. The models are used to identify the advantages from postponement by comparing the two scenarios. The effect of the single-item, multiple–product situation on the inventory-service level tradeoff is examined. A manufacturing system is considered that produces a single item and then the item is packaged into multiple products. The following assumptions are made:

- Each product contains different discrete quantities of the common item
- Products differ from one another only in the quantity of the common item
- The demand for the item is independent of the variety of the product sizes available

A single period, uncapacitated inventory model operating under a periodic review, order-up-to-level (R, S) inventory policy is examined.

3.1 Service Measure

Service level is the typical measure used to quantify a company's market conformance. Definition of service level varies from company to company. It is usually related to the ability to satisfy a customer. There is a direct relationship between the ability to achieve a certain level, and cost and performance of a supply chain. For example, variability of demand and lead times determine the amount of inventory that needs to be held in the supply chain. Estimating the back order penalty (stockout cost) that results from a lost sale is often difficult, companies set safety stock levels for products by setting a service level. Stockout cost includes components such as loss of goodwill and delays to other parts of the supply chain. A common substitute for a stockout cost is a service level (Nahmias 1997). Although there are a number of different ways to measure service level, it generally refers to either the probability of not stocking out or the proportion of demand satisfied directly from shelf. The term fill rate is often used to describe the proportion of demand satisfied directly from shelf. The symbol P_2 is used to represent fill rate. To satisfy a service level objective of P_2, it is necessary to obtain an expression for the fraction of demand that stocks out during the period. This is discussed in more detail in next section.

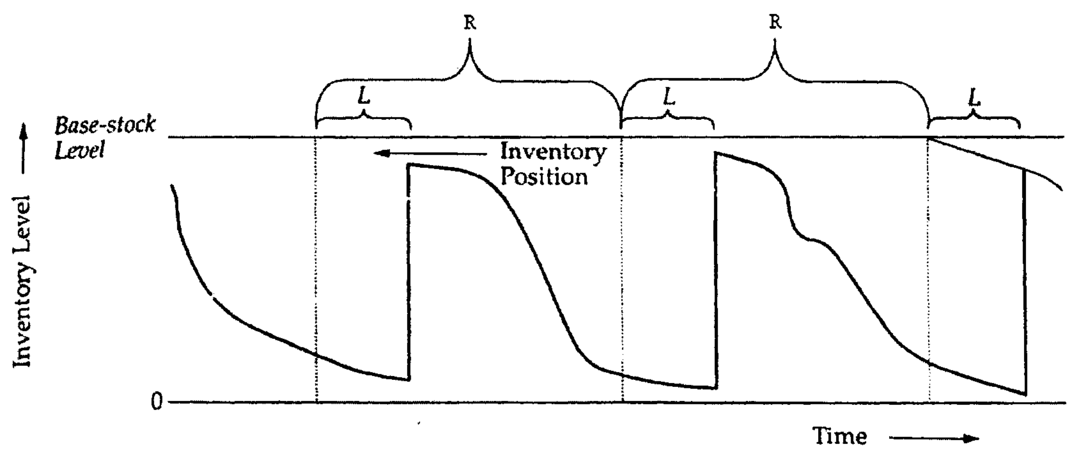
3.2 Model

Assumptions

1. The demand is probabilistic and follows a normal distribution
2. There is a negligible chance of no demand between reviews; consequently, a replenishment order is placed at every review
3. The value of R (review period) is assumed to be predetermined

A single period, uncapacitated inventory model operating under a periodic review, order-up-to-level (R, S) inventory policy is examined. In a (R, S) control system a replenishment order is placed every R units of time. The inventory policy is shown in figure 3.0.

Figure 3.0: Inventory level in a Periodic Review Policy
(Source: Simchi-Levi et al., 2003)



Model Parameters

D = demand (random) during one year period

$E(D)$ = mean demand during one year period

$$G_u(k) = \int_k^{\infty} (u_0 - k) \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-u_0^{\,2}}{2} \right) du_0$$

is a special function of the unit normal (mean 0, std dev 1) variable. $G_u(k)$ is used in finding the expected shortages/stockouts per replenishment cycle (ESPRC)

k = safety factor

L = replenishment lead time, in years

H = inventory holding cost, in \$ / unit / year

K = ordering cost in \$

J = cost of reviewing inventory level

SS = safety stock, in units

R = review interval, in years

S = order-up-to-level / base-stock level, in units

$\bar{x}_{L+R}$ = expected demand over a review interval plus a replenishment lead time, in units

σ_{L+R} = standard deviation over a review interval plus a replenishment lead time, in units

Because of assumption two, we have

$$\text{Number of replenishment orders placed per year} = \frac{1}{R} \qquad \text{....... (3.1)}$$

The relevant equations for safety stock, expected shortage per replenishment cycle (ESPRC) and service level are presented

Safety Stock

Safety stock is held in case demand exceeds expectation; it is held to counter uncertainty. As the demand is uncertain and may exceed expectation, safety stock is needed to satisfy an unexpectedly high demand.

Suppose that the demand (x) has a probability density function $f_x(x_0)$ such that

$f_x(x_0)dx_0$ = Prob {total demand lies between x_0 and $x_0 + dx_0$}

Then,

Safety Stock, SS = E (net stock just before replenishment arrives)

$$= \int_0^{\infty}(S - x_0)f_x(x_0)dx_0 \qquad \text{...... (3.2)}$$

That is,

$$SS = S - \bar{x}_{L+R} \qquad \text{...... (3.3)}$$

Equation 3.3 states that the average inventory level just before replenishment arrives is equal to the inventory level when the replenishment is placed reduced by the average demand during the lead time and review period.

Expected shortage per replenishment cycle,

$$\text{ESPRC} \;=\; \int_{S}^{\infty}(x_0 - S)f_x(x_0)dx_0 \qquad \text{...... (3.4)}$$

When the demand is probabilistic the inventories can be categorized into different levels. We are using Net stock as our stock level, which is defined as:

Net stock (NS) = On hand (OH) – Backorders (BO)

That is,

$NS = OH - BO$

Therefore,

$$E(NS) = E(OH) - E(BO) \qquad \text{...... (3.5)}$$

We assume that the average backorders are small relative to the average On-hand stock, we have

$$E(OH) \;\approx\; E(NS) \qquad \text{...... (3.6)}$$

Using equations 3.5 and 3.6,

E (OH just before a replenishment arrives) $\approx$ safety stock = $SS = S - \bar{x}_{L+R}$

E (OH just after a replenishment arrives) $\approx$ S - $\bar{x}_{L+R} + E(D)R$

The expected value of *E (OH)* over a cycle may be approximated by *0.5* (expected value of *OH* just before a replenishment arrives) + *0.5* (expected value of *OH* just after a replenishment arrives).

Thus,

$$E(OH) \approx S - \bar{x}_{L+R} + \frac{E(D)R}{2} \qquad \textbf{...... (3.7)}$$

The safety stock can be expressed as,

$$SS = k\sigma_{R+L} \qquad \textbf{...... (3.8)}$$

This is the amount of inventory required to protect against deviations from average demand during a period of *R+L* years. To this point the results hold for any probability distribution of *R+L* time demand. We assume a normal distribution and the safety stock is expressed as in Equation 3.8, then Equation 3.4 simplifies to

$$ESPRC = \sigma_{R+L} G_u(k) \qquad \textbf{...... (3.9)}$$

The normal loss function, $G_u(k)$, is defined by the fact that $\sigma_{R+L} G_u(k)$ is the expected number of shortages that will occur during a replenishment cycle.

P_2 Service Measure

Here, *E (D)* is the average annual demand. Let P_2 be the percentage of all the demand that is met on time.

$$\frac{Expected\ Shortages}{Cycle} = ESPRC \qquad \textbf{...... (3.10)}$$

$$\frac{Expected\ Shortages}{Year} = ESPRC\frac{1}{R}$$

$\frac{1}{R}$ = number of replenishment orders placed each year, and

Fraction of demand satisfied directly from shelf = 1- Fraction backordered

Therefore,

$$1 - P_2 = \frac{Expected\ Shortages\ per\ year}{Expected\ demand\ per\ year}$$

$$= \frac{ESPRC}{R} * \frac{1}{E(D)} \qquad \textbf{...... (3.11)}$$

Equation 3.11 can be used to determine the base stock that yields a desired service level. We assume the lead time demand to be normally distributed, with mean $\bar{x}_{R+L}$ and standard deviation σ_{L+R}.

To use Equation 3.11, we need to determine *ESPRC* and the determination of *ESPRC* requires knowledge of normal loss function $G_u(k)$. Where,

$$k = \frac{S - \bar{x}_{R+L}}{\sigma_{R+L}}$$

Therefore,

$$ESPRC = \sigma_{R+L} G_u\left(\frac{S - \bar{x}_{R+L}}{\sigma_{R+L}}\right) \qquad \textbf{...... (3.12)}$$

Substituting Equation 3.11 into 3.12, we get

$$G_u\left(\frac{S - \bar{x}_{R+L}}{\sigma_{R+L}}\right) = \frac{E(D)R(1-P_2)}{\sigma_{R+L}} \qquad \textbf{...... (3.13)}$$

Thus S can be determined from Equation 3.13. More details about the inventory policy can be obtained from Silver et al. (1998). Models of similar inventory systems to the ones developed above are discussed in Silver et al. (1998) and Winston (2004).

3.2.1 Non-Postponement Scenario

Here we describe the non-postponement case. We make the following assumptions:

- There are multiple products and each product contains a common item in various quantities
- The multiple products are managed as separate finished goods inventories

The demand during the single period for product y, $y = 1,2,....,m$, is a random variable, X_y, with a realization of demand denoted by x_y, having probability density function (p.d.f.) $f_y(x_y)$ and cumulative density function (c.d.f.) $F_y(x_y)$, with expectation

$$E(X_y) = \mu_y \quad \forall y \qquad \textbf{...... (3.14)}$$

and variance

$$\text{var}(X_y) = \sigma_y^2 \quad \forall y \qquad \textbf{...... (3.15)}$$

Let,

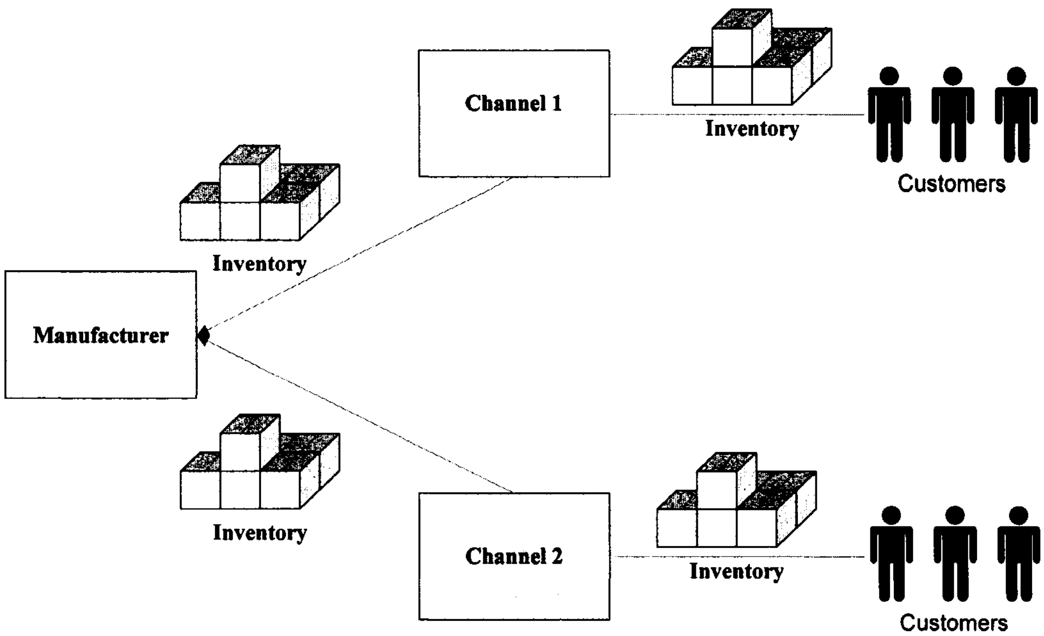
S_y = non postponement inventory level for product y

To compare the non-postponed and postponement inventory levels, we need to express both inventories in terms of the common item. The inventory level for the non-postponed case is the sum of product inventory levels expressed in terms of the common item,

$$I_N = \sum_y n_y S_y \qquad \textbf{...... (3.16)}$$

Where n_y is the quantity of the common item contained in product y

Figure 3.1: Traditional Supply Chain (Non-Postponement Case)



3.2.2 Postponement Scenario

In the postponement case, items are not packaged for shipment until a customer order for the product is received. Packaging postponement is more than just packaging the product and is discussed in more detail in chapter 2. Packaging postponement is used to improve the customer service levels. We simulate the postponement scenario and the results are further analyzed in chapter 4. The model assumes that postponement causes no shortages due to increased delivery lead-time caused by postponement.

Let,

J = Demand in terms of items as a random variable

Demand J is a linear combination

$$J = n'X = n_1X_1 + n_2X_2 + ... + n_mX_m$$

of m-product having probability density function $f(j)$, with mean

$$\mu = E[n'X] = \sum_{y=1}^{m} n_y \mu_y \qquad \text{...... (3.17)}$$

and variance

$$\sigma^2 = Var[n'X] = \sum_{y=1}^{m} n_y^2 \sigma_y^2 + 2\sum_{i=1}^{m-1} \sum_{y=i+1}^{m} n_i n_y \rho_{iy} \sigma_i \sigma_y \qquad \text{...... (3.18)}$$

Where,

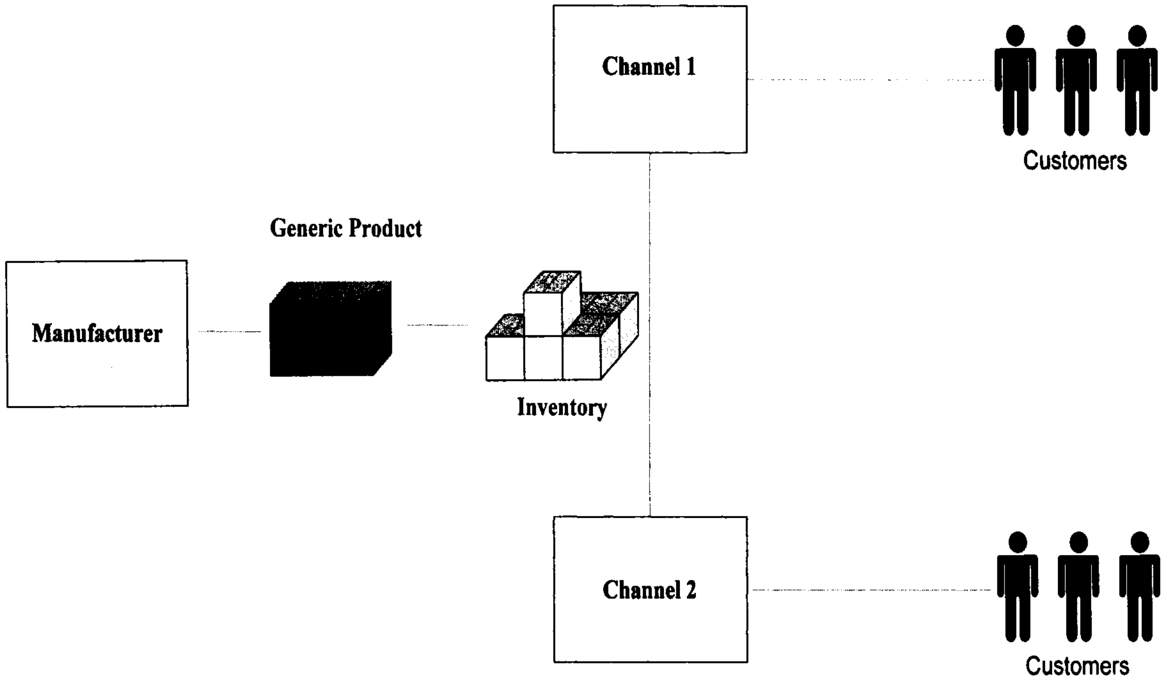
n = the column vector of quantities of item per product,

X = the product-demand random vector and

ρ_{iy} = the correlation of X_i with X_y.

Using the mean and variance, the postponement inventory I_P can be determined using equation 3.13. In postponement case the inventory is reduced because the standard deviation of demand in postponement is less than the sum of the standard deviations of demand for non-postponement. Due to the aggregation of demand across multiple products, one major benefit of postponement is the pooling of risk associated with the different customized end products. Risk pooling is an important concept in supply chain management. In risk pooling the demand variability is reduced by aggregating demands across different locations. This is due to the fact that as we aggregate demand across different locations, it becomes more likely that high demand from one customer will be offset by low demand from another. This reduction in variability allows a decrease in safety stock and therefore reduces average inventory. Risk pooling reduces the amount of inventory required to support the same level of service, the degree of benefit depends on the unpredictability (variance) and dependence (correlation) of the demand of the end products.

Figure 3.2: Supply Chain with a Generic Product (Postponement Case)



3.3 Description of Simulation Model

Simulation can be applied in many fields and industries and it is a very popular and powerful method. In simulation there is flexibility to model things as they are. It also allows uncertainty and non-stationarity in modeling. Simulation modeling facilitates describing the overall supply chain processes, helps capture the system dynamics with probability distributions, and helps compare alternatives with "what- if" games in a cost-effective way. Both postponement and non-postponement scenarios are coded as discrete event simulation models using Arena – Version 7.01. Arena is a simulation system that integrates a flexible modeling environment, graphical user interface, and all the simulation functions such as input analyzer, model verifier, and output analyzer (Kelton et al. 2004). The Rockwell Software Inc. first released Arena in 1993 developed with the basic language SIMAN (Simulation and Analysis). Arena is applied to industrial problems such as capacity analysis and scheduling of manufacturing units, system integration and staffing in industrial operations. Arena is being used all over the world with applications in health care manufacture, rail cargo logistics, automotive design plant operations, and United parcel Service package delivery service optimization, etc. Accordingly, Arena is considered appropriate for this study.

The models need some data as input. The inputs to the model are the inventory policy information and the demand information. We require the following information about the inventory policy:

- Safety stock level / base stock level
- Reorder point
- Review period
- Lead time

The time between demands are IID random variables having normal distribution. The company reviews the inventory level after every 12 days and the order arrives after the specified lead time. When a demand occurs, it is satisfied immediately if the inventory level is at least as large as the demand. If the demand exceeds the inventory level, the excess of demand over supply is backlogged and satisfied by future deliveries. When an order arrives, it is first used to satisfy the backlog and the remainder is added to the inventory. The model uses the following types of events;

- Arrival of an order
- Demand for the product
- Inventory evaluation at the review period
- End of simulation after n months

The first three events are flowcharted in Figure 3.3, 3.4, and 3.5 respectively. The order-arrival event must make the necessary changes when an order arrives. The inventory level is increased by the amount of the order. The demand event makes the changes to represent the demand's occurrence. The demand size is generated and the corresponding amount is decremented from the inventory. The time of the next demand is scheduled into the event list. Inventory evaluation event takes place at every review period. If the inventory level at the time of review is more than the base stock level, then no order is placed and the next evaluation event is scheduled into the event list. On the other hand, if the inventory level is less than equal to the base stock level, an order for the required quantity (base stock – inventory level) is placed and the next evaluation event is scheduled. The simulation model is developed in Arena keeping all this into consideration. Figure 3.6 presents a screen capture of the simulation model developed using Arena.

Figure 3.3: Order–Arrival Flowchart

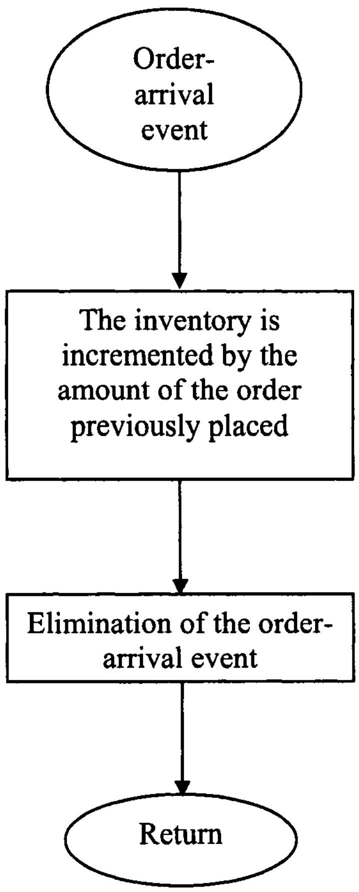


Figure 3.4: Demand Flowchart

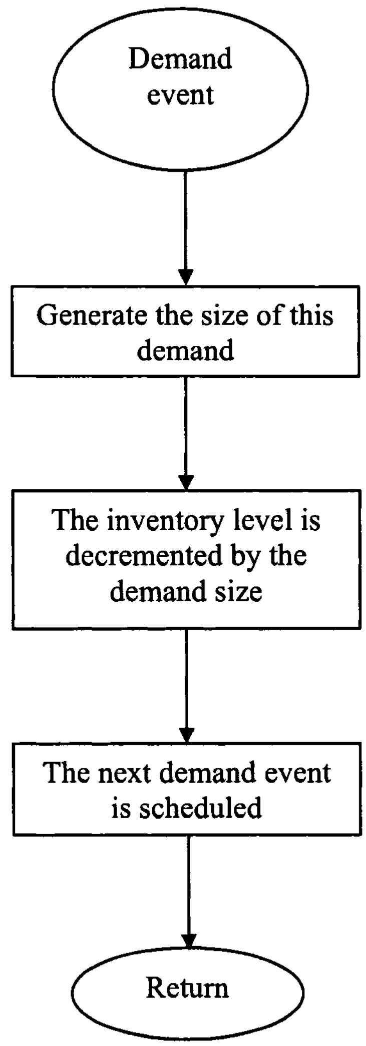


Figure 3.5: Inventory-Evaluation Flowchart

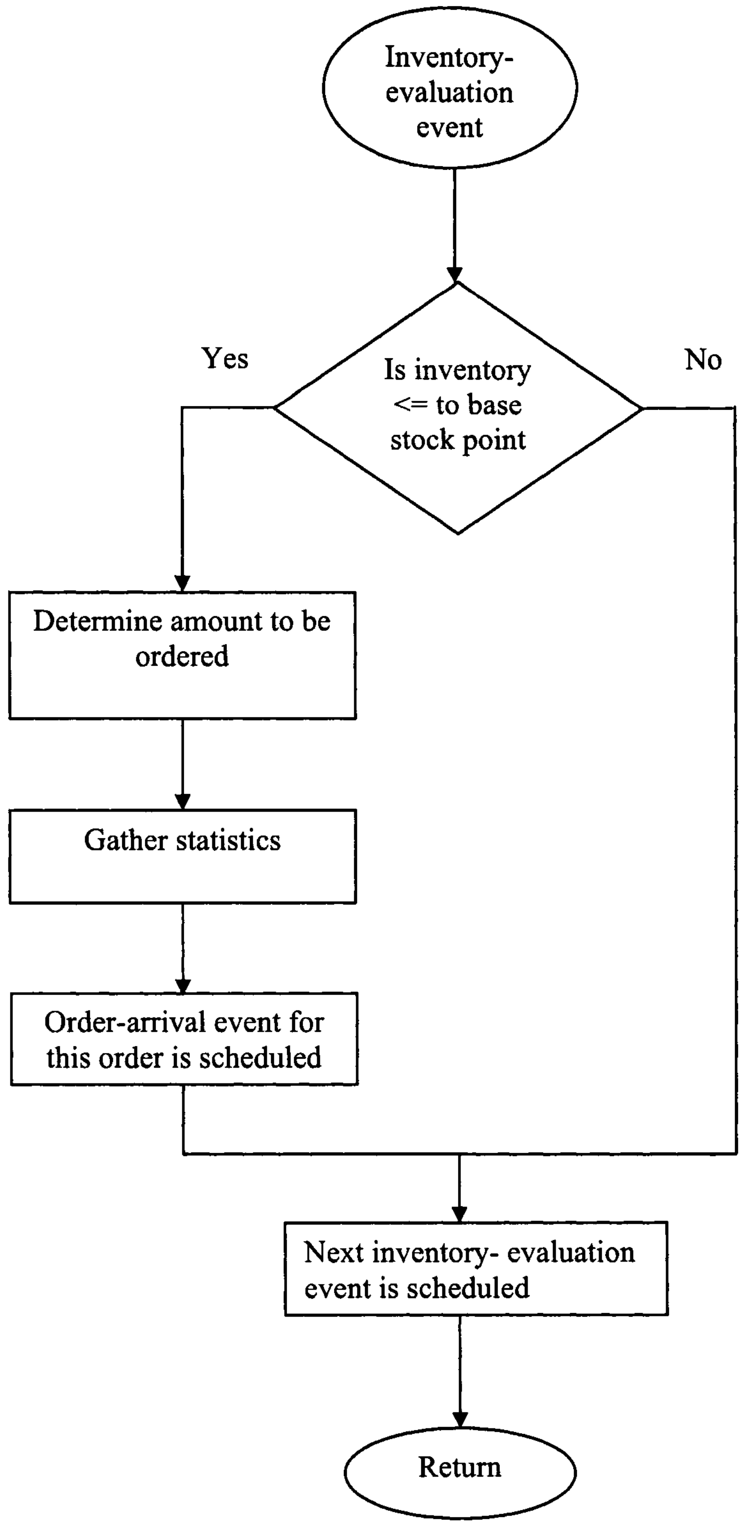
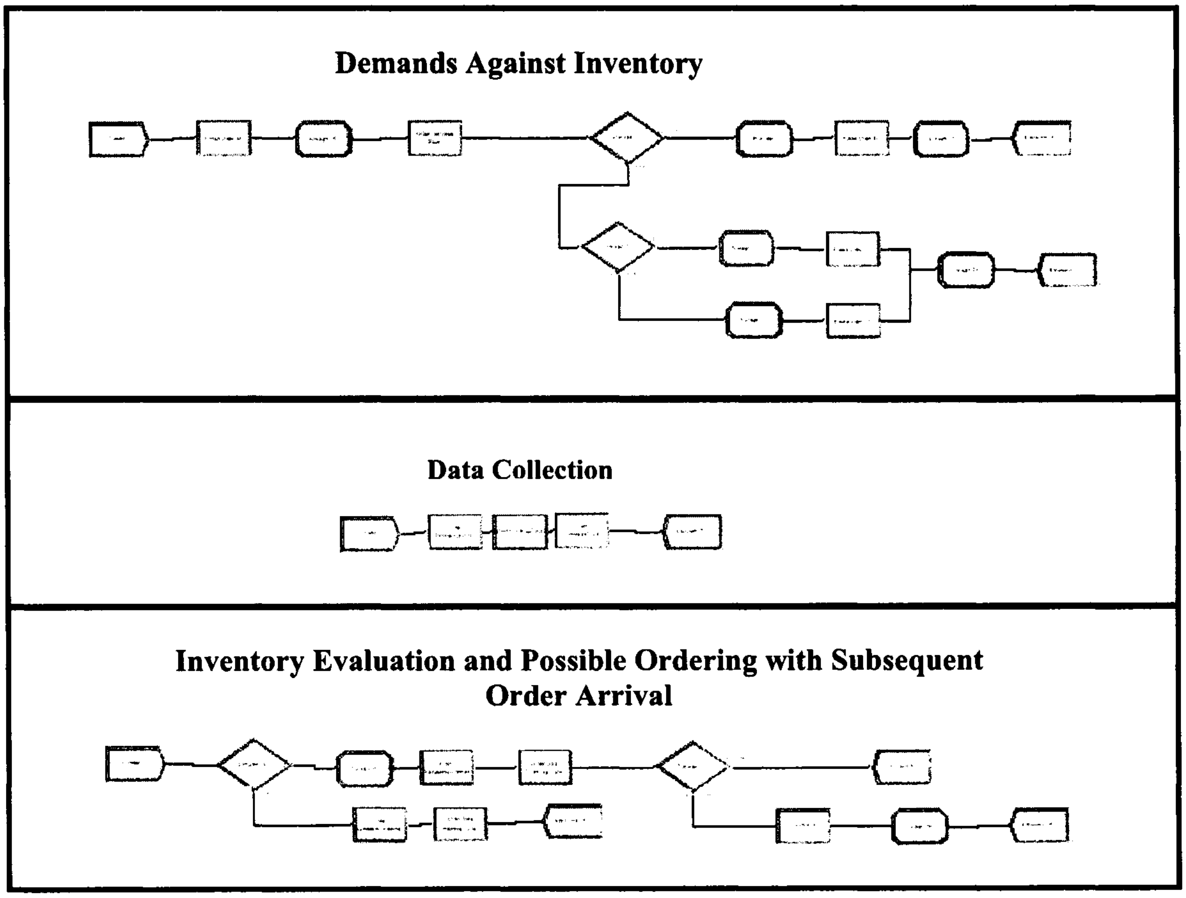


Figure 3.6: Arena Simulation Model



3.3.1 The use of Left-Truncated Normal Distribution

The normal or Gaussian distribution is widely used of all the random variables (Johnson and Thomopoulos, 2002). In decision rules of production planning and inventory management, normal distribution is the most important single probability distribution. It is also important in general usage of probability, particularly in the area of applied statistics (Silver et al. 1998). Though, there is one problem with normal distributions. The concept of negative demand is unrealistic. To make the simulation more realistic, negative demands are not allowed in the simulation (truncated to zero). In most cases the negative demands are considered to be zero which makes the case unrealistic. In our simulations we are using the left truncated normal distribution (Johnson and Thomopoulos, 2002) which helps us to mitigate the problem.

To determine the safety stock required to achieve a desired service level, demands are commonly assumed to follow a normal probability distribution. However, since demands are necessarily truncated at values below zero, the actual demand and results in achieved service levels are less than those targeted. Johnson and Thomopoulos (2002) has shown that by using a left-truncated probability distribution (normal probability distribution) in which values below a truncation point cannot be observed improves the achieved service level. The standardized, left-truncated normal distribution $f_{SLTN}(t)$ is given by (Johnson and Thomopoulos, 2002),

$$f_{SLTN}(t) = \begin{cases} 0, & t \leq 0 \\ \dfrac{f(t+K_L)}{\int_{K_l}^{\infty} f(z)dz}, & t \geq 0 \end{cases}$$

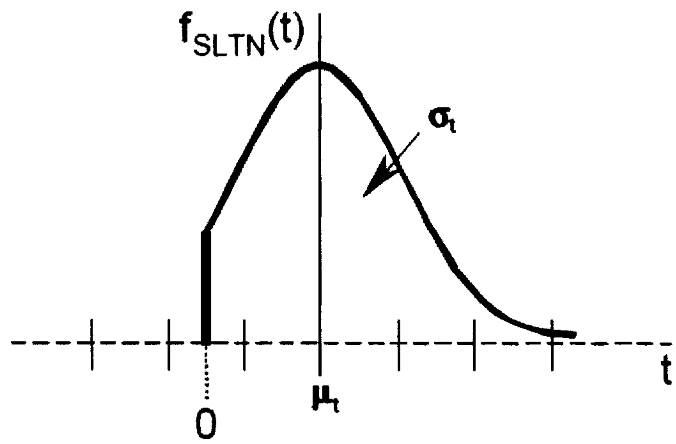
Where,

K_L = Point of truncation

t = a standardizing variable

$f(z)$ = the standard normal distribution

Figure 3.7: Standardized Left-Truncated Normal Distribution (Source: Johnson and Thomopoulos, 2002)



The model is using the standardized, left-truncated normal distribution to determine the daily demand. The code to calculate the demand is provided in Appendix 1.

3.4 Statistical Analysis of Simulation Outputs

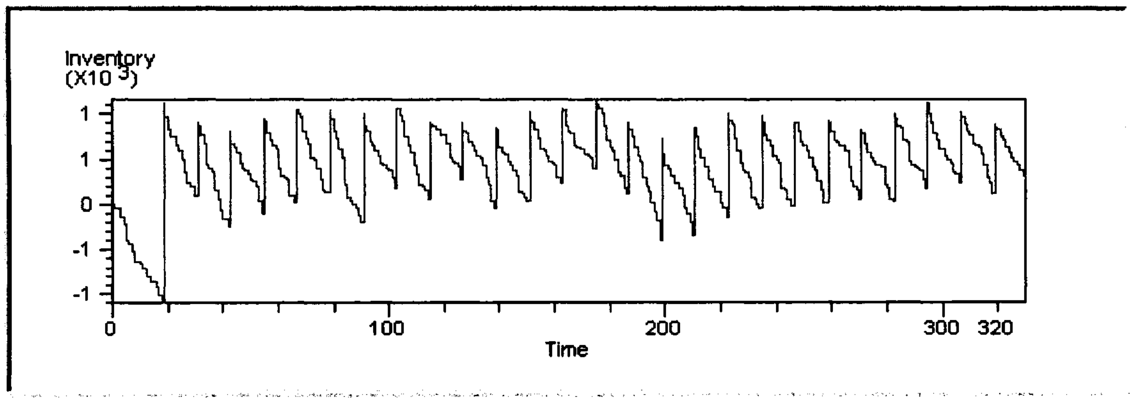
In simulation there is an issue of randomness and thus statistical analysis should be performed. By just running the model once, one cannot predict how valid the results might be. The estimates could differ greatly from the corresponding true characteristics and there could be a significant probability of making wrong inferences about the system under study. Thus, if the results of a simulation study are to have any meaning, appropriate statistical techniques must be used to design and analyze the simulation experiments (Law and Kelton,. 2000). This is discussed in more detail in section 3.4.1 and 3.4.2.

Type of simulation at hand is an important factor in designing and analyzing simulation experiments. Most simulations can be classified as terminating or non-terminating, depending on whether there is an obvious way for determining run length. Our supply chain model falls under the non-terminating category.

3.4.1 Warm-Up and Run Length

In steady-state simulation, initial conditions are not supposed to matter and the runs are quite long. But one has to initialize and stop the run. The technique most often suggested for dealing with this problem is called warming up the model or initial-data deletion. The theory is to delete some observations from the starting of a run and to use the remaining observations. The idea is to make plots of key outputs from within a run, and watch when they appear to stabilize. In our case we watched the behavior of the inventory level in the system. In case of lead time of one week, review period of twelve days, monthly demand of 1000 units and coefficient of variation of 0.4, the system stabilized after 19 days. Figure 3.8 shows the resulting plot of inventory across the simulations. The simulation was run for 336 days.

Figure 3.8: Inventory Plot for the Model in the Output Analyzer



The run length of simulations should still be long. Banks et al. (2005) suggests that the length of each replication beyond the deletion point should be at least ten times the amount of data deleted. In Arena it is very easy to specify an initial warm-up period. At the end of the warm-up period, all statistical accumulators are cleared and the reports reflect the data after the warm-up period ends. This helps to decontaminate the data from biasing initial conditions.

3.4.2 Estimation of Means

Law and Kelton (2000) have illustrated methods that result in a reliable and precise statistical analysis, which advocates sound decisions. We are using the replication/deletion approach for means (truncated replications) to estimate the means. If the warm-up period is reasonably short as compared to the run length, then the analysis is similar to that for terminating simulations except that only those observations beyond the warm-up in each replication are used to form the estimates. With the appropriate warm-up and run length values and by making independent replications, statistical analysis similar to terminating simulations can be carried out with warmed-up independent replications.

In our case the system stabilized after 19 days. This is quite small as compared to the run-length (336 days). With this into consideration we go for the replication/deletion approach to estimate the means. We have used Arena's output analyzer to determine the warm-up period and ten replications were performed for each replication.

- **Confidence Interval for Means**

A confidence interval gives an estimated range of values and the estimated range is calculated from a given set of sample data. The C.I. width gives some idea about how uncertain we are about the unknown parameter. A very wide interval indicates that more data should be collected before anything very definite can be said about the parameter.

Two-level Fractional Factorial Experimental designs are used to study and analyze the output from simulations. Design of Experiments (DOE) is used to analyze the performance of service level, inventory levels and to determine which variables are most influential. Additionally we determine how the variables interact among themselves in the supply chain environment with and without postponement strategies.

Chapter Four

Numerical Examples and Analysis

This chapter presents numerical analysis of the problem of the model introduced in the previous chapter. The model developed has been tested for various instances of the problem. Postponement is considered to be advantageous if the amount of item inventory required for postponement is less than the item inventory required for non-postponement given same service levels. The item inventory is considered equal to the base stock level which is defined in chapter 3. The greater the difference in the two inventories, the greater the benefit of postponement. Also postponement enables companies to dramatically reduce inventory while improving customer service. The objective of this section is to get insight into the response of item inventory levels and fill rate in both non-postponement and postponement scenarios by changing the model parameters. Demand variability, correlation of demands, number of products being postponed, inventory levels and fill rate will be explored. Design of Experiment (DOE) is used to conduct and analyze controlled tests to evaluate the factors that control the value of fill rate and inventory level. Experimental methods are used to quantify intermediate measurements of factors and interactions between factors.

4.1 Factors Affecting Postponement

To study the effects of changing different parameters, we consider a single-period, two-product model where the p.d.f.s of demand follows normal distribution. The inventory levels for both scenarios are generated for several sets of two-product pairs that differ only in the value of factor being examined. We consider a numerical example that will be referred to as the base case. In the base case total item expected demand is 2000. Each of the two products have demands that are independent and identically distributed (i.i.d.) ~ $N(\mu,\sigma)$ with $\mu_y = 1000$, σ_y=500, n_y=1 for y = 1,2,...., m, and P_2 = 0.95. The $ESPRC$ is determined by equation 3.9.

Where,

$ESPRC$ = Expected shortages/stockouts per replenishment cycle

n_y = is the quantity of the common item contained in product y

P_2 = Service Level / Fill Rate

The coefficient of variation (C.V.) is defined as $\frac{\sigma_y}{\mu_y}$ and is computed to be 0.50. In the non-postponement scenario, we solve equation 3.13 for each S_y.

Therefore,

S_1 = 1667 and S_2 =1667

The total non-postponement inventory in terms of the common item is determined from equation 3.16.

$I_N = 1(1667) + 1(1667) = 3334$

In the postponement scenario,

μ = 1(1000) + 1(1000) = 2000, using equation 3.17.

The correlation coefficient is assigned a value of zero indicating that the $\mu_y s$ are independent, thus using equation 3.18, we get

$\sigma^2 = (1)^2(500)^2 + (1)^2(500)^2 = 500{,}000$

$\sigma = 707$

The $ESPRC$ and the postponement inventory is calculated using equations 3.9 and 3.13 respectively.

$I_P = 2603$

For this example there is a reduction in inventory between the non-postponement and postponement scenarios, 3334-2603=731. This result can be expressed as a percent reduction in the item inventory using the equation, where R is the percent reduction in total item inventory from the non-postponement inventory in terms of items

$$R = \frac{I_N - I_P}{I_N}.100,$$

$$= (731/3334)*(100\%) = 21.93\%.$$

4.1.1 Demand Variability

The effect of demand variability on inventory levels is studied by changing the coefficient of variation (C.V.) for sets of two-product pairs, each with i.i.d. demand. Each pair differs from every other pair only in the value of the C.V. The results of the computations are shown in Table 4.1. Figure 4.1 shows the benefit from postponement as a function of the coefficient of variation. We see that the benefits from postponement increases as the variability of demand increases. This is consistent with a similar finding reported by Lee and Billington (1994) showing how the inventory and postponement relationship changes as a function of more variable demand. Our model is in more detail as compared to Lee and Billington and they both consistently lead to the same conclusion.

Table 4.1: Inventory Results for Non-postponement and Postponement Scenarios for Selected Coefficients of Variation

Non Postponement
Product 1
n_1=1 **Fill Rate = 95%**
n_2=1

Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)
1	1000	0.5	500	1667	94.62	0.057
2	1000	0.4	400	1415	94.86	0.023
3	1000	0.3	300	1175	95.19	0.013
4	1000	0.2	200	954	95.85	0.012
5	1000	0.1	100	764	96.23	0.012

Product 2
n_1=1 **Fill Rate = 95%**
n_2=1

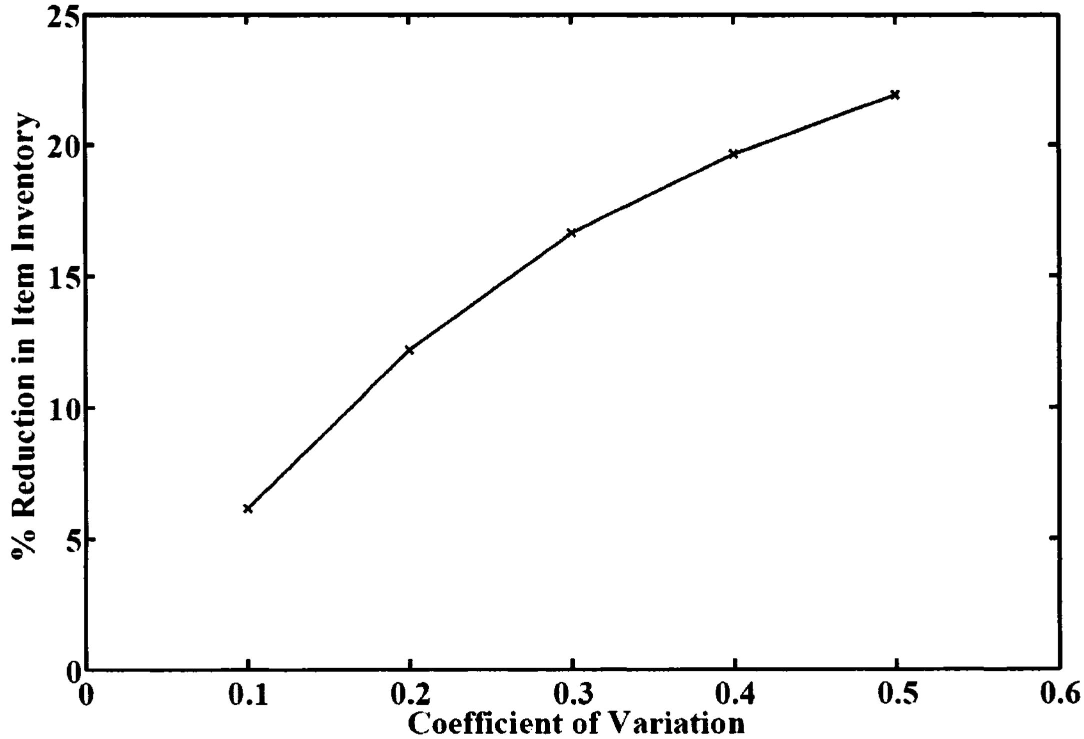
Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)	I_N
1	1000	0.5	500	1667	94.62	0.057	3334
2	1000	0.4	400	1415	94.86	0.023	2830
3	1000	0.3	300	1175	95.19	0.013	2350
4	1000	0.2	200	954	95.85	0.012	1908
5	1000	0.1	100	764	96.23	0.012	1528

Postponement

Scenario	Mean	rho_{12}	Std. Dev.	S	Simulated P_2	Confidence Interval Half width (95%)	I_P
1	2000	0	707	2603	95.42	0.147	2603
2	2000	0	566	2273	95.51	0.117	2273
3	2000	0	424	1959	95.63	0.074	1959
4	2000	0	283	1676	95.96	0.032	1676
5	2000	0	141	1434	96.26	0.014	1434

Scenario	% Reduction $R = \frac{I_N - I_P}{I_N}.100$
1	21.93
2	19.68
3	16.64
4	12.18
5	6.15

Figure 4.1: Effect of Demand Variability on the Benefit of Postponement by the Percent Reduction in the Non-Postponement Inventory



The effect of variability of demand on inventory levels was also analyzed by keeping the coefficient of variation constant for the sets of two-product pairs, with i.i.d. demand and each pair differing from every other pair in the values of the mean and standard deviation of demands. The result of the computation is shown in Table 4.2. Figure 4.2 shows the benefit of postponement as a function of total item expected demand and the standard deviation of total item expected demand.

Table 4.2: Inventory Results for Non-postponement and Postponement Scenarios with different Means

Non Postponement
Product 1
n_1=1 **Fill Rate = 95%**
n_2=1

Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)
1	500	0.2	100	477	94.72	0.012
2	700	0.2	140	668	94.72	0.012
3	900	0.2	180	859	94.72	0.012
4	1100	0.2	220	1050	94.72	0.012
5	1300	0.2	260	1241	94.72	0.012

Product 2
n_1=1 **Fill Rate = 95%**
n_2=1

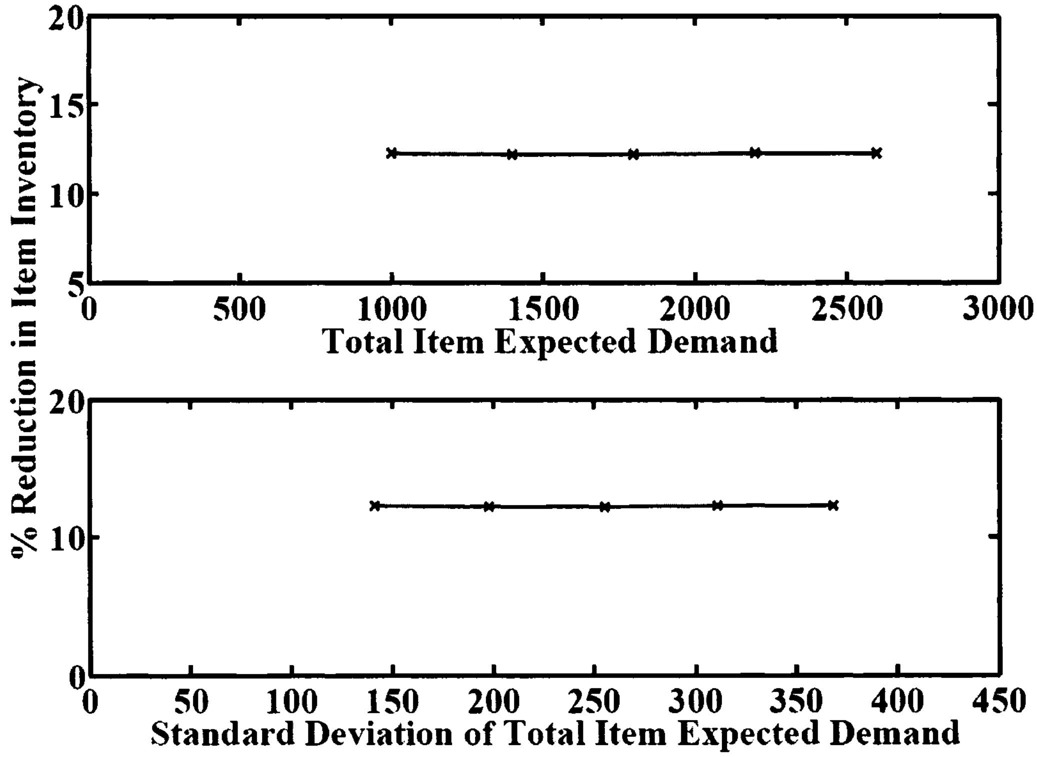
Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)	I_N
1	500	0.2	100	477	94.72	0.012	954
2	700	0.2	140	668	94.72	0.012	1336
3	900	0.2	180	859	94.72	0.012	1718
4	1100	0.2	220	1050	94.72	0.012	2100
5	1300	0.2	260	1241	94.72	0.012	2482

Postponement

Scenario	Mean	rho_{12}	Std. Dev.	S	Simulated P_2	Confidence Interval Half width (95%)	I_P
1	1000	0	141	837	94.7	0.012	837
2	1400	0	198	1173	94.7	0.012	1173
3	1800	0	255	1509	94.7	0.012	1509
4	2200	0	311	1843	94.7	0.014	1843
5	2600	0	368	2178	94.7	0.014	2178

Scenario	% Reduction $R = \frac{I_N - I_P}{I_N}.100$
1	12.26
2	12.20
3	12.17
4	12.24
5	12.25

Figure 4.2: Benefits of Postponement as a Function of Total Item Expected Demand and the Standard Deviation for Sets of Two i.i.d. Products with the same Coefficient of Variation and Different Means and Standard Deviations of Demand



Thus from figure 4.2, the benefit of postponement are constant for a given coefficient of variation and do not vary as a function of the mean or standard deviation of demand.

4.1.2 Correlated Demand

The effect of demand correlation on inventory levels is studied by changing the correlation coefficient for sets of two-product pairs, each with i.i.d. demand. Each pair differs in the value of the correlation coefficient. The result of the computation is shown in Table 4.3. Figure 4.3 shows the benefit of postponement as a function of the correlation coefficient of total item expected demand. The benefit of postponement increases at an increasing rate as the demands of the two products become negatively correlated. This is consistent with a similar finding reported by Lee and Billington (1994) showing how the inventory and postponement relationship changes as a function of increasingly strong negative correlation.

Table 4.3: Inventory Results for Non-postponement and Postponement Scenarios with Dependent and Identically Distributed Normal Demand

Non Postponement

Product 1
n_1=1 **Fill Rate = 95%**
n_2=1

Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)
1	1000	0.2	200	954	95.85	0.012
2	1000	0.2	200	954	95.85	0.012
3	1000	0.2	200	954	95.85	0.012
4	1000	0.2	200	954	95.85	0.012
5	1000	0.2	200	954	95.85	0.012

Product 2

n_1=1 **Fill Rate = 95%**

n_2=1

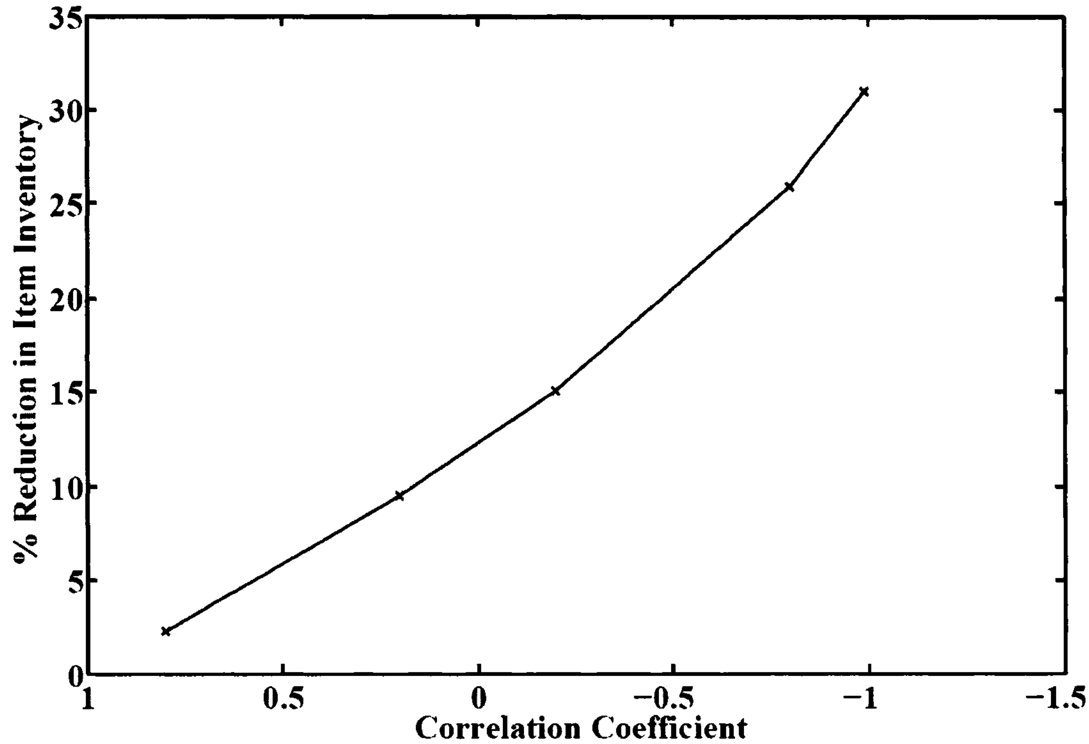
Scenario	Mean	C.V.	Std. Dev.	S1	Simulated P_2	Confidence Interval Half width (95%)	I_N
1	1000	0.2	200	954	95.85	0.012	1908
2	1000	0.2	200	954	95.85	0.012	1908
3	1000	0.2	200	954	95.85	0.012	1908
4	1000	0.2	200	954	95.85	0.012	1908
5	1000	0.2	200	954	95.85	0.012	1908

Postponement

Scenario	Mean	rho_{12}	Std. Dev.	S	Simulated P_2	Confidence Interval Half width (95%)	I_P
1	2000	-0.99	28	1316	95.6	0.012	1316
2	2000	-0.8	126	1413	95.23	0.013	1413
3	2000	-0.2	253	1620	95.07	0.024	1620
4	2000	0.2	310	1727	94.79	0.040	1727
5	2000	0.8	379	1865	94.13	0.062	1865

Scenario	% Reduction $R = \frac{I_N - I_P}{I_N}.100$
1	31.03
2	25.94
3	15.10
4	9.49
5	2.25

Figure 4.3: Effect of Demand Correlation on the Benefit of Postponement as Measured by the Percent Reduction in the Non-postponement Inventory



4.1.3 Products being Postponed

Here we consider a single-period, m-product system with i.i.d. demands where the total item expected demand is equal to 2000 regardless of the number of products. The effect of the number of products y, being postponed is studied by varying y. The result of the computation is shown in Table 4.4. Figure 4.4 shows the benefits from postponement as a function of the number of products being postponed. The benefits from postponement increase as the number of products being postponed increases. This is consistent with a similar finding reported by Lee and Billington (1994) showing how the inventory and postponement relationship changes as a function of more product variety. The above results are also consistent with the findings by Whang and Lee (1998). Our model is in more detail as compared to Lee and Billington, Whang and Lee and they consistently lead to the same conclusion.

Table 4.4: Inventory Results for Non-postponement and Postponement Scenarios for Sets of m-Products with Independent and Identically Distributed Normal Demands for Different Number of Products being Postponed

Non Postponement
Fill Rate = 95%

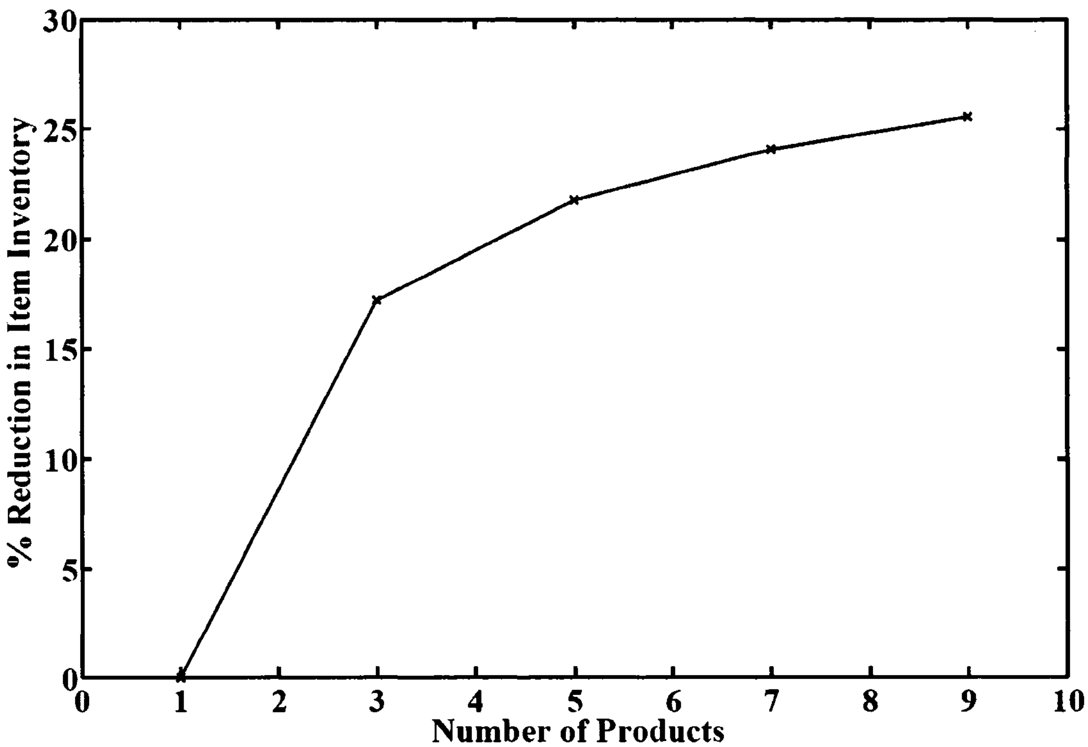
Scenario	No. of Products	Mean	C.V.	Std. Dev.	S_j	Simulated P_2	Confidence Interval Half width (95%)	I_N
1	1	2000	0.2	400	1908	94.83	0.068	1908
2	3	667	0.2	133	636	94.85	0.012	1908
3	5	400	0.2	80	382	94.89	0.012	1908
4	7	286	0.2	57	273	94.92	0.012	1908
5	9	222	0.2	44	212	94.95	0.012	1908

Postponement

Scenario	No. of Products	Mean	rho_{12}	Std. Dev.	S	Simulated P_2	Confidence Interval Half width (95%)	I_P
1	1	2000	0	400	1908	94.83	0.068	1908
2	3	2000	0	230	1579	95.15	0.021	1579
3	5	2000	0	179	1493	95.25	0.015	1493
4	7	2000	0	151	1449	95.28	0.014	1449
5	9	2000	0	132	1421	95.3	0.013	1421

Scenario	No. of Products	% Reduction $R = \frac{I_N - I_P}{I_N}.100$
1	1	0.00
2	3	17.24
3	5	21.75
4	7	24.06
5	9	25.52

Figure 4.4: Effect of Number of Products being Postponed on the Benefits of Postponement as Measured by the Percent Reduction in the Non-postponement Inventory



4.1.4 Inventory Levels for Different Fill Rates

The effect of inventory levels with different fill rates is examined for sets of two-product pairs, each with i.i.d. demand. The result of the computation is shown in Table 4.5. Figure 4.5 shows that overall inventory levels are lower in postponement while maintaining the customer service level or customer service level improves for a given level of inventory (Figure 4.6).

Table 4.5: Inventory Results for Non-postponement and Postponement Scenarios for different Fill Rates

Non Postponement

Product 1
n_1=1
n_2=1

Scenario	Mean	C.V.	Std. Dev.	S1	P_2	Simulated P_2	Confidence Interval Half width (95%)
1	1000	0.5	500	1194	80	80.17	0.057
2	1000	0.5	500	1446	90	90.48	0.053
3	1000	0.5	500	1667	95	94.62	0.052
4	1000	0.5	500	1866	97.5	97.80	0.050
5	1000	0.5	500	2104	99	99.18	0.047
6	1000	0.5	500	2611	99.9	99.80	0.047

Product 2

Scenario	Mean	C.V.	Std. Dev.	S1	P_2	Simulated P_2	Confidence Interval Half width (95%)	I_N
1	1000	0.5	500	1194	80	80.17	0.057	2388
2	1000	0.5	500	1446	90	90.48	0.053	2892
3	1000	0.5	500	1667	95	94.62	0.052	3334
4	1000	0.5	500	1866	97.5	97.80	0.050	3732
5	1000	0.5	500	2104	99	99.18	0.047	4208
6	1000	0.5	500	2611	99.9	99.80	0.047	5222

Postponement

Scenario	Mean	rho_{12}	Std. Dev.	S	P_2	Simulated P_2	Confidence Interval Half width (95%)	I_P
1	2000	0	707	1885	80	84.3	0.148	1885
2	2000	0	707	2270	90	90.89	0.146	2270
3	2000	0	707	2603	95	95.42	0.145	2603
4	2000	0	707	2899	97.5	97.82	0.143	2899
5	2000	0	707	3250	99	99.3	0.143	3250
6	2000	0	707	3991	99.9	99.7	0.142	3700

Scenario	% Reduction $R = \frac{I_N - I_P}{I_N}.100$
1	21.06
2	21.51
3	21.93
4	22.32
5	22.77

Figure 4.5: Improvements in Inventory Levels While Maintaining Same Service level

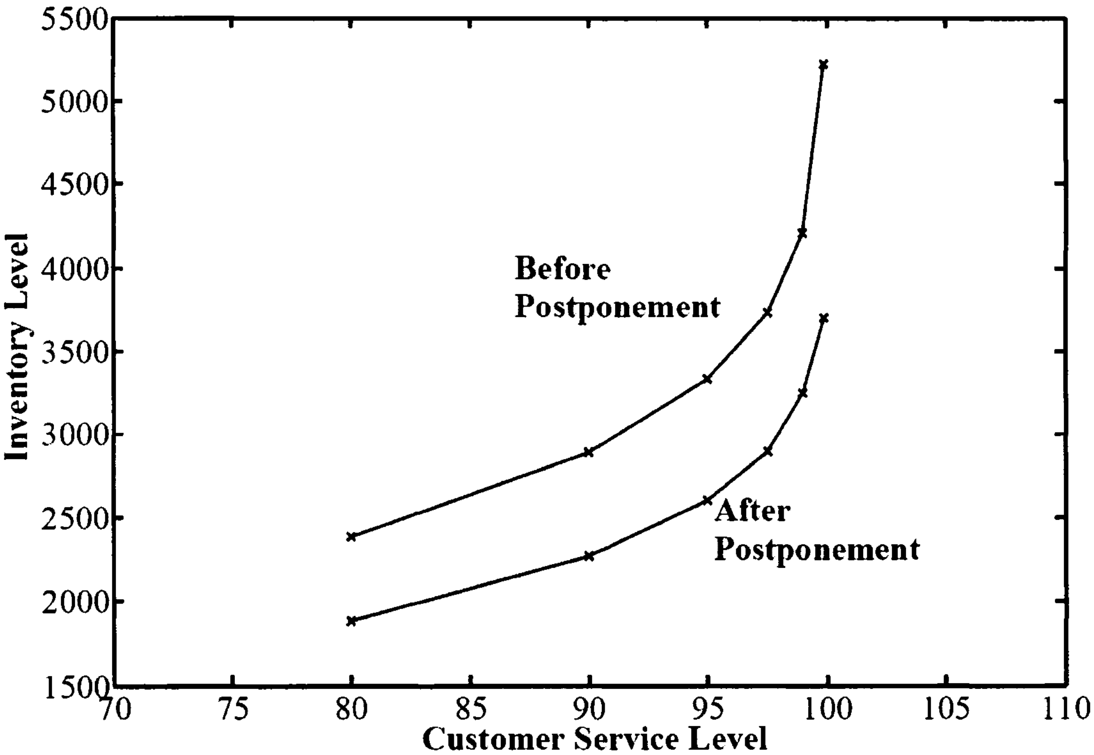


Table 4.6: Fill Rates for Non-Postponed and Postponed Product with Different C.V. and Inventory Policy

Sc	C.V.	Average Inventory (Weeks of Supply)	Non-Postponement Calculated Fill Rate	Non-Postponement Simulated Fill Rate	Non-Postponement Confidence Interval Half width (95%)	Postponement Calculated Fill Rate	Postponement Simulated Fill Rate	Postponement Confidence Interval Half width (95%)
1	0.4	2	75.96	75.98	0.06	76.27	76.3	0.05
2	0.4	2.2	79.27	79.35	0.04	81.16	81.21	0.03
3	0.4	2.4	82.23	82.31	0.03	85.22	85.27	0.02
4	0.3	2	86.49	86.57	0.15	88.72	88.75	0.17
5	0.3	2.2	89.09	89.18	0.13	91.98	92.02	0.13
6	0.3	2.4	91.28	91.33	0.12	94.43	94.5	0.1
7	0.2	2	95.27	95.38	0.23	97.32	97.38	0.29
8	0.2	2.2	96.74	96.78	0.21	98.56	98.62	0.2
9	0.2	2.4	97.81	97.85	0.2	99.26	99.32	0.15

Sc = Scenario

Figure 4.6: Fill Rate for Non-postponed and Postponed Product for Different Inventory Policy (C.V. = 0.3)

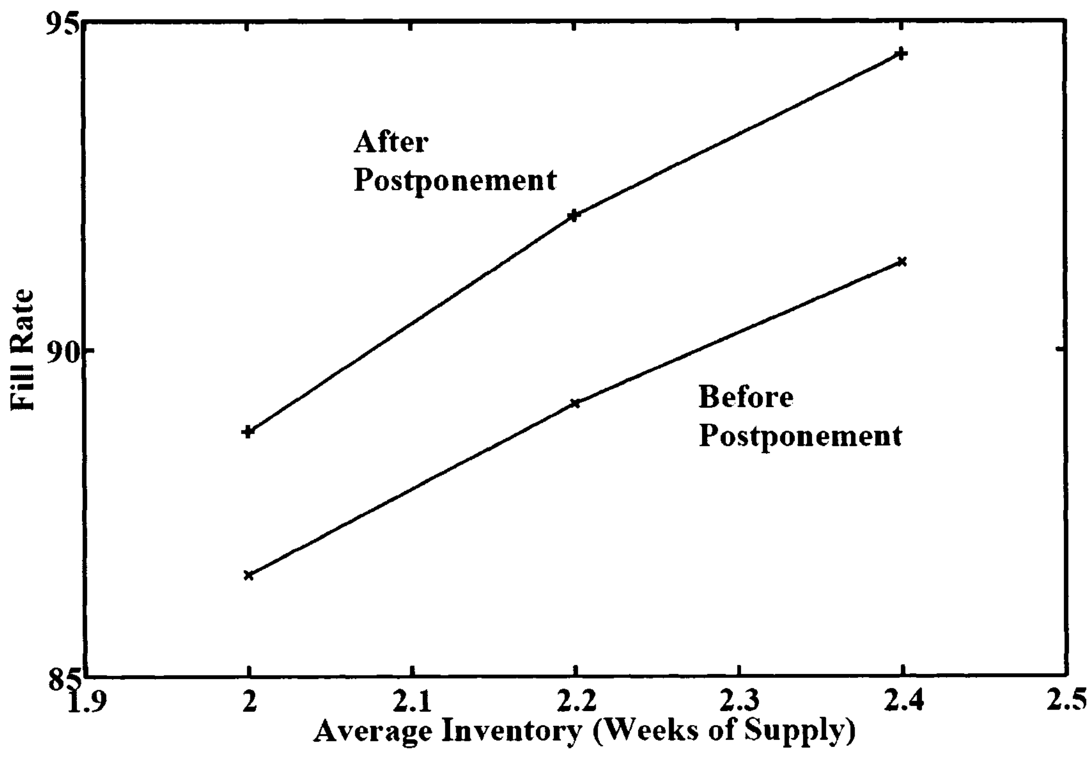


Figure 4.6 gives a plot of average inventory by fill rate for different inventory polices with same C.V. of 0.3. It shows that for the same inventory policy, the fill rate achieved using postponement is higher than non-postponement.

4.2 Experimental Design and Analysis

The goal of Design of Experiments (DOE) is to determine the impact of different factors so that the desired information may be gained cost-effectively (Montgomery, 2005). Simulation experiments are conducted to evaluate and analyze the various parameters that affect the fill rate and inventory level. In this study factors such as demand variability, demand correlation, lead time, weeks of inventory and number of products are used to conduct a thorough investigation of the interactions of postponement along with other system parameters. Two-level Fractional Factorial Experimental designs are used to study and analyze the performance of fill rate, inventory levels and to determine which variables are most influential. Additionally we determine how the variables interact among themselves in the supply chain environment with and without postponement strategy.

4.2.1 Performance of Fill Rate

Here we analyze the performance of fill rate under various factors defined above. Table 4.7 provides the design matrix and an overview of the DOE factors used to access the performance of fill rate under various operating conditions. It also shows the response values. Table 4.8 shows the interval of factors under consideration. The levels of factors under consideration are taken from the previous published work. The experimental design is implemented using statistical software Minitab – Release 14. Minitab uses analysis of variance to decide which factors have an effect on the response.

Table 4.7: The Design Matrix and DOE Factors

Fractional Factorial Design	
Factors :7	Resolution : IV
Runs : 16	Fraction : 1/8

Factors

Std Order	**Run Order**	**Post**	**D Var1**	**D Var2**	**DCor**	**LT**	**WI**	**NP**	**FR**
1	10	Low	Low	Low	Low	Low	Low	Low	**89.98**
2	6	High	Low	Low	Low	High	Low	High	**91.4**
3	2	Low	High	Low	Low	High	High	Low	**93.3**
4	11	High	High	Low	Low	Low	High	High	**94.31**
5	9	Low	Low	High	Low	High	High	High	**87.53**
6	12	High	Low	High	Low	Low	High	Low	**93.82**
7	13	Low	High	High	Low	Low	Low	High	**83.9**
8	5	High	High	High	Low	High	Low	Low	**89.15**
9	8	Low	Low	Low	High	Low	High	High	**95.54**
10	7	High	Low	Low	High	High	High	Low	**96.97**
11	16	Low	High	Low	High	High	Low	High	**89.26**
12	14	High	High	Low	High	Low	Low	Low	**94.32**
13	3	Low	Low	High	High	High	Low	Low	**80.97**
14	15	High	Low	High	High	Low	Low	High	**89.31**
15	4	Low	High	High	High	Low	High	Low	**90.65**
16	1	High	High	High	High	High	High	High	**93.07**

Post - Postponement **FR**- Fill Rate

DVar1– Demand Variability1 **DVar2**– Demand Variability2

DCorr– Demand Correlation **LT**- Lead Time

WI- Weeks of Inventory **NP**- Number of Products

Table 4.8: The Levels of Factors and their Intervals of Variation

Notation		**Post**	**DVar 1**	**DVar 2**	**DCorr**	**LT**	**WI**	**NP**
Upper Limit	High	Using postponement	0.4	1100	0.8	8	2.4	9
Lower Limit	Low	Not using postponement	0.2	700	-0.8	4	1	3

The sequence of experiments should be randomized. The randomization of run order ensures that replicate runs are at the same experimental conditions and that variation between runs and biases are eliminated or considered at all conditions. In the analysis the totally confounded terms were not taken into consideration. The confounding pattern is shown in table 4.9. Figure 4.7 presents a normal probability plot of the effect estimates from this experiment. The main effects of A, C, and F and the interaction AC and AF are significant at 95% confidence level. Figure 4.8 is a normal probability plot of the residuals and the plot is satisfactory. An approximate 95% confidence intervals (curved lines) for the fitted distribution are displayed in figure 4.8. These confidence intervals are point-wise and they are calculated separately for each point on the fitted distribution. As the diagnostic check, the residual plot confirms that the model developed is adequate. Table 4.10 contains the estimated effects and coefficients from the experiment.

Table 4.9: Confounding Pattern of the Factors

Alias Structure of the Factors
Postponement
DVar1
DVar2
DCorr
LT
WI
NP
Postponement*DVar1 + DVar2*LT + WI*NP
Postponement*DVar2 + DVar1*LT + DCorr*NP
Postponement*DCorr + DVar2*NP + LT*WI
Postponement*LT + DVar1*DVar2 + DCorr*WI
Postponement*WI + DVar1*NP + DCorr*LT
Postponement*NP + DVar1*WI + DVar2*DCorr
DVar1*DCorr + DVar2*WI + LT*NP

Table 4.10: Estimated Effects and Coefficients for FR (coded units)

Term	Effect	Coef	SECoef	T	P
Constant		90.843	0.0525	1730.33	0
Postponement	3.902	1.951	0.0525	37.17	0.017
DVar1	0.305	0.153	0.0525	2.9	0.211
DVar2	-4.585	-2.293	0.0525	-43.67	0.015
DCorr	0.837	0.419	0.0525	7.98	0.079
LT	-1.115	-0.558	0.0525	-10.62	0.06
WI	4.612	2.306	0.0525	43.93	0.014
NP	-0.605	-0.302	0.0525	-5.76	0.109
Postponement*DVar1	-0.468	-0.234	0.0525	-4.45	0.141
Postponement*DVar2	1.672	0.836	0.0525	15.93	0.04
Postponement*DCorr	0.41	0.205	0.0525	3.9	0.16
Postponement*LT	0.98	0.49	0.0525	9.33	0.068
Postponement*WI	-1.273	-0.636	0.0525	-12.12	0.049
Postponement*NP	-0.937	-0.469	0.0525	-8.93	0.071
DVar1*DCorr	0.822	0.411	0.0525	7.83	0.081

Figure 4.7: Normal Probability Plot of Effects

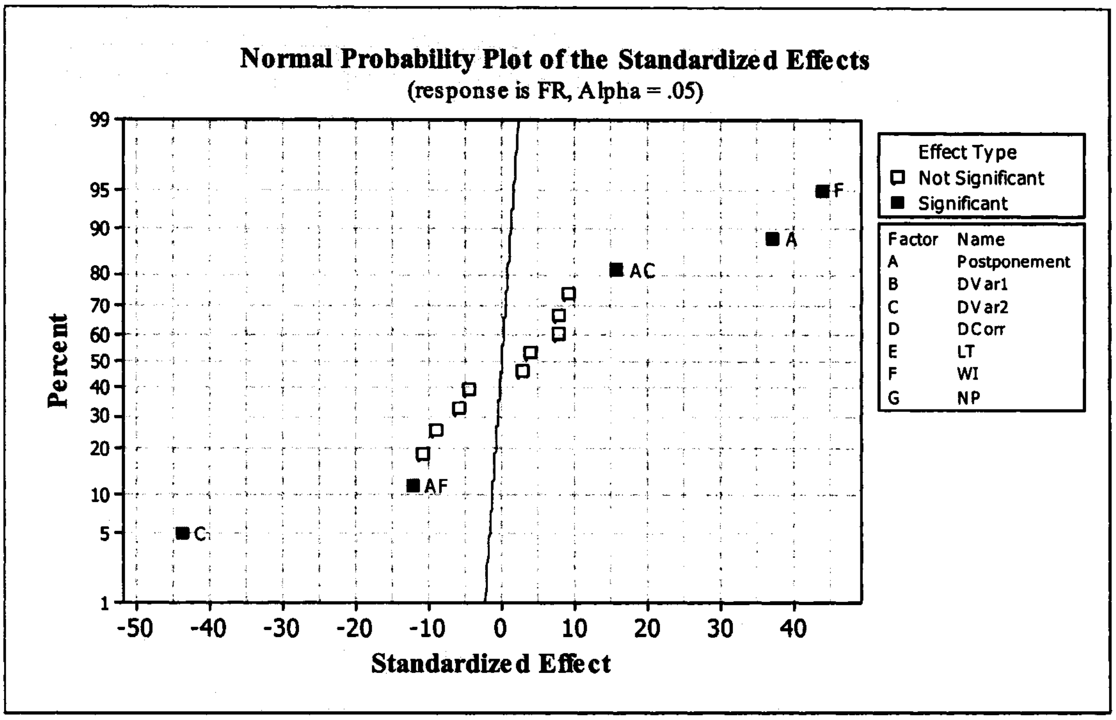


Figure 4.8: Normal Probability Plot of the Residuals

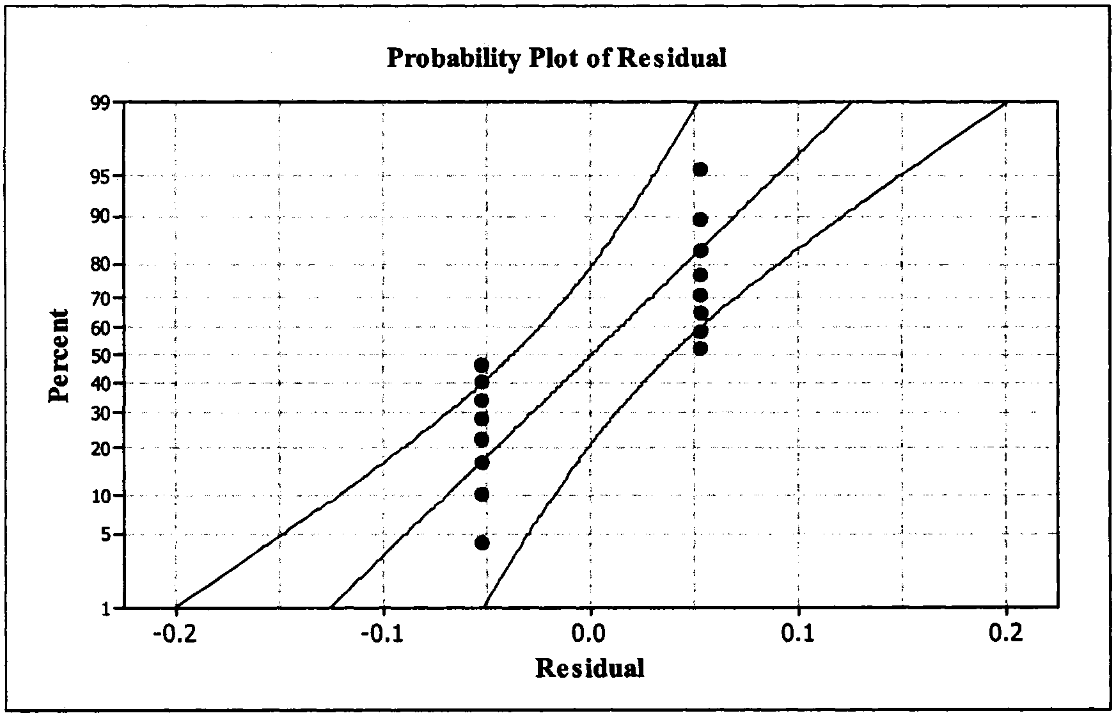
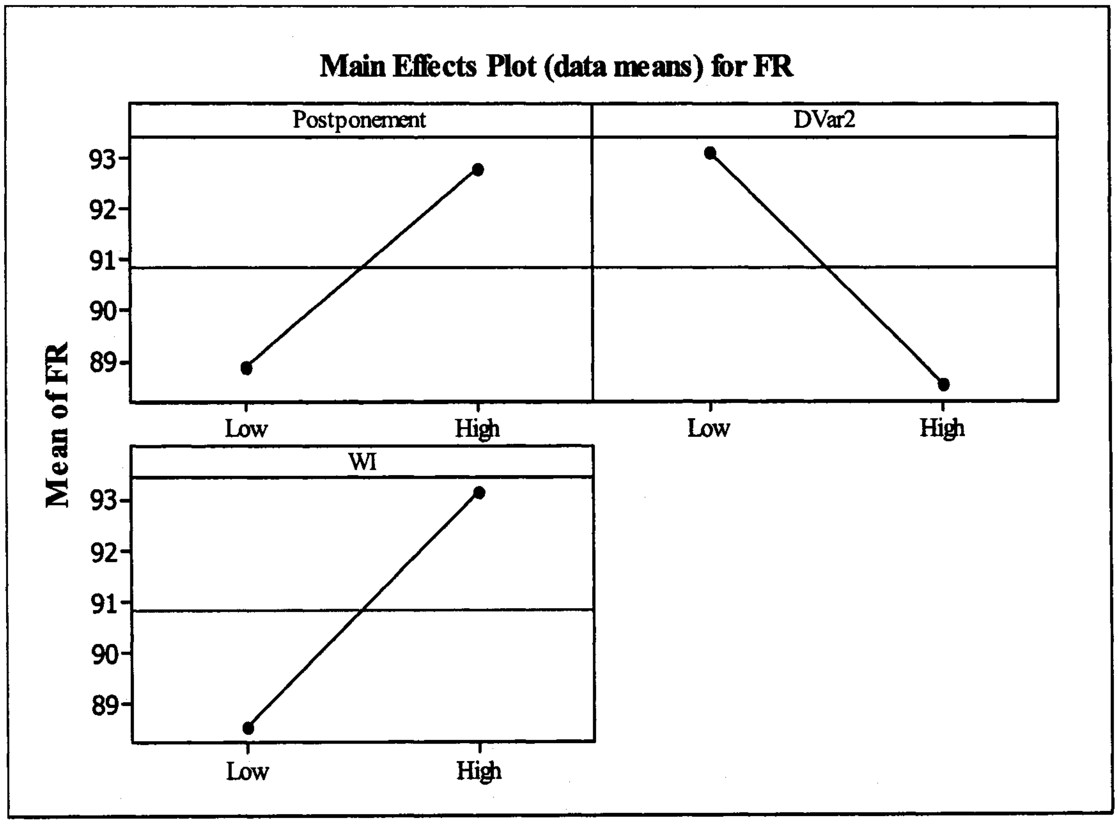


Figure 4.9: Main Effect Plot for FR



Equation 4.1 gives the regression model for predicting the fill rate.

$$\hat{FR} = 90.84 + (\frac{3.9}{2}) * Postponement - (\frac{4.59}{2}) * DVar2 + (\frac{4.61}{2}) * WI + (\frac{1.67}{2}) * Postponement * DVar2 - (\frac{1.27}{2}) * Postponement * WI \quad \text{....... (4.1)}$$

If we shift from non-postponement to postponement, its main effect will be to increase fill rate by an amount of 3.9. Postponement will have a positive effect on the fill rate. The main effect of demand variability, DVar2 causes a decrease in fill rate when DVar2 increases. As the demand variability increases the fill rate decreases by an amount of

4.59. The main effect of inventory level, WI causes an increase in fill rate when WI increases. More the inventory level, more demand is satisfied and the fill rate increases. The main effect of this factor is 4.61. A simultaneous increase in Postponement and demand variability also improves the fill rate. This interaction effect is 1.67. We believe postponement being a dominating factor, the interaction effect of increasing both the values increases the fill rate. The interaction effect of postponement and weeks of inventory is also found to be significant. A simultaneous increase in both factors decreases the fill rate by an amount of 1.27.

Figure 4.9 shows the main effect plot for FR. The factors postponement and weeks of inventory have positive effects. If one shifts from non-postponement to postponement the fill rate increases and also if the inventory level is increased, the fill rate increases. Demand variability has a negative effect on the fill rate. If the demand variability is less, more is the fill rate and more the demand variability, less is the fill rate. Figure 4.10 and 4.11 represents the interaction plots for fill rate. According to figure 4.10 overall inventory levels are lower in postponement while maintaining the fill rate or the fill rate increases for a given level of inventory. According to figure 4.11 if demand variability is high, postponement maintains a high fill rate as compared to non-postponement. As the demand variability increases the uncertainty increases and postponement performs better in this situation.

Figure 4.10: Interaction Plot of Postponement and Weeks of Inventory

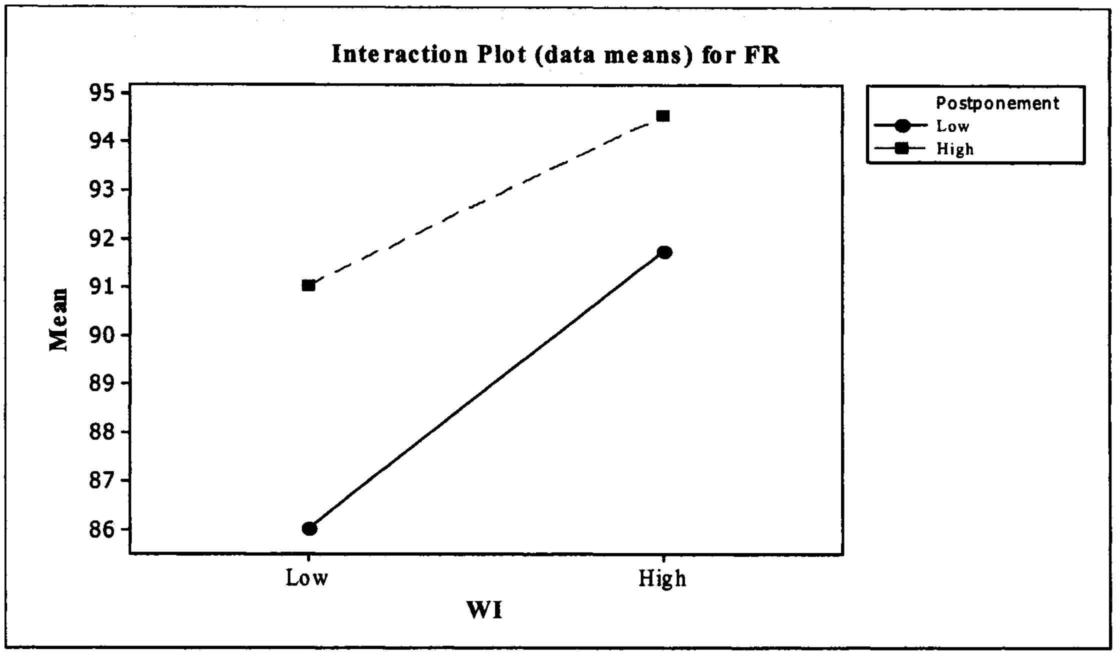
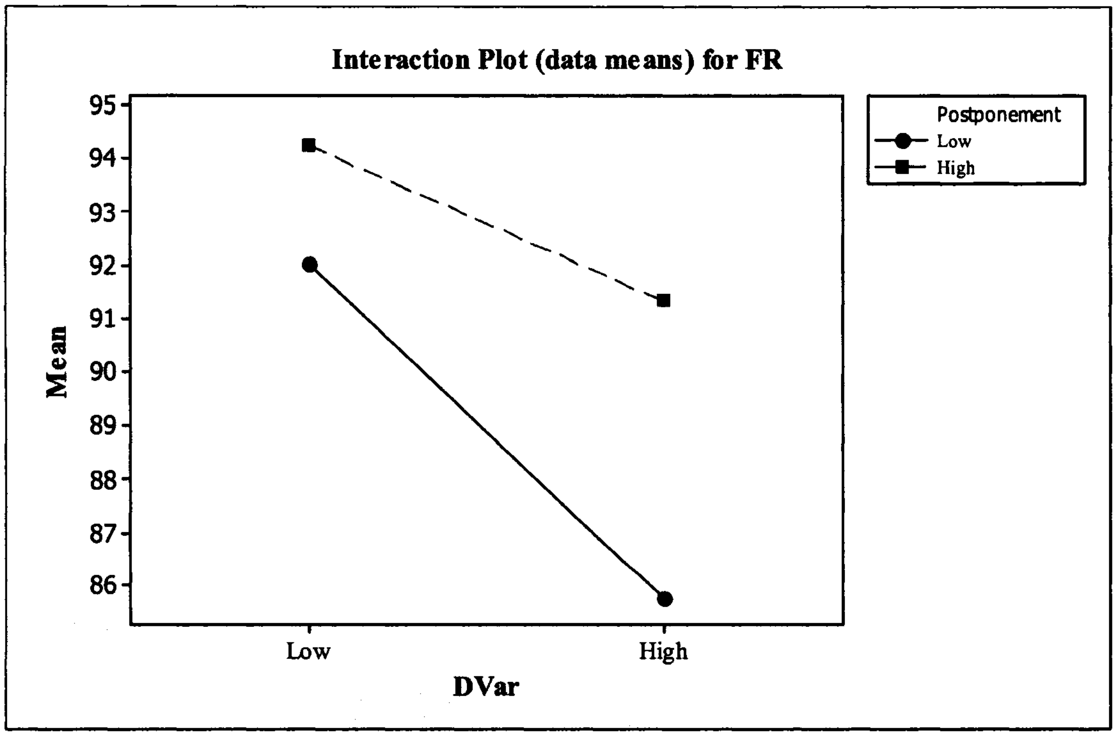


Figure 4.11: Interaction Plot of Postponement and Demand Variability



4.2.2 Performance of Inventory Level

Here we analyze the performance of inventory level under various factors defined earlier. Table 4.11 shows the interval of factors under consideration. The levels of factors under consideration are taken from the previous published work. Table 4.12 provides the design matrix and an overview of the DOE factors used to access the performance of inventory level under various operating conditions. It also shows the response values. Here also statistical software Minitab – Release 14 is used to conduct the experimental design. As mentioned earlier Minitab uses analysis of variance to decide which factors have an effect on the response.

Table 4.11: The Levels of Factors and their Intervals of Variation

Notation		**Post**	**DVar 1**	**DVar 2**	**DCorr**	**LT**	**FR**	**NP**
Upper Limit	High	Using postponement	0.4	1100	0.8	8	95	9
Lower Limit	Low	Not using postponement	0.2	700	-0.8	4	80	3

The sequence of experiments should be randomized. The randomization of run order ensures that replicate runs are at the same experimental conditions and that variation between runs and biases are eliminated or considered at all conditions. In the analysis the totally confounded terms were not taken into consideration. The confounding pattern is shown in table 4.13. Table 4.14 contains the estimated effects and coefficients from the experiment.

Table 4.12: The Design Matrix and DOE Factors

Fractional Factorial Design	
Factors :7	Resolution : IV
Runs : 16	Fraction : 1/8

Factors

Std Order	**Run Order**	**Post**	**D Var1**	**D Var2**	**DCorr**	**LT**	**FR**	**NP**	**WI**
1	10	Low	Low	Low	Low	Low	Low	Low	**0.93**
2	6	High	Low	Low	Low	Low	Low	High	**0.75**
3	2	Low	High	Low	Low	High	High	Low	**2.67**
4	11	High	High	Low	Low	High	High	High	**2.10**
5	9	Low	Low	High	Low	High	High	High	**3.56**
6	12	High	Low	High	Low	High	High	Low	**2.89**
7	13	Low	High	High	Low	Low	Low	High	**2.13**
8	5	High	High	High	Low	Low	Low	Low	**1.58**
9	8	Low	Low	Low	High	High	High	High	**2.48**
10	7	High	Low	Low	High	High	High	Low	**2.02**
11	16	Low	High	Low	High	Low	Low	High	**1.29**
12	14	High	High	Low	High	Low	Low	Low	**0.79**
13	3	Low	Low	High	High	Low	Low	Low	**2.45**
14	15	High	Low	High	High	Low	Low	High	**1.47**
15	4	Low	High	High	High	High	High	Low	**3.92**
16	1	High	High	High	High	High	High	High	**2.64**

Post - Postponement **FR-** Fill Rate

DVar1– Demand Variability1 **DVar2**– Demand Variability2

DCorr– Demand Correlation **LT-** Lead Time

WI- Weeks of Inventory **NP-** Number of Products

Table 4.13: Confounding Pattern of the Factors

Alias Structure of the Factors			
Postponement			
DVar1			
DVar2			
DCorr			
LT			
FR			
NP			
Postponement*DVar1	+ DVar2*LT	+ FR*NP	
Postponement*DVar2	+ DVar1*LT	+ DCorr*NP	
Postponement*DCorr	+ DVar2*NP	+ LT*FR	
Postponement*LT	+ DVar1*DVar2	+ DCorr*FR	
Postponement*FR	+ DVar1*NP	+ DCorr*LT	
Postponement*NP	+ DVar1*FR	+ DVar2*DCorr	
DVar1*DCorr	+ DVar2*FR	+ LT*NP	

Table 4.14: Estimated Effects and Coefficients for FR (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		2.1044	0.00438	481	0.001
Postponement	-0.649	-0.324	0.00438	-74.14	0.009
DVar1	0.0712	0.0356	0.00438	8.14	0.078
DVar2	0.9513	0.4756	0.00438	108.71	0.006
DCorr	0.0562	0.0281	0.00438	6.43	0.098
LT	0.0312	0.0156	0.00438	3.57	0.174
FR	1.3612	0.6806	0.00438	155.57	0.004
NP	-0.104	-0.052	0.00438	-11.86	0.054
Postponement*DVar1	-0.076	-0.038	0.00438	-8.71	0.073
Postponement*DVar2	-0.221	-0.111	0.00438	-25.29	0.025
Postponement*DCorr	-0.156	-0.078	0.00438	-17.86	0.054
Postponement*LT	-0.096	-0.048	0.00438	-11	0.058
Postponement*FR	-0.096	-0.048	0.00438	-11	0.058
Postponement*NP	0.0237	0.0119	0.00438	2.71	0.225
DVar1*DCorr	-0.016	-0.008	0.00438	-1.86	0.314

Figure 4.12 presents a normal probability plot of the effect estimates from this experiment. The main effects of A, C, and F and the interaction AC are significant at 95% confidence interval. Figure 4.13 is a normal probability plot of the residuals and the plot is satisfactory. An approximate 95% confidence intervals (curved lines) for the fitted distribution are displayed in figure 4.13. These confidence intervals are point-wise and they are calculated separately for each point on the fitted distribution. As the diagnostic check, the residual plot confirms that the model developed is adequate.

Figure 4.12: Normal Probability Plot of Effects

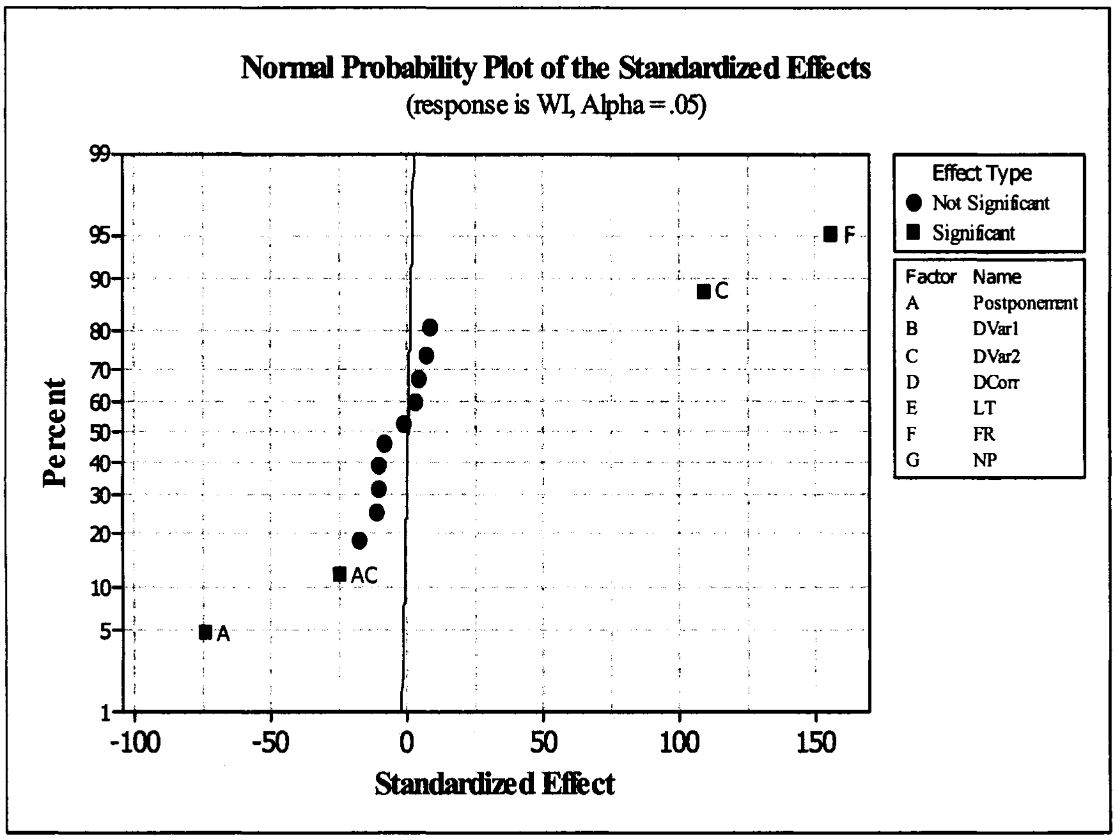
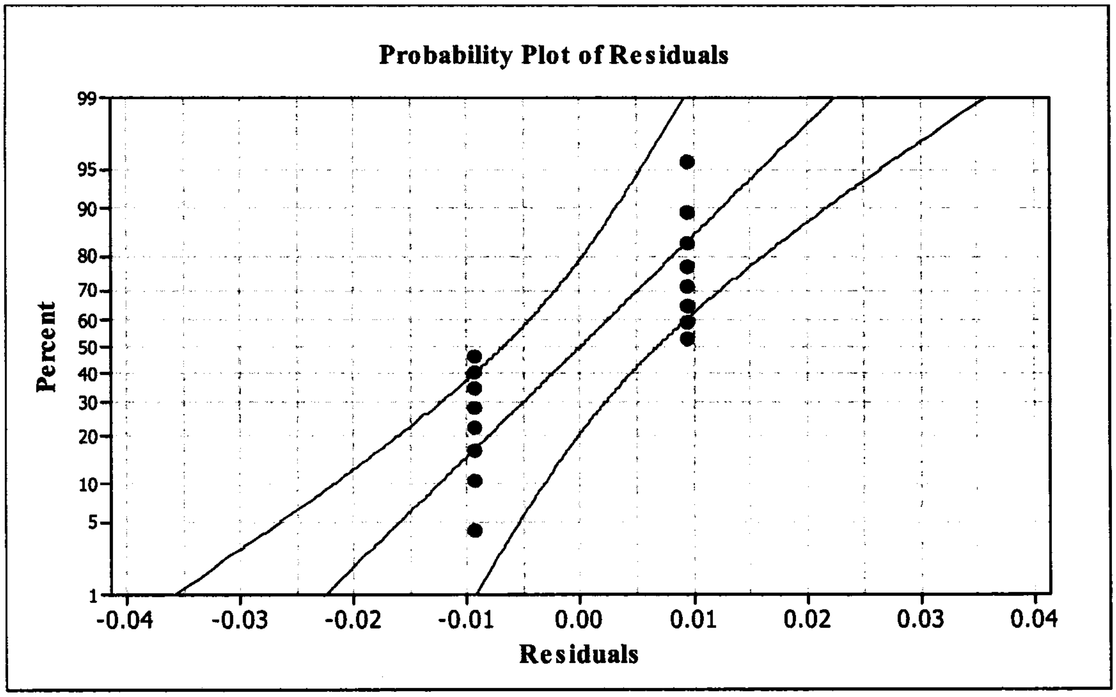


Figure 4.13: Normal Probability Plot of the Residuals



Equation 4.2 gives the regression model for predicting the weeks of inventory.

$$\hat{WI} = 2.10 - (\frac{0.65}{2}) * Postponement + (\frac{0.95}{2}) * DVar2 + (\frac{1.36}{2}) * FR - (\frac{0.22}{2}) * Postponement * DVar2 \qquad \text{....... (4.2)}$$

If we shift from non-postponement to postponement, its main effect will be to decrease inventory level by an amount of 0.65. Postponement will have a negative effect on inventory level. Postponement helps to reduce the inventory required. The main effect of demand variability, DVar2 causes an increase in inventory level when DVar2 increases. As the demand variability increases the inventory level increases by an amount of 0.95. More the demand variability more inventory will be required to satisfy the demand. The main effect of fill rate, FR causes an increase in inventory level when FR increases. To satisfy more demand or to increase the fill rate more inventory is required. The main effect of this factor is 1.36. A simultaneous increase in postponement and demand variability decreases the inventory level. This interaction effect is 0.22. We believe postponement being a dominating factor, the interaction effect of increasing both the values decreases the inventory level.

Figure 4.14: Main Effect Plot for WI

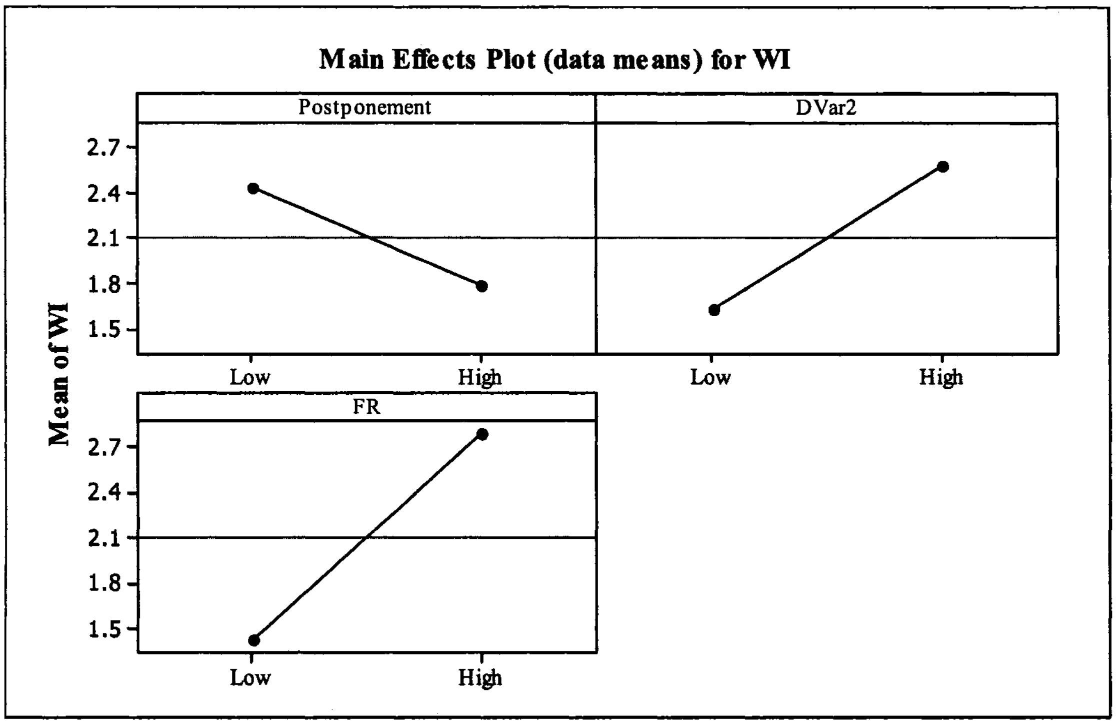
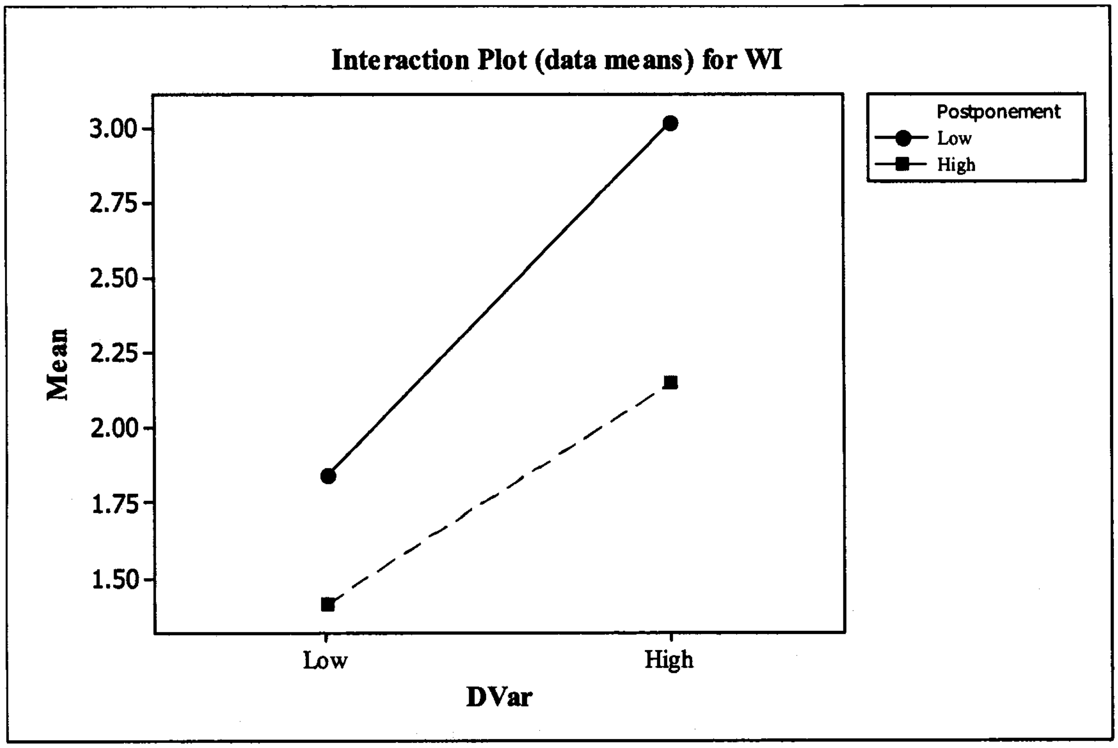


Figure 4.14 shows the main effect plot for inventory level. Postponement has a negative effect and factors such as fill rate and demand variability have a positive effect on the inventory level. If one shifts from non-postponement to postponement the inventory level decreases. If one desire to have a better fill rate the weeks of inventory increases. Demand variability has a positive effect on inventory level. If the demand variability is less, fewer inventories are required and if the demand variability is more, more inventories are required.

Figure 4.15 represents the interaction plots for inventory level. According to the figure if the demand variability is more, overall inventory levels are lower in postponement. As the demand variability increases the uncertainty increases and postponement performs better in this situation.

Figure 4.15: Interaction Plot of Postponement and Demand variability



4.3 Summary

Insights are gained in this chapter into the effects of changing the model parameters such as demand variability, demand correlation, number of products, inventory levels and fill rate. The results stated in this chapter were based on changing the value of only one model parameter at a time. A model based on changing more than one parameter at a time could provide results about the interaction between the model parameters. An experimental design was conducted to mitigate the problem and was also used to quantify the results.

The results suggest that postponement is always beneficial and there would be no conditions under which we would not want to do postponement. In section 4.2.1 we have seen that overall inventory levels are lower in postponement while maintaining the fill rate or the fill rate increases for a given level of inventory. At the same time if demand variability is high, postponement maintains a high fill rate as compared to non-postponement. In section 4.2.2 we observe that under high demand variability postponement helps to keep the inventory levels down. As the demand variability increases the uncertainty increases and postponement performs better in this situation

Chapter Five

Conclusion and Future Directions

This chapter provides concluding remarks about the postponement strategies in supply chain and future directions for research in this area.

5.1 Concluding Remarks

In today's manufacturing environment, where supplier variability and demand uncertainty cause chaos, and where customers want what they want, this results in excess inventory levels and fill rate is decreased. Hence a proper strategy is required to mitigate the effects of uncertainty while at the same time satisfy customer needs. Also various factors should be considered to quantify their measurements.

In this thesis we study the effectiveness of strategies like component commonality and delayed product differentiation. We also study how customer service level as well as inventory levels is affected by various parameters. Simulation modeling is used to capture the uncertainty and stochastic nature of the model. Several example problems are solved to identify the parameters which significantly influence the inventory level and fill rate and the results from the non-postponement and postponement scenarios are compared. The results showed that postponement requires fewer inventories than non-postponement. In addition, the benefits of postponement increases as the demand variability increases, demand gets negatively correlated, the number of products being postponed increases. Also for a given inventory policy, the fill rate achieved using postponement is higher than non-postponement.

Design of experiment is used to conduct and analyze controlled tests to evaluate the factors that control the value of fill rate and inventory level. In section 4.2.1 we found that the main effects of A (postponement), C (demand variability), and F (weeks of inventory) and the interaction AC and AF are significant. We found that if one shifts from non-postponement to postponement the fill rate increases and also if the inventory level is increased, the fill rate increases. If the demand variability is less, fill rate is more and more the demand variability less is the fill rate. Also overall inventory levels are lower in postponement while maintaining the fill rate or the fill rate increases for a given level of inventory. Postponement performs better with demand variability; postponement maintains a high fill rate as compared to non-postponement in case of high demand variability. As the demand variability increases the uncertainty increases and postponement performs better in this situation.

In Section 4.2.2 we found that the main effects of A (postponement), C (demand variability), and F (fill rate) and the interaction AC are significant. If one shifts from non-postponement to postponement the inventory level decreases. If one desire to have a better fill rate the inventory level increases. Demand variability has a positive effect on inventory level. If the demand variability is less, fewer inventories are required and if the demand variability is more, more inventories are required. If the demand variability is more, overall inventory levels are lower in postponement. As the demand variability increases the uncertainty increases and postponement performs better in this situation.

5.2 Future Directions for Research

In this research a single-period inventory-service-level model was constructed to compare the benefits of postponement. However, the scope of the thesis is confined to analyze the important factors. It does not consider other aspects such as postponement premium, the postponement capacity, and the point of postponement. The model presented in the thesis includes basic features of a stochastic modeling.

We would consider the following aspects for future research of this study:

- The decision cost model will recognize the cost of postponement that will influence the choice between non-postponement and postponement. Considering the cost perspective can give more insight into the benefits of postponement.
- A capacitated postponement model can further gain insight into the effects of postponement capacity on the ability to understand the benefits of postponement.
- More robust stochastic models can be developed which are capable of handling more complex supply chain networks.
- Other issues such as product life cycle, delivery frequency, economies of scale and product/process design can be integrated to construct a more sophisticated model.

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Appendix 1

Matlab Code to Calculate the Demand

```
clear all
clc
mu=35.71;
sigma2=5714.29;
left=0;
for i=1:336
result(i) = normlt_rnd(mu,sigma2,left);
end
result'
function result = normlt_rnd(mu,sigma2,left)

% computes random draws from a left-truncated normal
% distribution, with mean = mu, variance = sigma2
% y = normlt_rnd(mu,sigma2,left)
% where:   mu = mean
% sigma2 = variance
% left = left truncation point
% Returns: y =  the size of mu, sigma2

if nargin ~= 3
error('normlt_rnd: Wrong # of input arguments');
end;
right = mu + 5*sqrt(sigma2);
result = normt_rnd(mu,sigma2,left,right);
if result<left
   result=left;
end
function result = normt_rnd(mu,sigma2,left,right)

% random draws from a normal truncated to (left,right) interval
% y = normt_rnd(mu,sigma2,left,right)
% where:   mu = mean (nobs x 1)
% sigma2 = variance (nobs x 1)
% left = left truncation points (nobs x 1)
% right = right truncation points (nobs x 1)
% RETURNS: y = (nobs x 1) vector
%  y = normt_rnd (mu,sigma2,left,mu+5*sigma2)
```

```
% to produce a left-truncated draw
if nargin ~= 4
error('normt_rnd: wrong # of input arguments');
end;
std = sqrt(sigma2);

% Calculate bounds on probabilities
lowerProb = Phi((left-mu)./std);
upperProb = Phi((right-mu)./std);

% Draw uniform from within (lowerProb,upperProb)
u = lowerProb+(upperProb-lowerProb).*rand(size(mu));

% Find needed quantiles
 result = mu + Phiinv(u).*std;
 function val=Phiinv(x)

% Computes the standard normal quantile function of the vector x, 0<x<1.
val=sqrt(2)*erfinv(2*x-1);
function y = Phi(x)

% Phi computes the standard normal distribution function value at x
y = .5*(1+erf(x/sqrt(2)));
```