STUDY OF THE IMPACT OF SAFETY STOCK PLACEMENT ON SHIFTING BOTTLENECK STAGES IN CAPACITATED SUPPLY CHAINS

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DEDICATION

To Amma, Appa, my sister and my dear friends

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Lastly, I am thankful to my parents and family, without whom all of this would not have been possible.

ABSTRACT

Uncertainty in a modern supply chain structure originates at the supplier, manufacturing process and the consumer. Different types of products and supply chain structures add to the complexity of managing a supply chain. Safety stock in a supply chain acts like a shock absorber against these uncertainties. Current safety stock models are very effective in tackling strategic level problems, however are inept to understand the relation between the placement of safety stock in a supply chain and tactical level uncertainties. A bottleneck in a supply chain determines the capability of a supply chain. The shifting of stage bottlenecks is tactical level uncertainty. This thesis addresses the impact of placement of safety stock on shifting bottleneck stages. Simulation models establish the effects of varying stock levels on shifting bottleneck stages in capacitated assembly environment.

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CHAPTER I

INTRODUCTION

In the 1990's, industries across all sectors had to change their philosophy of meeting consumer demand. The strategy of "sell what you produce" no longer worked. The consumer began to drive the revenue of the companies. The advent of the Internet era in conjunction with the technological revolution increased the potential of the industries and the consumers manifold. On one hand consumers demanded variety of products immediately. On the other hand faster computing power and the availability of point of sales data forced industries to strive towards faster responsiveness and lower inventory costs. Today, supply chain management or the "system thinking" management has made suppliers, manufacturers, distributors and retailers to work together to form a supply chain. Each element in the supply chain is referred to as a stage. This chain has the flow of products toward the downstream stages (customer) and the flow of information towards the upstream stages (suppliers). In a perfect world, there would be no supply shortages, no break downs and every stage would work in unison to satisfy the customer demand. But in reality there are factors that deteriorate the performance of the supply chain. Lee, H.L., Padamanabhan, V. (1997) indicate that how some of those factors like improper demand forecast updating, order batching, price fluctuations and rationing can lead to excessive inventory investment, poor customer service, lost revenues, misguided capacity plans and missed production schedules.

The focus of the inventory manager has shifted from the localized optimization of the inventory costs to managing the inventory at every stage so that the total supply chain inventory cost is minimized. The uncertainty in the characteristics of the supply chain such as different supply chain networks, variety of products, variable capacity of the suppliers and uncertain customer demand makes the task of managing the inventory costs over the entire even more challenging. Elaborating further on the different supply chain characteristics, Stefan Miller (2000) classified the different supply chain networks such as assembly or convergent networks, divergent or distribution networks, cyclic, serial and acyclic networks. Marshall Fisher (1997) classified the products into two categories, functional and innovative. The product life cycle for the functional products (e.g. bread, soup) is larger as compared to that of the innovative products (e.g. electronic items, fashion wear). When a supply chain produces a mix of both functional and innovative products, also including the variety in each category, uncertainty causes havoc in managing common or independent inventory. The supply chain caters to different market segments and to satisfy the demand for these segments manufacturers procure raw material from different suppliers. Fluctuations in the delivery lead time of the suppliers and the disruptions caused within the manufacturer are also important characteristics that induce uncertainty making it a challenge to maintain the desired service levels.

Countermeasures to this uncertainty include either having safety stock at the stages in the supply chain, a flexible capacity or both. Now the question arises of how much of this safety stock is required to be carried at every stage which would take into account the various types of uncertainty discussed previously. Carrying inventory more than required results in an increase in the inventory holding costs and this is amplified in the case of expensive innovative products. This interest led to development of “Safety stock models”. These optimization models focus on determining the optimum safety stock inventory levels with simplifying assumptions such as no batches, stationary demand and fixed capacity. Relaxing any of these assumptions adds to the complexity of the model and could make the solution NP hard. Graves (2000) broadly classified safety stock models into two types. The stochastic-service model assumes the delivery or service time between stages can vary based on the material availability at the supplier stage. In other words the delivery times of the stages are stochastic in nature. The guaranteed service model assumes that each stage can quote a delivery or service time that it can always satisfy. This can be achieved by bounding the demand at stage. Bounding the demand to an upper bound makes it feasible and logical since this takes into account the practical bounds observed in the real world. This also facilitates in the solving the safety stock problem in more simplified and efficient manner which can be communicated with the upper management. Research conducted by Graves (2000) showed that at lower service levels the guaranteed service models yields lower total safety stock levels compared to the stochastic service models.

Since 2000, efforts have been made to incorporate various uncertainties such as non stationary demand, modeling for new products, general networks, cluster commonality and capacity to the safety stock models. There has been a shift in the nature of these models. Today the models stress being both strategic and tactical in nature.

Sitompul et.al, (2007) successfully show us the effect of taking capacity considerations in the safety stock model. However according to Orcun (2007) and Hopp and Spearman (2001) the delivery time of the stage follow a non linear relationship with resource utilization of the stage. Thus traditional safety stock models fail to the give an optimum advantage in setting safety stock when the lead times depend on the workload stressed on it.

The throughput of any network of the supply chain is governed by the bottleneck stage in the supply chain. All efforts are made so that the service levels at the bottlenecks are high. According to the Theory of Constraints principles the bottleneck should never be starved or sufficient safety stock levels must be maintained before the bottleneck stage. Also companies in order to be more efficient and reduce costs have incorporated process improvement techniques such as Lean, TQM and Kaizen. This in effect causes the lead time of the stages to constantly change and hopefully reducing the lead times. This effect can cause the bottlenecks to shift within the supply chain, introducing uncertainty in the supply chain. Roser et.al, (2002) further justify and detect, using simulation that the depending on the utilization of the different stages the bottleneck has the potential to shift within the supply chain.

Given the importance of developing the right strategies to counterattack uncertainty through solutions from the safety stock model, we take an effort to incorporate stage utilization and understand the impact of strategic safety stock placement on shifting bottleneck stages in capacitated supply chains.

1.1. Research Focus and Objectives

The focus of the research is to understand the relation between the placements of safety stock at the various stages on the shifting of bottleneck stages. The research takes its inspiration from Glasserman and Tayur (1995) and Roser (2002) to understand this relation between the placement of safety stock and shifting of bottleneck stages. Since there is little literature in this area, a counter intuitive approach is taken to firstly understand the effects of stock levels across the stages in a capacitated multi stage assembly environment. Thus the research objective is two fold

1. Analyze the increasing base stock levels on the stage bottleneck shifting characteristics
2. Analyze the effect of variation of demand, increasing base stock levels on the stage bottleneck shifting characteristics to achieve a desired fill rate.

1.2. Research Organization

Chapter 2 gives a background and overview of the areas in the research focus and Chapter 3 establishes the steps to develop the required simulation model for achieving the objectives. Chapter 3 further establishes the input variables and the performances measures needed. These variables and performances measures are linked to the simulation model developed to address the objectives of the thesis. In Chapter 4 the simulation results for various scenarios are analyzed and discussed. Chapter 5 presents the different conclusions based of the data analysis performed in Chapter 4. It also delves into arenas of future research.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

Production planning and inventory management are operations research areas that have a vast literature base. Over the years researchers have tried to understand the details of the different parameters in manufacturing. Nevertheless we have taken leaps and bounds in developing models that lower costs, decrease manufacturing lead time and simulate different scenarios helping manufacturing managers take better decisions.

Today, industries are focused on improving their throughput, delivery performance and lower manufacturing costs. One of the most evident outcomes, while embracing concepts such as JIT and Theory of Constraints (TOC), is reduction in waste and WIP to achieve higher throughput and lower costs. No doubt these approaches have shown to improve results. The goal is to understand the aftereffects while these principles are in place and utilize the conclusions to our best advantage.

Specifically, safety stock placement models give supply chain analysts the ability to counterattack uncertainty of demand by placing safety stock at the right place and with the right amount. However these safety stock models are strategic in nature and do not take into account the tactical level effects in the supply chain. A shifting bottleneck stage phenomenon is one such tactical level effect. “These shifts may for example be due to the sequence of random events or due to a gradual change in the manufacturing system” (Roser,2002).

Since connecting a strategic and tactical level problems is a challenging task, it is vital to understand the nature of the safety stock placement model and the shifting bottleneck phenomenon. A comprehensive literature review was conducted to the best of knowledge. The literature review comprises of three areas present in inventory management.

- Strategic safety stock placement models and Base stock analysis models in supply chains
- Workload dependent lead times for safety stock placement
- Shifting bottleneck detection model.

Each area gives a perspective and eventually leads to model our objective of studying the impact of safety stock placement and base stock levels on shifting bottleneck stages in the supply chain. While each area is reviewed, the background, the key performance indictors and the important concepts are also given the spotlight.

2.1 Strategic Safety Stock Placement

Supply chain is a network through which there is a flow of material from the supplier, manufacturer, retailer to the end customer. There is flow of information from the customers to the manufacturer. The diagram below illustrates the definition of a supply chain for the Kodak's digital camera assembly. Here the circles at different stages represent an operation and the triangles represent the presence of a safety stock.

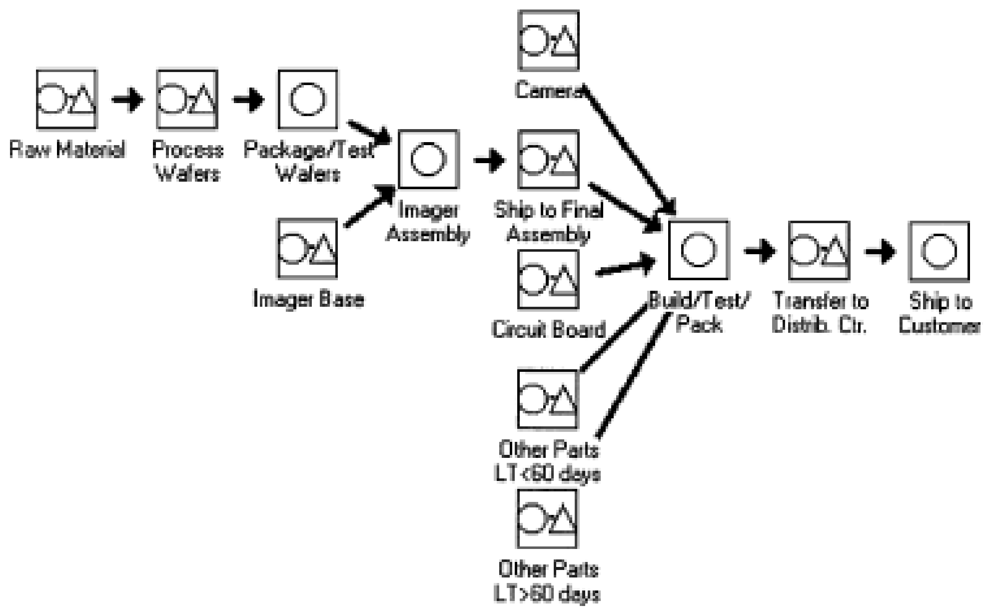


Figure 1. Kodak's Digital Camera Assembly Supply Chain (Graves and Williems, 2000)

In supply chain each stage adds value to the product either by physically changing it as in the case of manufacturing and assembly stages or transporting and storing the product as in the case of distribution stages. Regardless of the type, each stage has a processing time and a delivery lead time to the next stage.

2.1.1 Need for a Safety Stock Placement Model

There are three sources of uncertainty in a supply chain.

1. **Supply**: Uncertainty develops from the supplier when the supplier does not deliver the goods or raw material to the manufacturer when intended to.
2. **Manufacturing**: When machines break down unexpectedly, processing and delivery lead time of the manufacturing centers deviate from the normal time and is a source of uncertainty.
3. **Customer**: Customer demand is the most uncontrollable source of uncertainity. Depending on the market conditions or product marketability this is always a source of uncertainty that is introduced in the supply chain.

Uncertainty in a supply chain increases the operating costs and thereby reduces the supply chain profits. Inventory is one of the most prominent methods to counterattack uncertainty primarily because of the inability of the manufacturing and other supply operations to be highly flexible in short term. “Safety stocks are ‘excess’ inventories held beyond the minimum inventory level that would be possible in a deterministic and uncapacitated world” (Graves, 1998).

Safety stocks in operations help in smoothing of the production and “de-couple” the operations in the supply chain. By having safety stock between operations or stages of a supply chain uncertainty of the flow through either stages can minimize as the safety stock behaves like a “shock absorber”. Today, there has been a growing need for companies to simultaneously improve the delivery performance, maintain high service levels and reduce operating costs. This forces the various companies to look at supply chain perspective and develop a better coordination among them.

Safety stock placement models are used to determine the amount and the location of the safety stock in the stages of a supply chain with the objective of having the lowest supply chain operating costs at the determined service level.

2.1.2 Concepts

In this section we discuss in brief the concepts that are used in safety stock placement models.

2.1.2.1 Structure of the Supply Chain

Depending on the boundaries of investigation in general there are serial, assembly networks, divergent and general networks. Serial networks are those in which only a stage precedes and succeeds a particular stage. Assembly networks have two or more stages preceding a stage. In divergent networks a particular stage is succeeded by two or more stages. A general network is a combination of all of the above.

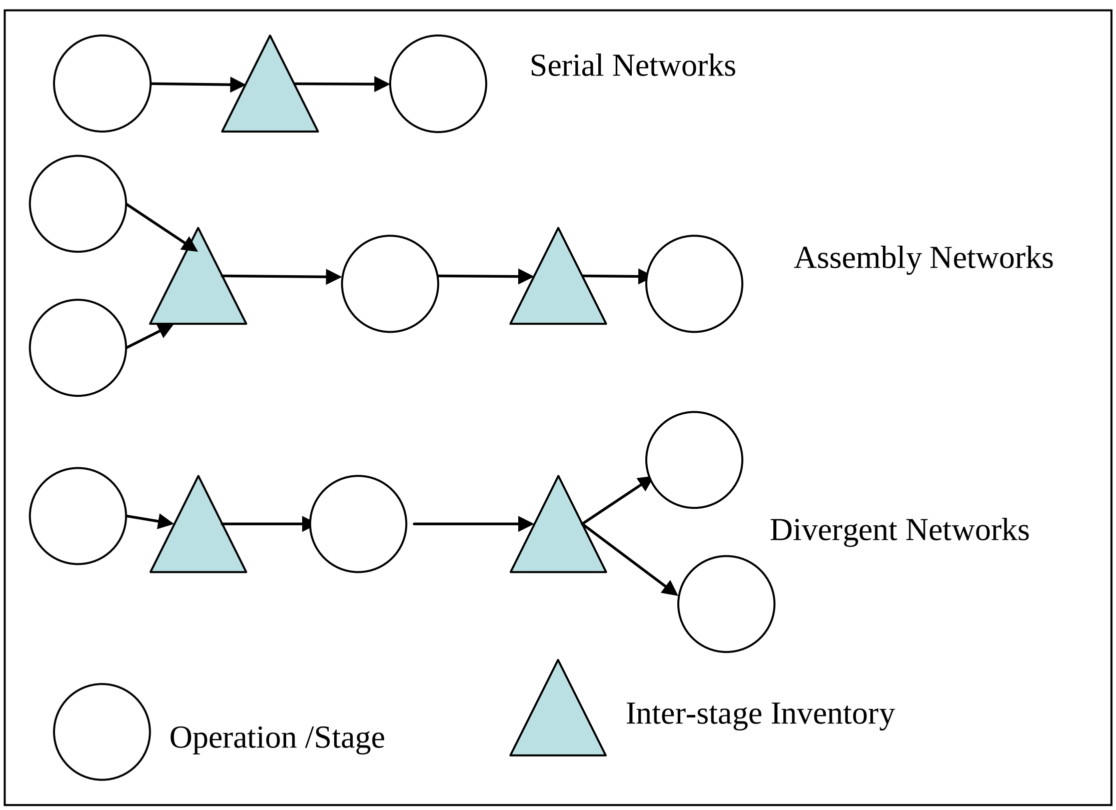


Figure 2. Different Types of Supply Chain Networks

2.1.2.2. Service Levels

In the safety stock models there are two types of service levels considered. The α type service level which is the probability of satisfying the demand from stock and γ type service level also known as the fill rate (Silver et al, 1998) is defined as 1- (The expected backorders at the end period/The expected demand during that period). Inderfurth and Minner (1998) considered these two types of service levels while solving the safety stock problem

2.1.2.3. Service Time

Service Time is the time a particular stage takes to supply material to the next stage. S_{it} is the delivery time for stage to the next stage i at the time period t.

2.1.2.4. Processing Time

Processing time or T_{it} is the time processing time required by stage i

2.1.2.5. Replenishment Lead Time and Net Replenishment Lead Time.

Replenishment Time for a particular stage is the time required to replenish a part once a production request has been made. Thus replenishment lead time is the service time quoted to that stage plus the production lead time. Net Replenishment Time is equal the replenishment lead time minus the service lead time at that stage. The Figure 3 below illustrate the various times with examples.

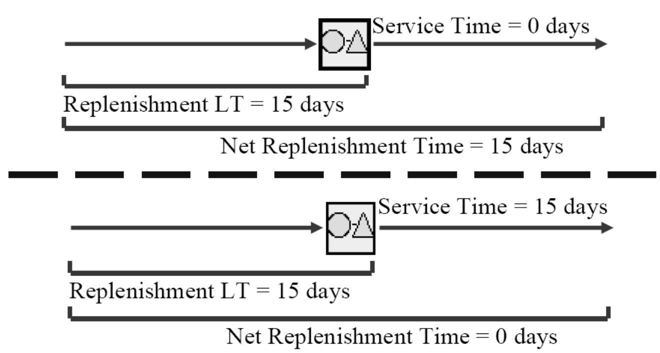


Figure 3. Service, Replenishment and Net Replenishment Time (Graves, 2005)

The Net replenishment time is denoted by τ_i as defined below

$$\tau_i = S_{i-1} + T_i - S_i \tag{2.1}$$

where i denotes the stage i

2.1.2.6. Demand and Bounded Demand.

Demand or the customer demand is placed at the last stage of the supply chain and that is communicated through the supply chain. The demand can either be modeled to be deterministic or stochastic in nature. When it is stochastic in nature the demand follows a distribution. Most of the models for simplicity assume the normal distribution with μ as the mean and σ as the standard deviation of the demand. Bounded Demand is that presumes that there is an upper limit on the demand at the end item level. The bounded demand concept is generally seen in guaranteed safety stock placement models. A bounded demand provides a tactical guidance for the placement of safety stock in a supply chain (Graves, 2000).

2.1.2.7. Stochastic Service and Guaranteed Service Model

According to Graves & Willems (2003) in the stochastic-service model "each stage in the supply chain maintains a safety stock sufficient to meet its service level target. In this setting a stage that has one or more upstream adjacent supply stages has to characterize its replenishment time taking into account the likelihood that these suppliers will meet a replenishment request from stock." And we know that due to the variability of the industrial environment, the suppliers cannot always satisfy the demand immediately from stock. Thus each stage will have a lag in getting its demand from its suppliers. Hence this stochastic nature of the delay causes the replenishment time for every stage to also be stochastic "The inventory level required at each stage to meet its service level target depends on its replenishment time." (Graves & Willems, 2000).

This view is changed in the guaranteed-service model. Here every stage gives a guaranteed service to its consequent stages. “In this setting, a supply stage sets a service time to its downstream customer and then must hold sufficient inventory so that it can always satisfy the service-time commitment.”(Graves & Willems, 2003, p.7). Here one of the main assumptions is that the demand is bounded so that the service provided can be guaranteed. As an effect, the service-time guarantee can be achieved with stocking the inventory to a fixed level. “The guaranteed nature of these service times ensures that the replenishment time for downstream stages is predictable and deterministic”. This then allows subsequent stages to arrange its inventory so that it can also make a service-time guarantee to its customers.

2.1.3. Safety Stock Models

The safety stock model has evolved over the years. Simpson (1958) was among the first to address the safety stock placement problem. This model address the problem on how big the “in process inventory” should be for optimum operating efficiency. The assumption of bounded demand makes sure that the inventory between two production stages can handle a demand only to a realistic level. For the proposed model the solution space is a convex polyhedron in Euclidean n-1 space where n is the number of stage. After solving the model the conclusion was to either have inventory equal to the base stock or have nothing .The Figure 4 below illustrates the solution space for 2 stages. Here Simpson (1958) states that the solution can occur at the vertices of the polyhedron.

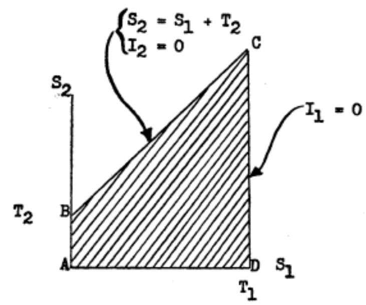


Figure 4. Solution space of convex polyhedron for 2 stages (Simpson, 1958)

Later Graves (1988, 2000 and 2003) established a model in lines of Simpson (1958) that would determine the amount and position of safety stock in serial, assembly and divergent supply chains. These models were solved using dynamic programming. Minner (2006) also established that the guaranteed service safety stock model developed by Graves was far more superior than the stochastic service approach to safety stock placement. The only assumption that Graves (2003) didn't work on is that of the capacitated model. Sitompul et.al., (2007) are one of the latest authors to have established a ground for capacitated safety stock placement. The meaning of the capacitated supply chain is that each production stage lead time is dependent on the order batch size. Since Sitompul et.al., (2007) encompasses the model created by Graves and Williems (2000) and Mapes(1992) and since this model of the capacitated safety stock placement is of interest we describe briefly their research. Sitompul et.al., (2007) establish a relationship between the excess capacity, demand variability and service levels to determine the influence of capacity on uncapaciated supply chain to maintain the same service level. The Figure 5 below gives us the diagrammatic relationship between the above parameters.

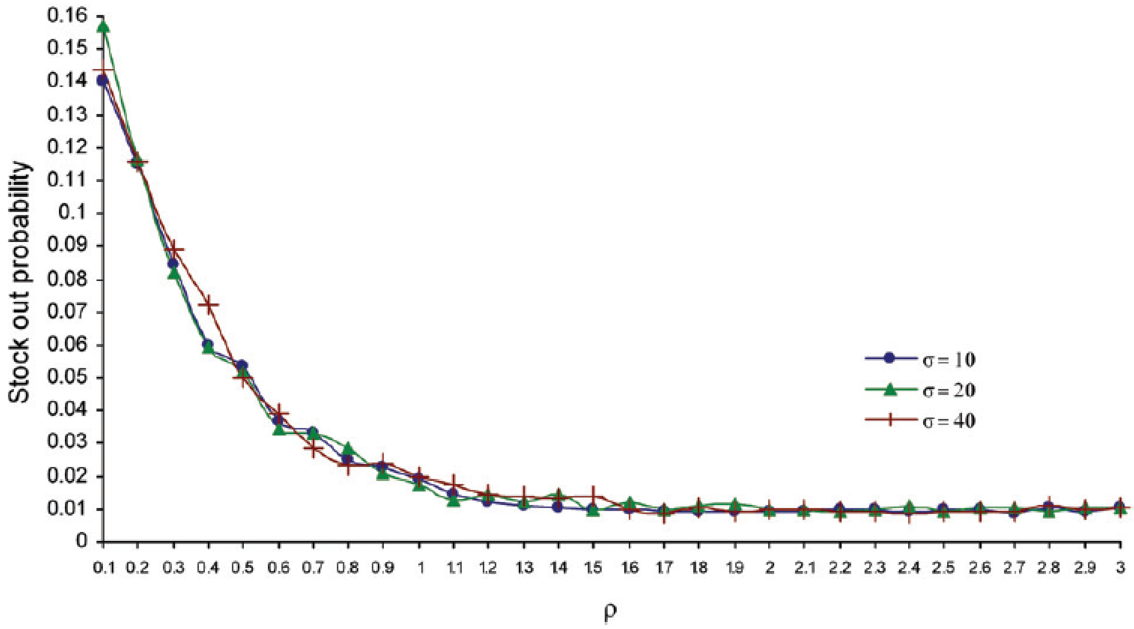


Figure 5. Relationship between the stock out probability, excess capacity and demand variability (Simtompul et. al., 2007)

Simulating the model for three different variance of the demand, they plot a graph between the ρ and the stock out probability.

$$\text{Where } \rho = \frac{\textit{Excess Capacity} - \textit{Demand}}{\textit{Standard Deviation of the Demand}} \qquad (2.2)$$

They also state that the effect of capacity is felt when ρ <1.5 .The Figure 6 below gives us the effect of ρ on safety stock.We can also the observe the effects on the standard deviation of demand. Thus as the standard deviation of the demand becomes more pronounced the effect of capacity is felt more when ρ <1.5.

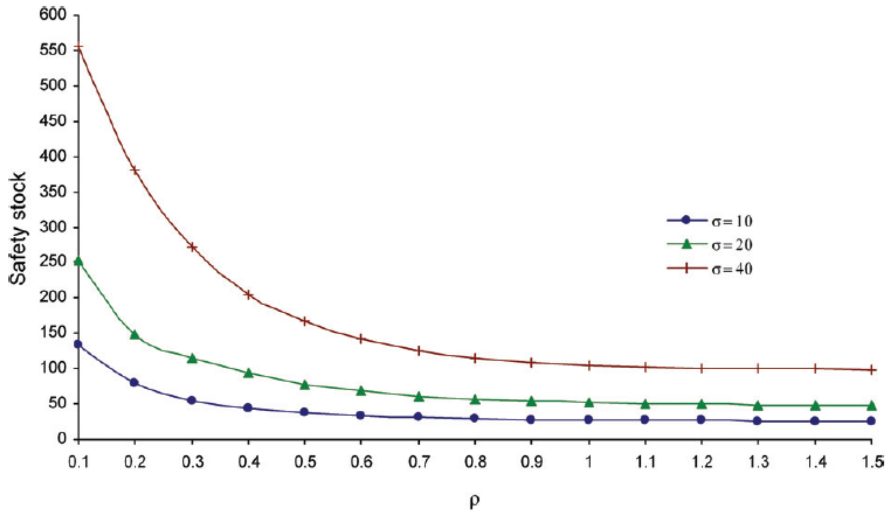


Figure 6. Effect of on safety stock with stock probability of 1% (Simtompul et.al. , 2007)

Thus it would be safe to assume that the safety stock placement problem behaves like an uncapacitated supply chain with *p*>1.5. They develop and add a correction factor (θ) to the already establish guaranteed model developed by Graves.

$$\theta = 1 + 5.25e^{-5.25(\rho - 0.075)} \tag{2.3}$$

Naturally the safety stock levels are high and can reach 6 times that of uncapacitated supply chain for a stock out probability of 0.01. For the maximum allowable demand (bounded demand) assumption according to Graves and Willems (2000) the base stock (B_i) for a stage i is given by

$$B_i = \mu\tau_i + z_\alpha\sigma\sqrt{\tau_i} \tag{2.4}$$

Here the safety stock (SS) is the second part of the equation. So in conjunction with the conclusion established by Simpson (1958) if τ<=0 there is no safety stock in supply chain. Sitompul et.al, (2007) added the correction factor to this part of the safety stock to take the capacity of the stage into account. Sitompul et.al, (2007) formulates the model for a single stage and then extended it to n stages. Thus service times for each stage is found based of the objective function of the minimizing the overall holding costs of the supply chain. From that the safety stock is calculated for each stage. They then simulated various capacity levels using Monte Carlo simulation. The detailed discussion of the safety stock levels at the different stages would be discussed in the model and simulation.

2.1.4. Models Analyzing Base Stock Levels for Multi Stage Supply Chains

Three papers by Glasserman and Tayur(1995), Lee and Billington (1993) and Ettl et al.(1996) develop strategies to identify the optimal base stock levels in a multi stage supply chain. Glasserman and Tayur (1995) do this by using infinitesimal perturbation analysis and simulation for capacitated supply chains. The other two papers try to identify the replenishment lead times using performance evaluation models for inventory at multiple stages. Eventually they solve the non linear optimization problem to minimize inventory costs subject to specific customer service levels.

2.2 Workload Dependent Lead Times for Safety Stock Placement

This literature has a connection in relation with the Graves model. Orcun (2007) is the latest author to reinstate the rule by Hopp and Spearman (2000) that “In capacitated environments the lead time increases as the resource utilization of the machines increases”. Orcun et.al, (2007) classifies their literature into three areas.

a. Optimization models for production planning

b. Stochastic inventory models

c. Queuing models.

a. **Optimization models for production planning:** The objective of production planning models is to allocate production capacity among different products over time in order to optimize some objective function, most commonly the sum of variable production costs, inventory holding and backorder costs over a finite planning horizon. These models have generally approached the problem as a deterministic optimization problem, where stochastic quantities are represented by deterministic estimates.

b. **Stochastic inventory models**: These models focus heavily on the stochastic nature of the demand and have a very simple replenishment process. Very few have considered limited production capacity and those who consider them assume workload independent lead times. Liu et al (2004) link a queuing model with an inventory model to examine the effects of lot-sizing on inventory levels in a multi-stage production-inventory system. A different approach by Graves (1988) hypothesizes a linear relationship between inputs to the production system and the outputs by having the production output as a fraction of the WIP level. Their approach characterizes the distribution of the finished goods inventory level and set safety stock level accordingly. Stochastic inventory models focus on long-run expected performance, and generally do not consider workload dependent lead times.

c. **Queuing models**: Queuing models capture the workload dependent nature of lead times correctly, but their long-run steady-state nature does not lend itself to planning safety stocks in the short term.

The literature indicates that when the replenishment lead time is dependent on the workload, the conventional models do not provide the base stock levels to satisfy the required service levels. Orcun (2007) uses a simulation environment to examine the problem of setting the safety stock in environments with workload dependent lead times. In a sense they examine how the classical inventory models faced difficulty in setting the safety stocks in capacitated environment.

Following were the characteristics of the model by Orcun (2007)

1. Two stage serial supply chain
2. The capacitated production facility has its behavior represented by the clearing function used in Orcun (2006)
3. The model is developed in a SCOPE (Supply Chain Optimization and Protocol Environment) environment. SCOPE environment is used for the rapid evaluation of supply chain configurations. SCOPE views a supply chain as a directed graph whose nodes represent facilities such as manufacturing plants and distribution centers, while arcs represent both information and material flows. Information flows are divided into a backward information flow (backward pass) and forward information flow (commit pass) in addition to forward material flow (realization pass)

Here Orcun (2006) take the utilization factor into consideration while determining the cycle time. The formula below gives the relationship between total cycle time, raw processing time (RPT) and the WIP in the system.

$$CT = RPT + U_d\left(\frac{WIP}{C_d}\right) \tag{2.5}$$

Where Ud is the desired average utilization and the C_d is the desired capacity that is utilized.

In general following were the main highlights of their conclusions.

1. Firstly they simulate a scenario wherein the supplier would behave in a make to order model (Baseline scenario).Then three scenarios are analyzed. Scenario “a” uses the simulation history generated in the baseline scenario to estimate the mean and variance of the lead time to determine the base sock level. Scenario “b” takes the historical data from the baseline scenario but takes variance as zero and lastly scenario “c” sets the mean of the lead time is set to the desired utilization levels.

2. Due to non-linear dependence of lead time to utilization, throughput no longer follows the demand stream's independently identically distributed characteristic and hence the safety stock does not guarantee the customer satisfaction level.
3. Scenario "b" does not perform as well as scenario as the cost of unit improvement in customer satisfaction is lower than scenario "a" which indicates diminishing rate of return.
4. Scenario "c" highlights the fact that it is not cheap to hedge the demand variability with work-in-progress inventory.

2.3 Shifting Bottleneck Detection Model

The Shifting bottleneck approach is based on the Theory of Constraints Goldratt (1992). Roser et al (2002) state in their paper that even though there is a primary bottleneck in the a supply chain its not necessarily static (Lawrence and Buss 1994; Moss and Yu 1999). "These shifts may for example be due to the sequence of random events or due to a gradual changes in the manufacturing system"(Roser,2002, p1). Thus in a long term there exists secondary and tertiary bottlenecks. Thus depending on the configuration and the characteristics of supply chain, a machine would remain a certain percentage of the time as primary or a sole bottleneck and certain percentage of time as a shifting or a momentary bottleneck. A primary bottleneck or sole bottleneck according to Roser et.al.,(2002) is that machine that has the longest average active duration that it remains active. A shifting bottleneck is a bottleneck which is for temporary period the stage that has the longest active duration depending on the active state of another stage in its immediate vicinity. The term secondary bottleneck refers to the second highest average active stage. Another important measure used for bottleneck shiftiness is β cited in Roser et.al.,(2002)

$$\beta = 1 - \frac{c_v}{\sqrt{n}} \tag{2.6}$$

c_v is the coefficient of variation of the bottleneck probability, which is the probability that it is the bottleneck and n is the number of machines or stages. Roser et. al., (2002) use simulation to identify the shifting bottlenecks. They further use this model to establish the size of the buffer or inventory between the machines. Although the model does not take into account the demand on the system. Depending on the active duration and the inactive time of particular stage found out in the simulations and the utilization of stage/machine, the machine or in this case the stages behave for certain percentage of time as a primary bottleneck and a secondary bottleneck. The Figure 7 below illustrates a snapshot of the simulation run performed by Roser (2002). Here we the percentage of simulation run the stages M1 and M2 were shifting and sole bottlenecks.

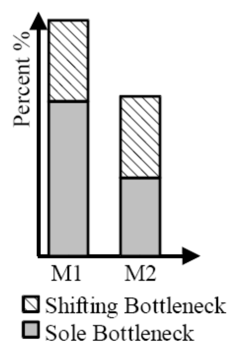


Figure 7. Primary and Secondary Bottleneck percentage for different stages (Roser, 2002)

Wang et.al,(2008) identify a unique approach to use the queue length before stages to identify the bottleneck and its shifting nature. They associate every stage with a global bottleneck degree which is a parameter obtained from exponentially transforming the queue length. Thus a real time comparison of the global bottleneck degree can be performed at the various stage to detect the bottleneck and shifting characteristics. Later on the simulation model used in this paper primarily relies on this method to detect the shifting bottleneck stages.

2.4 Insights from each area to establish the objective.

Sitompul et.al,(2007) capacitated model is based on an already well established and easy to understand model developed by Graves which addresses the placement of safety stock in guaranteed supply chains. Here they use dynamic programming and Monte Carlo simulation to solve their problem. Orcun’s model gives a firm model of the effects of utilization of production stage lead time. They use simulation to solve their scenarios. The bottleneck detection model is clear in its purpose of establishing the fact of shifting of bottlenecks. They use simulation to solve their model. Also this model is not complex and can be solved in a single simulation run.

After a comprehensive review it was found that these three different areas should not be seen differently and must viewed as whole. Roser et.al, (2003) has made an effort to study the placement of buffer stock in the different stages based on the shifting bottleneck. But this model does take into account the advantages of the bounded demand in capacitate supply chain as seen in the case of Sitompul’s capacitated model.

In order to the take into take account the non linear characteristic of the stage lead time in safety stock placement in capacitated supply chains it is vital to include the utilization of the stage in it. By taking the advantages of all these three models we can better understand the impact of safety stock placement on shifting bottleneck stages in capacitated supply chains. However to solve with such models derived in section 3.1 would be results in the solution to NP hard without giving insight to the understanding of the relation between the bottlenecks shifting stages and the placement of safety stock. Furthermore all the previous models try to minimize inventory costs meeting a certain service levels. In order to understand the relation between the shifting bottleneck phenomenon and the placement of safety stock one would have perform experiments to analyze the effect varying base stock levels on the stage bottleneck shifting.

CHAPTER III

SOLUTION METHOD

Ideally the solution approach would be to develop an analytical model that incorporates the effects of the resource utilization to determine the proportion of safety stock in the supply chain with an objective to reduce the supply chain costs. In the next section an analytical model is constructed. Later on, the disadvantage of solving such a model is discussed and a more pragmatic approach to understand the problem is stated.

3.1 Safety Stock Model Incorporating the Utilization Factor

In this section we use the equation derived by Roser et.al., (2002) as a constraint on the model developed by Sitompul et.al., (2002).

From equation (2.5) we see that

$$CT = RPT + U_d\left(\frac{WIP}{C_{di}}\right)$$

where *RPT* is the Raw Processing time of a stage.

CT is the cycle time or service time of stage i

U_{di} is the desired utilization of stage i

C_{di} is the desired capacity of stage i and *WIP* is the work in progress of stage i

For consistency of the notation we replace CT_i by S_i.Also assuming that the processing time for all the stages is 1 we have

$$S_i = 1 + U_{di}\left(\frac{WIP_i}{C_{di}}\right) \tag{3.1}$$

Now by Little's Law

$$WIP_i = S_i \times Throughput \tag{3.2}$$

Throughput is the desired demand or μ. So substituting μ and equation (3.2) in equation (3.1) we have.

$$S_i = 1 + U_{di}\left(\frac{S_i\mu}{c}\right) \tag{3.3}$$

Therefore, we can state the limit constraint for the delivery time of a stage as

$$S_i = \frac{C_{di}}{(\mu C_{di} - U_{di})\mu} \tag{3.4}$$

For consistency of the notation we have the service time for a stage as

$$S_i = \frac{C_i}{(\mu C_i - U_i)\mu} \tag{3.5}$$

This additional constraint (3.5) to the mathematical model formulated by Sitompul (2007) takes into account the utilization factor necessary for the safety stock model in capacitated supply chains.

So, the model is similar to the Sitompul's (2007) model with the additional constraint. Thus if h_i is the holding cost of each stage, safety stock model with the additional constraint would be

$$\text{Minimize } \sum_{i-1}^{N} h_i SS_i$$

Subject to

$$\rho_i = \begin{cases} \dfrac{(c_i - \mu)\sqrt{\tau_i}}{\sigma} \; if\ \tau_i > 0\ \forall_i = 1\ to\ n \\ \dfrac{(c_i - \mu)}{\sigma} \; if\ \tau_i \leq 0\ \forall_i = 1\ to\ n \end{cases} \tag{3.6}$$

$$\theta_i = 1 + 5.25e^{-5.25(\rho_i - 0.075)}\forall_i = 1\ to\ n \tag{3.7}$$

$$SS_i = \begin{cases} \theta_i\ z_\alpha \sigma\sqrt{\tau_i}\ if\ \tau_i > 0\ \forall_i = 1\ to\ n \\ \theta_i\ \sigma(\max\ (0, z_\alpha - \rho_i)\ if\ \tau_i \leq 0\ \forall_i = 1\ to\ n \end{cases} \tag{3.8}$$

$$S_1 = 0, S_{n+1} = 0$$

$S_n \leq M\forall_i = 2\ to\ n$; where M is the maximum allowable service time

$$S_i = \frac{C_i}{(\mu C_i - U_i)\mu}$$

Though the analytical model formulated above would be appropriate to solve the problem of determining the amount of safety stock when an effect of the utilization is imposed. However the model could render a NP hard solution and does not clearly give us an understanding between the effects of placement of safety stock and the bottleneck shifting stages.

3.2 Problem Definition

A bottleneck stage in a supply chain is a stage that has the longest average utilization and determines the throughput of the supply chain. However, in a particular period depending upon the utilization of the stages the bottleneck in the supply chain shifts through the supply chain. Thus when the utilization of each stage is the same, the probability that the bottleneck may shift increases (Roser, 2002).This is an uncertainty that is introduced in the supply chain. So far the cheapest and the least capital intensive way to tackle demand and process uncertainty is to allocate safety stock. However current models are inept to understand the relation between the shifting phenomenon and the stock levels at the different stages. Since the base stock levels at stage comprise of pipeline and safety inventory. It is imperative to primarily to develop an understanding between base stock levels and the stage bottleneck shifting parameter. In other words, the research problem is to prove a relation between the two. The research problem would be addressed by

1. Analyzing the increasing base stock levels on the stage bottleneck shifting characteristics
2. Analyzing the effect of variation of demand, increasing base stock levels on the stage bottleneck shifting characteristics to achieve a desired fill rate.

3.3 Solution Approach

The solution required adopting an assembly model of three parts which were processed parallel. Complexities such as different routing patterns and lead times were chosen such that the effect of the shifting of bottleneck stages could be analyzed clearly. A simulation model of the above supply chain structure was done under a base stock control policy. The simulation model was used to address the two fold research problem. Then case studies were used to run the models with increasing base stock levels and different combinations of coefficient of variation of demand and base stock levels. The results obtained from the simulation model using the different case studies were analyzed to see if they were significant. Later on appropriate conclusions were drawn on the effect of the varying parameters on the shifting bottleneck stages. A schematic diagram of the solution approach is shown in Figure 8.

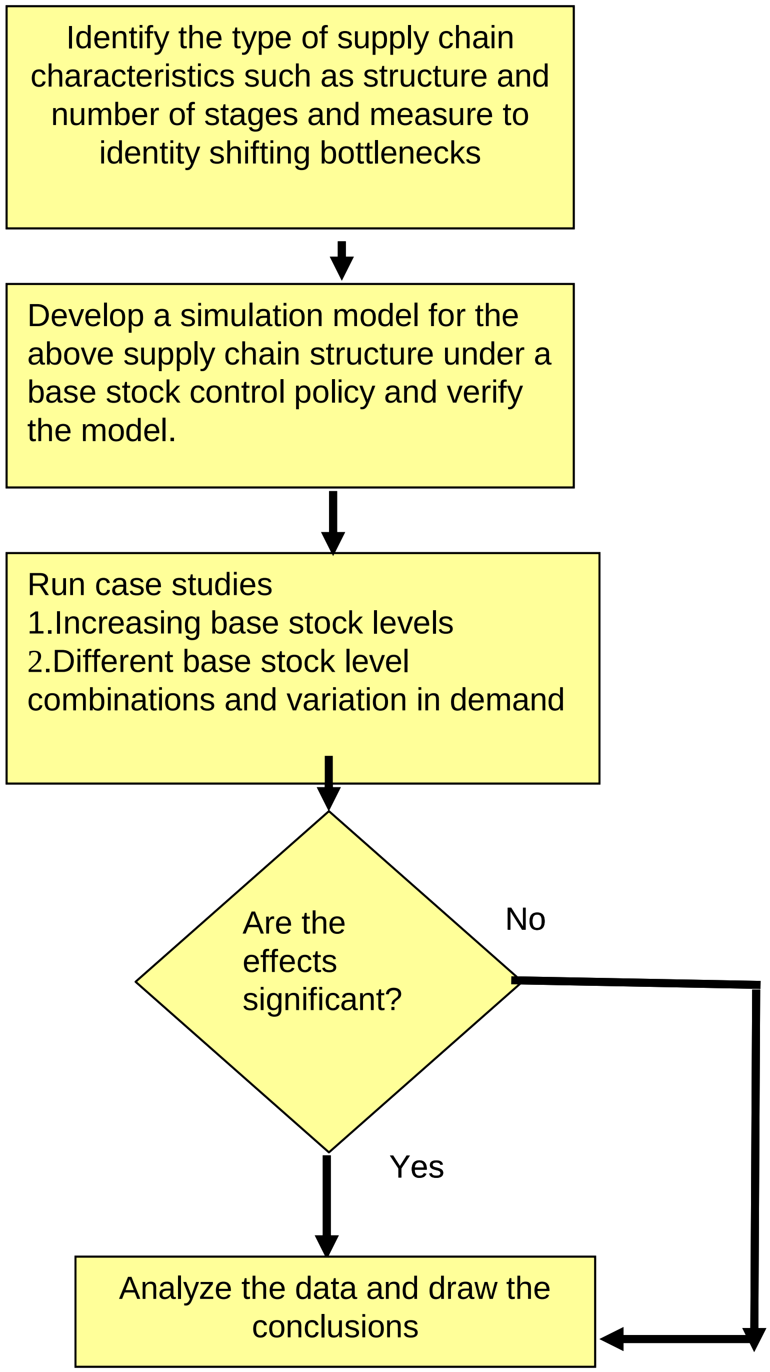


Figure 8. Solution Road Map

3.4. Simulation Model Architecture

In order to address the objectives of the research design, the simulation model had to be designed in way that it performed the following main functions in a capacitated assembly enviorment.

1) Calculate the signal for production for a stage when demand occurs under a base stock control policy

2) Control the Bottleneck shiftiness parameter (β)

3) Set Base Stock Levels and Demand

4) Capture the Bottleneck Shiftiness parameter (β), Fill rate ,Utilization and Cycle Time

Before delving into the details on how each of functions were designed into the model, the next two sections would discuss the basic structure and the assumptions taken in consideration while designing the model.

3.4.1 Basic Structure

Essentially the model is that of a 2 echelon 4 stage push assembly system of three parts. The three parts; Part A,B and C together at the end are assembled to form one final product. Specifically, the Part A and Part B flow through Stage 1 and Stage 2 while Part C flows parallely through Stage 3 and Stage 4. Figure 9 below illustrates the same.The triangles before each Stage are the inventory holding locations for the respective parts. E1A would be the inventory holding location for Part A after it has been processed by Stage 1. During a production signal, Stage 2 sources Part A from inventory holding location E1A. Similarly the Finished good is assembled from one part from each inventory holding loaction E2A, E2 B and E2C.

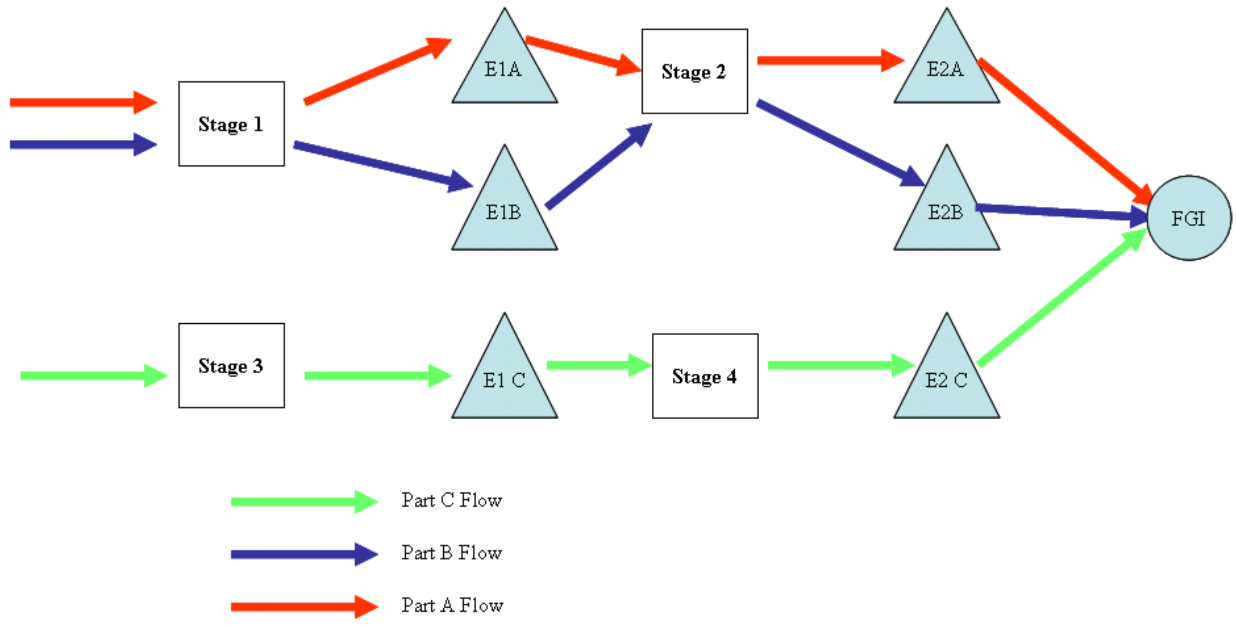


Figure 9. Three Part Assembly Model

The lead times are exponentially distributed and different processing time of parts at the different processes are listed below.

TABLE 1 LEAD TIMES (HOURS)

Part	Stage1	Stage2	Stage3	Stage4
A	0.5	0.5	-	-
B	1.5	1.5	-	1
C	-	-	2	2

The reasons for choosing these lead times and the Part B having a Stage 4 lead time is explained in the section 3.4.4. which descibes how the bottleneck shiftiness parameter is controlled. Theoretically one unit Part A and Part B after processing through Stage 1 and Stage 2 takes 4 hours. Likewise one unit of Part C gets processed parallely through Stage 3 and Stage 4 after 4 hours.Thus one Finished Good Inventory(FGI) can be assembled in every 4 hours.

The level of stock at after each stage and for each part is called the base stock level for that stage and part. Every stage must process depending on the avaliability of raw material to fulfill that stock level when demand at the FGI occurs.So the parts are pushed till FGI Level and the customer pulls from the FGI level according to the base stock control policy.

3.4.2 Assumptions taken Designing the Simulation Model

1) Lead times for the products at each stage are exponentially distributed

2) The supply in unlimited .i.e. there always be raw material available

3) The demand is unlimited. Here the definition of demand being unlimited is in relation to the capacity of the assembly system .So ideally the system should assemble one Product every 4 hours. The demand is unlimited by having 3 parts every six hours

The next for section would describe how the main functions were designed into the basic structure.

3.4.3 Production Signal to a Stage when Demand occurs under a Base Stock Control Policy

The Base stock control policy is that of an installation base stock control policy which indicates the presence of decentralized inventory control policy. Here every stage takes the decision independently on how much it must order from the previous stage. However the time every stage takes that decision depends on when the customer places an order. Taking this analogy to the basic structure of the model every stage has its own inventory holding location for each part it can process. This inventory holding location has a set base stock level that the stage must try to achieve when a demand by the customer is placed. As soon as the demand occurs, every stage would access the level of stock at the inventory holding location add it to the amount of parts that are in process and compare it to the base stock level set. Since this is an assembly environment with lost sales for the purpose of simplicity the model does not take into considerations of any backorders.

Thus,

$$\text{Production Signal } (i-1) = B(i) - IP(i) \tag{3.9}$$

Where B(i) is the Base stock level at stage i , for i= 1 to n

IP(i) is the Inventory postion at stage i, for i = 1 to n

3.4.4 Control over the Bottleneck Shiftiness Measure

The control over the bottleneck shiftiness measure can be achieved in two ways

1) Processing Times of the Parts through the stages
2) Route that the Parts flow through the Stages

A Bottleneck Stage is defined when the demand at the stage is greater than the capacity. Lawrence and Buss (1994) devised a bottleneck shiftiness measure β as shown in equation below where Cv is the coefficient of variation of the bottleneck probability of the different machines and n is the number of machines in the system. The bottleneck shiftiness measure β ranges from zero for a system with a unique bottleneck to one for a system where all machines are equally likely to be the bottleneck. From equation(2.6) we have,

$$\beta = 1 - \frac{c_v}{\sqrt{n}}$$

β =1 we have all the processes/Stages to be a bottleneck.

So we determine the process to be a bottleneck by measuring the number of parts in the front of the process. Ideally the process that has maximum number of parts in front of it can be called a bottleneck machine but this measure has many short comings due to space constraints and also it is very variable. Wang (2008) method exponentially transforms this number into a value that lies between 0 and 1. Thus every moment of time every machine will have a Bottleneck degree that lies between zero and 1. As this measure is highly sensitive at lower values, an exponential smoothing process is used and the resulting number is compared to determine the Bottleneck. The stage that has the highest bottleneck measure is the bottleneck for that moment of time.

The reason for choosing the processing times for parts at their respective stage is for the purpose having a balanced system. A balanced system here is the all the stages would a bottleneck. Ideally every stage takes 2 hours to process parts necessary to make a complete assembly. Thus the processing times chosen allows achieving a system where in all the stages are bottlenecks When all the four stages are bottlenecks the bottleneck probability of the four stages is 25%. Thus the bottleneck shiftiness measure is 1.

In order to understand the effects of setting base stock levels on the bottleneck shiftiness measure it is also necessary to control the bottleneck shiftiness measure. So in order to achieve that certain percentage of Part B after getting processed from Stage 1 is diverted to Stage 4. Thus this decreases the bottleneck shiftiness measure or in other words reduces the number of bottlenecks. After initial simulation runs with different percentages of Part B diverted to Stage 4 it was found that the system would have one bottleneck when 20% of the Part B coming out Stage 1.This concept not only control the bottleneck shiftiness measure but also helped develop three types of Models or system with progressively decreasing nature of bottleneck shiftiness.
Model 100 is a balanced system with all the Stages as bottlenecks. Model 90 has 10% of part B diverted to Stage 4 thus makes giving us a slightly biased system. Lastly Model 80 is completely biased system with 10% of the part B diverted to Stage4.

The Schematic diagram below shows the flow of the parts A ,B and C. for Model 100.Model 90 and Model 80.

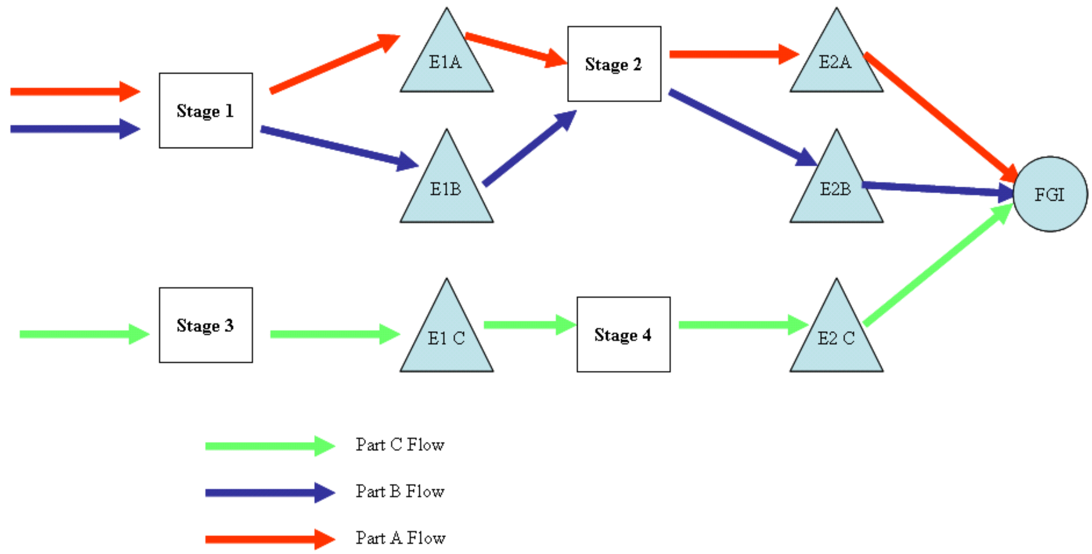


Figure 10. Model 100 (Balanced System)

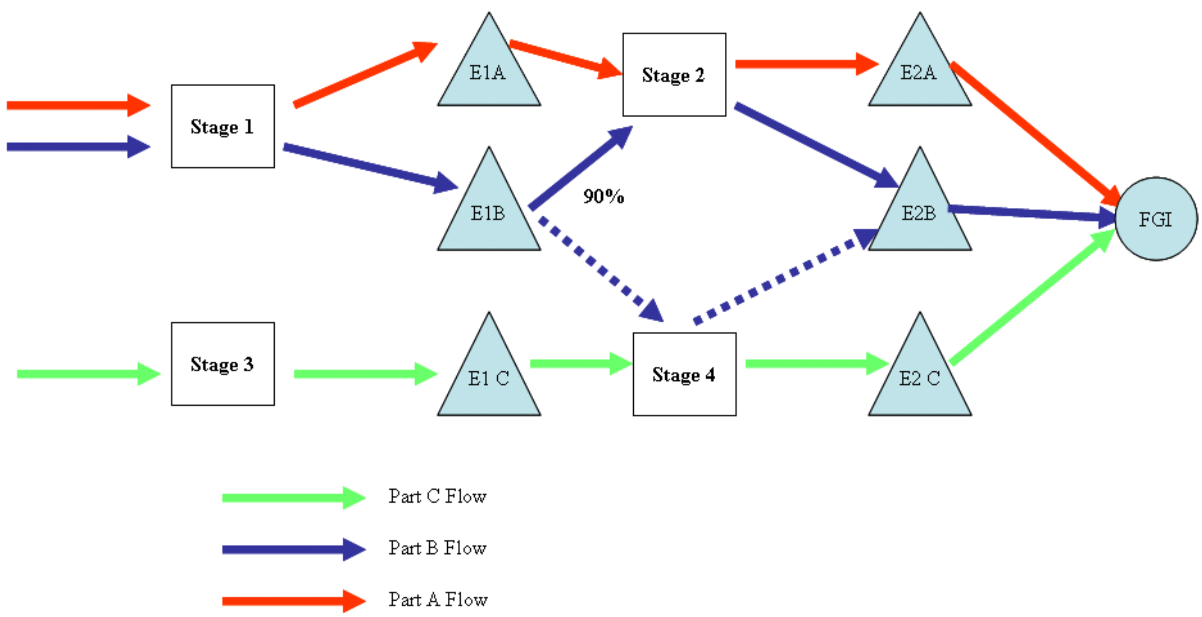


Figure 11. Model 90 (Slightly Biased System)

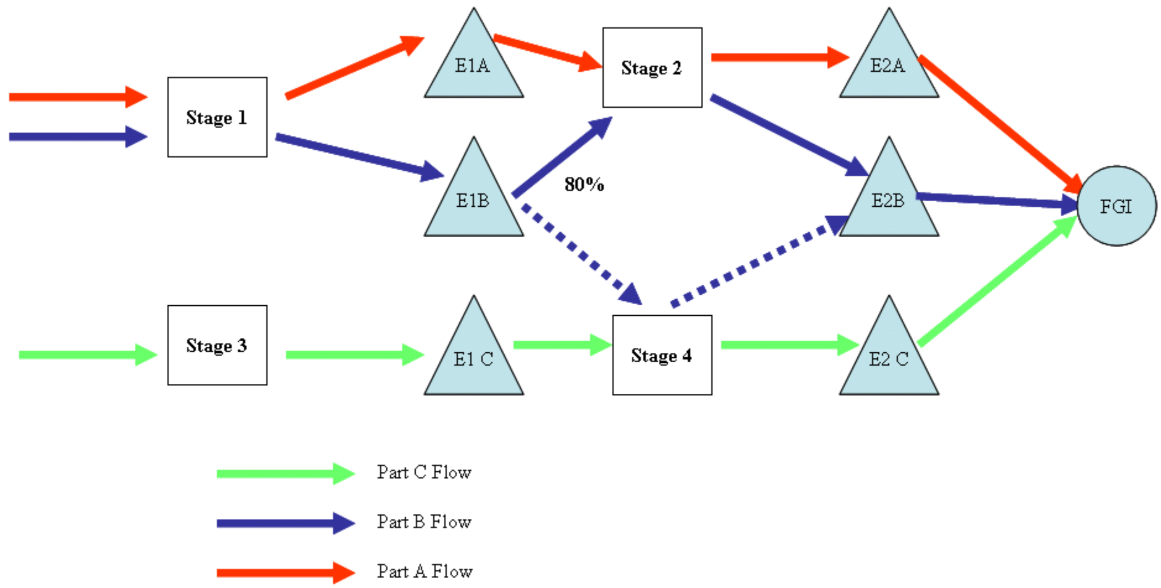


Figure 12. Model 80 (Fully Biased System)

3.4.5 Setting the Base Stock Levels and Demand

The base stock levels for each stage and the respective part is set manually and is one of the simulation variables. Thus when the simulation calculates the production signal by comparing the inventory level to the base stock of that stage, it is necessary that the appropriate base stock level variables are entered before the simulation run. This also gives the flexibility to change the base stock levels during the analysis.

In the simulation model the customer demand is normally distributed .The mean and standard deviation of the demand are the input variables to the simulation model and is set manually before the simulation model is run.

3.4.6 Capture Bottleneck Shiftiness Parameter (β), Fill rate ,Utilization and Cycle Time

In order to understand and capture the bottleneck shiftiness parameter it is necessary to monitor and capture the number of parts that are being processed at stage at a particular point of time. This data is in turn used to determine the bottleneck shiftiness parameter β as discussed in the earlier section 3.4.5. This data is very unique to the simulation model and can only be extracted by placing an output function from Arena to an Excel File. This output function exports the required queue data every hour of the total simulation run cycle. In the total simulation run of 4000 hours only the last 3000 hours is taking to determine the Bottleneck shiftiness measure. Thus the data is discarded when the simulation model is in the transient state. Thus bottleneck probability of the stages is obtained for a simulation run. Thus the Cv of the bottleneck probability and β is calculated

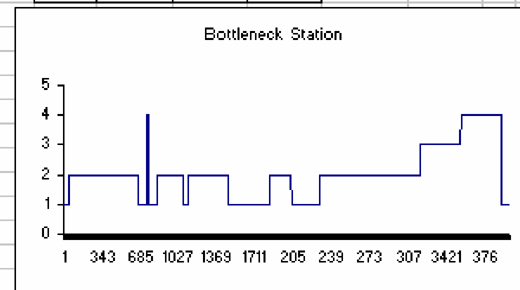
A snapshot of the Excel template used for capturing β is shown in Figure 13 .

			Queue Length				Bottleneck Degree				Bottleneck Degree				Bottleneck
2	Run	Time	P1	P2	P3	P4	1	2	3	4	1	2	3	4	Station
3	1	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1
4	1	1	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1
5	1	2	0	1	0	0	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	2
6	1	3	0	1	0	0	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	2
7	1	4	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
8	1	5	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
9	1	6	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
10	1	7	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
11	1	8	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
12	1	9	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
13	1	10	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
14	1	11	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
15	1	12	6	0	2	0	0.21	0.00	0.06	0.00	0.00	0.00	0.00	0.00	1
16	1	13	6	0	2	0	0.21	0.00	0.06	0.00	0.00	0.00	0.00	0.00	1
17	1	14	8	0	3	0	0.27	0.00	0.10	0.00	0.00	0.00	0.00	0.00	1
18	1	15	8	0	3	0	0.27	0.00	0.10	0.00	0.00	0.00	0.00	0.00	1
19	1	16	8	0	2	0	0.27	0.00	0.06	0.00	0.01	0.00	0.00	0.00	1
20	1	17	6	0	1	0	0.21	0.00	0.03	0.00	0.01	0.00	0.00	0.00	1
21	1	18	5	0	0	0	0.18	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1
22	1	19	3	0	0	0	0.11	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1
23	1	20	1	0	0	0	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1
24	1	21	7	6	0	3	0.24	0.17	0.00	0.06	0.01	0.00	0.00	0.00	1
25	1	22	7	5	0	3	0.24	0.15	0.00	0.06	0.01	0.00	0.00	0.00	1
26	1	23	5	5	0	3	0.18	0.15	0.00	0.06	0.01	0.00	0.00	0.00	1
27	1	24	4	5	0	3	0.14	0.15	0.00	0.06	0.01	0.00	0.00	0.00	1
28	1	25	8	7	2	5	0.27	0.20	0.06	0.10	0.01	0.00	0.00	0.00	1
29	1	26	8	7	2	5	0.27	0.20	0.06	0.10	0.01	0.01	0.00	0.00	1
30	1	27	8	4	2	5	0.27	0.12	0.06	0.10	0.02	0.01	0.00	0.00	1
31	1	28	7	3	1	4	0.24	0.09	0.03	0.08	0.02	0.01	0.00	0.00	1
32	1	29	9	3	2	5	0.30	0.09	0.06	0.10	0.02	0.01	0.00	0.00	1
33	1	30	9	3	2	4	0.30	0.09	0.06	0.08	0.02	0.01	0.00	0.00	1
34	1	31	8	3	3	2	0.27	0.09	0.10	0.04	0.02	0.01	0.00	0.00	1
35	1	32	6	3	3	2	0.21	0.09	0.10	0.04	0.02	0.01	0.00	0.00	1
36	1	33	6	3	2	2	0.21	0.09	0.06	0.04	0.02	0.01	0.00	0.00	1
37	1	34	8	5	3	2	0.27	0.15	0.10	0.04	0.02	0.01	0.01	0.00	1
38	1	35	8	4	3	1	0.27	0.12	0.10	0.02	0.03	0.01	0.01	0.00	1

α	T	MAXP1	MAXP2	MAXP3	MAXP4
0.005	0.7	18	22	21	32

Station	1	2	3	4
	823	1417	369	392
PB	27.42%	47.22%	12.30%	13.06%

Mean	SD	CV	β
0.25	0.16	0.6546	0.6727



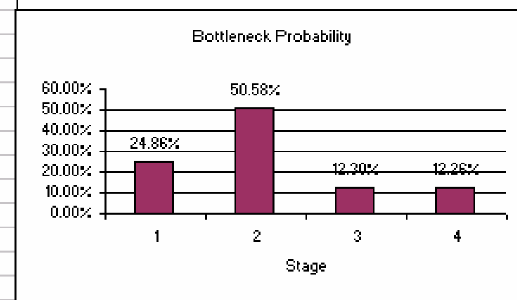


Figure 13. Bottleneck Shiftiness capture template

The Fill Rate, Utilization and the cycle time are output performance measures that are built within the Arena simulation model. Fill rate is defined as the amount of customer demand fulfilled by the available stock or it ratio of the demand satisfied by the available stock to the customer demand. Thus every time a customer demand is places a demand at the FGI. The simulation model captures the Fill Rate. After the simulation model has run for the specified duration it returns an average Fill Rate. Likewise the utilization of the stages and the cycle time required to assemble a product at FGI is calculated after every simulation period.

3.4.6 Simulation Model Settings

Different case studies were run by changing the input variables according to the scenario needed. The following table gives the summary of the various settings and simulation input and put variables

TABLE 2 SIMULATION MODEL SETTINGS

Simulation Run	Every case study is run twice with simulation period of 4000 hours. Only the later 3000 hours is taken into consideration
Input /Control Variables	Base stock level for every stage, Mean and Standard deviation of the customer demand, Lead Time, Inter arrival time of the customer demand
Output Variables/Performance Measure	Bottleneck Shiftiness Measure (β),Fill Rate, Assembly Cycle Time

3.5 Simulation Model Validation

Since the simulation model is not only an assembly model simulation but also a base stock control policy on the model, the validation of the model was done in two steps. First the base stock control policy was switched off and parts were sent to through Model 100. The simulation model captured the utilization levels of the stages were compared to the shiftiness measure. Even though the utilization levels depended on the inter arrival times of the raw parts the utilization levels of the all were nearly equal indicating a β =1 which matched approximately at 0.91. Further after switching on the base stock control policy the change in β corresponded to the variation of the utilization levels observed at the different stages.

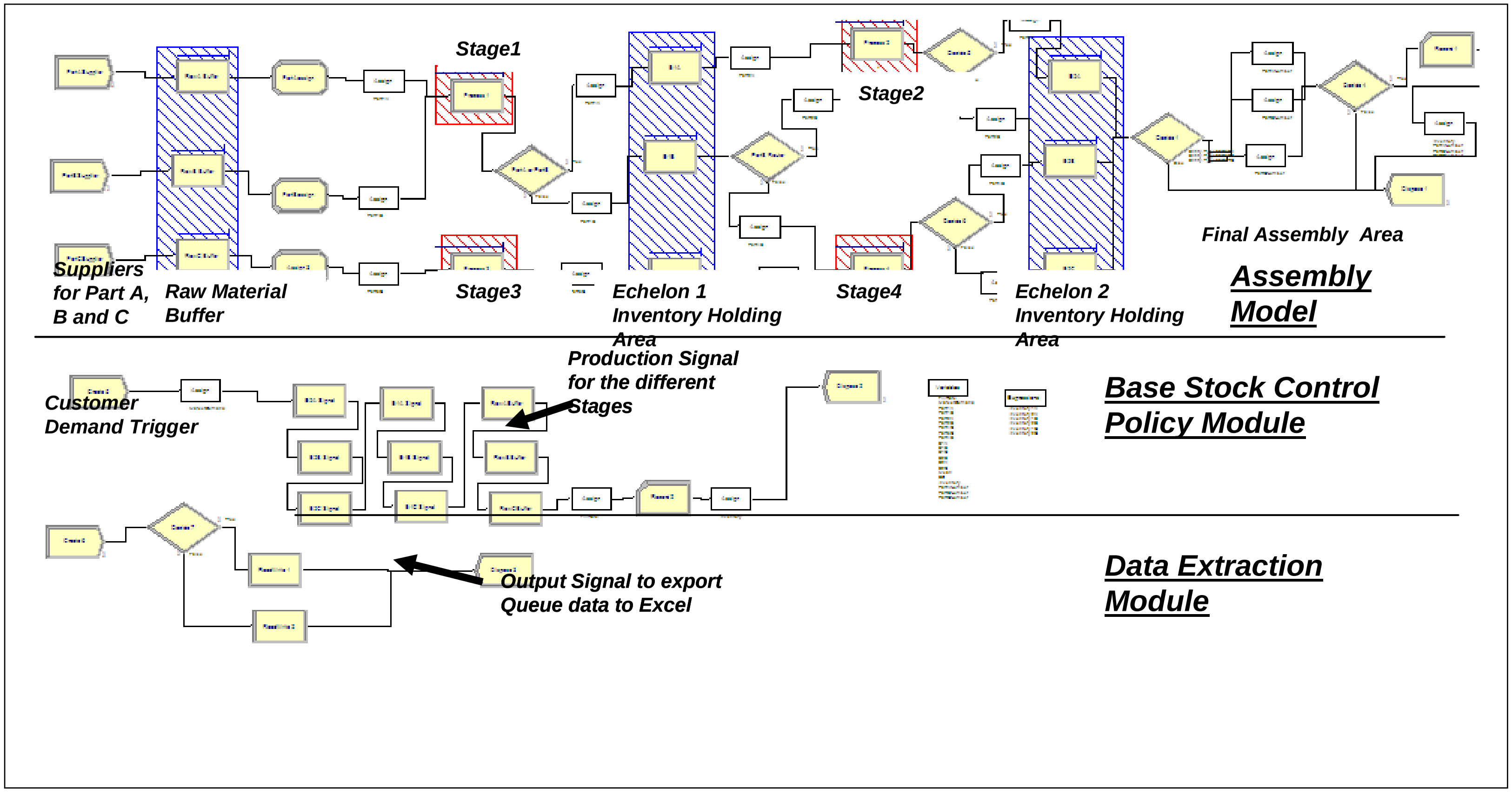


Figure 14. Arena Simulation Model

CHAPTER IV

RESULTS AND DISCUSSION

The simulation model described in the earlier section was used to understand and address the research question. Since the research question was two fold, the results are discussed and analyzed in two sections. In the first section the effect of the increasing base stock levels on the bottleneck shiftiness parameter β and the other performance measures. The second section discusses the effect of different CV of Demand on the bottleneck shiftiness parameter β for Model 100, 90 and 80

4.1 Increasing Stock Levels

To address the basic question on how a the bottleneck shiftiness parameter for a system would behave with increasing stock levels , the simulation model tested and demand parameters are kept constant.31 case studies were run with the coefficient of variation (C.V.) of the demand at 0.125 for Model 100. Table 3 illustrates the simulation output for the respect case studies. The simulation output captures the assembly cycle time, stage utilization, stage bottleneck percentage, customer demand fill rate and bottleneck shiftiness measure for each of the case studies. The case studies have progressively increasing base stock levels for all the parts at their respective inventory holding location.

Since Model 100 is a balanced system having a base stock level of 5 for across every stage gives us a bottleneck shiftiness measure of 0.9 which indicates that approximately all the stages are bottlenecks. The next section the effect of increasing stock levels on the performance measures is seen.

TABLE 3 CASE STUDY SIMULATION OUTPUT FOR INCREASING STOCK LEVELS

	Base Stock						Demand		Utilization					Fill Rate	Bottleneck Percentage				Shiftiness Ratio	Assembly Time
Case	S1	S2	S3	S4	S5	S6	Mean	SD	μ1	μ2	μ3	μ4	Model	Mean	Stage 1	Stage 2	Stage 3	Stage 4	β	Mean
1	5	5	5	5	5	5	2	0.25	0.8879	0.885	0.8117	0.8813	100	0.8413	27.59%	21.76%	19.33%	31.32%	0.891	23
2	7	7	7	7	7	7	2	0.25	0.91	0.9629	0.8703	0.9127	100	0.8946	26.72%	20.59%	24.23%	28.46%	0.932	31
3	8	8	8	8	8	8	2	0.25	0.9303	0.9204	0.9158	0.9218	100	0.8821	27.42%	18.76%	33.16%	20.66%	0.868	34
4	9	9	9	9	9	9	2	0.25	0.9552	0.941	0.9036	0.9412	100	0.9177	30.62%	18.43%	24.53%	26.42%	0.899	38
5	10	10	10	10	10	10	2	0.25	0.9606	0.9571	0.9406	0.9152	100	0.9191	28.52%	19.86%	37.05%	14.56%	0.802	41
6	11	11	11	11	11	11	2	0.25	0.9648	0.9356	0.9534	0.9058	100	0.9191	32.46%	20.09%	26.69%	20.76%	0.884	44
7	12	12	12	12	12	12	2	0.25	0.9648	0.9573	0.955	0.9143	100	0.9199	29.29%	12.50%	34.69%	23.53%	0.810	48
8	13	13	13	13	13	13	2	0.25	0.9826	0.9625	0.9395	0.946	100	0.9367	40.09%	13.40%	20.53%	25.99%	0.774	53
9	14	14	14	14	14	14	2	0.25	0.9655	0.9903	0.9073	0.9509	100	0.9282	16.93%	24.36%	21.53%	37.19%	0.826	58
10	15	15	15	15	15	15	2	0.25	0.9738	0.9542	0.9463	0.9828	100	0.955	39.79%	14.00%	23.43%	22.79%	0.785	60
11	18	18	18	18	18	18	2	0.25	0.9774	0.9809	0.9774	0.9414	100	0.944	32.56%	19.99%	37.69%	9.76%	0.748	71
12	19	19	19	19	19	19	2	0.25	0.984	0.9711	0.948	0.9709	100	0.9585	25.19%	26.46%	23.76%	24.59%	0.977	77
13	20	20	20	20	20	20	2	0.25	0.9863	0.978	0.997	0.9466	100	0.9582	26.59%	18.13%	51.88%	3.40%	0.594	78
14	21	21	21	21	21	21	2	0.25	0.9891	0.9792	0.9815	0.9587	100	0.956	32.16%	24.39%	29.62%	13.83%	0.839	81
15	22	22	22	22	22	22	2	0.25	0.9991	0.9841	0.9992	0.9217	100	0.9702	26.06%	2.27%	71.61%	0.07%	0.336	82
16	23	23	23	23	23	23	2	0.25	0.9837	0.9965	0.9813	0.9478	100	0.9622	3.07%	48.75%	45.95%	2.23%	0.483	92
17	24	24	24	24	24	24	2	0.25	0.9847	0.991	0.9659	0.9911	100	0.968	13.46%	60.68%	12.66%	13.20%	0.524	96
18	25	25	25	25	25	25	2	0.25	0.9722	0.9906	0.9766	0.9662	100	0.9702	7.23%	50.45%	20.23%	22.09%	0.638	98
19	27	27	27	27	27	27	2	0.25	0.9825	0.9865	0.9992	0.9768	100	0.9639	4.37%	8.30%	74.28%	13.06%	0.339	101
20	28	28	28	28	28	28	2	0.25	0.991	0.9596	0.9992	0.9529	100	0.9625	43.79%	4.10%	50.85%	1.27%	0.481	104
21	29	29	29	29	29	29	2	0.25	0.9991	0.953	0.973	0.9931	100	0.9411	48.15%	11.16%	1.73%	38.95%	0.558	115
22	30	30	30	30	30	30	2	0.25	0.9991	0.9843	0.9791	0.9636	100	0.9494	34.32%	15.29%	23.79%	26.59%	0.843	112
23	31	31	31	31	31	31	2	0.25	0.9991	0.9675	0.976	0.9619	100	0.9456	63.35%	0.00%	29.26%	7.40%	0.432	108
24	32	32	32	32	32	32	2	0.25	0.9937	0.9976	0.9786	0.9957	100	0.9532	49.38%	34.22%	5.63%	10.76%	0.591	124
25	33	33	33	33	33	33	2	0.25	0.9919	0.982	0.968	0.9984	100	0.9502	36.62%	31.29%	1.27%	30.82%	0.679	129
26	35	35	35	35	35	35	2	0.25	0.9807	0.9986	0.9831	0.9984	100	0.9674	20.33%	55.68%	5.80%	18.19%	0.571	136
27	40	40	40	40	40	40	2	0.25	0.9949	0.9807	0.9992	0.9702	100	0.9757	28.69%	28.82%	42.22%	0.27%	0.647	141
28	43	43	43	43	43	43	2	0.25	0.9859	0.9776	0.9987	0.9985	100	0.9699	26.36%	42.52%	10.30%	20.83%	0.731	154
29	45	45	45	45	45	45	2	0.25	0.9991	0.9874	0.9899	0.9736	100	0.9629	36.49%	32.76%	15.23%	15.53%	0.776	167
30	47	47	47	47	47	47	2	0.25	0.9991	0.9797	0.9878	0.9984	100	0.9564	77.51%	3.50%	7.80%	11.20%	0.297	173
31	50	50	50	50	50	50	2	0.25	0.9925	0.9942	0.9992	0.9937	100	0.9655	19.86%	10.00%	70.11%	0.03%	0.377	187

4.1.1 Effect of Increasing Stock Levels on Cycle Time

The effect of the increasing stock levels on cycle time for assembly of the parts is logical as the WIP in the system, the assembly cycle time also increases. Figure 15 illustrates the effect.

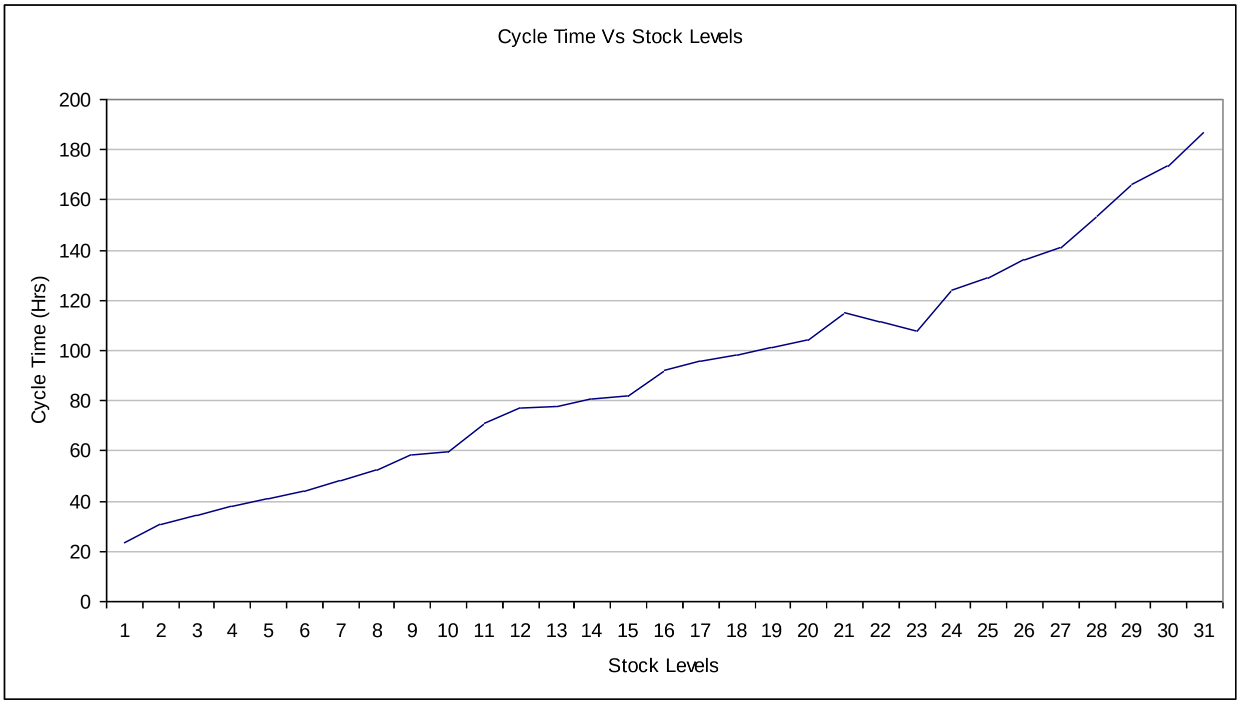


Figure 15. Cycle Time Vs Stock Levels

4.1.2.Effect of Increasing Stock Levels over Stage Utilization.

Figure 16 illustrates the effect of progressively increasing the stock levels on the utilization of the stages. As the amount of base stock increases in the system the stage utilization levels also increases. In case 1 the utilization for stages 1, 2 and 4 are nearly around 88% however as the stock levels increases the utilization increases to 99%.

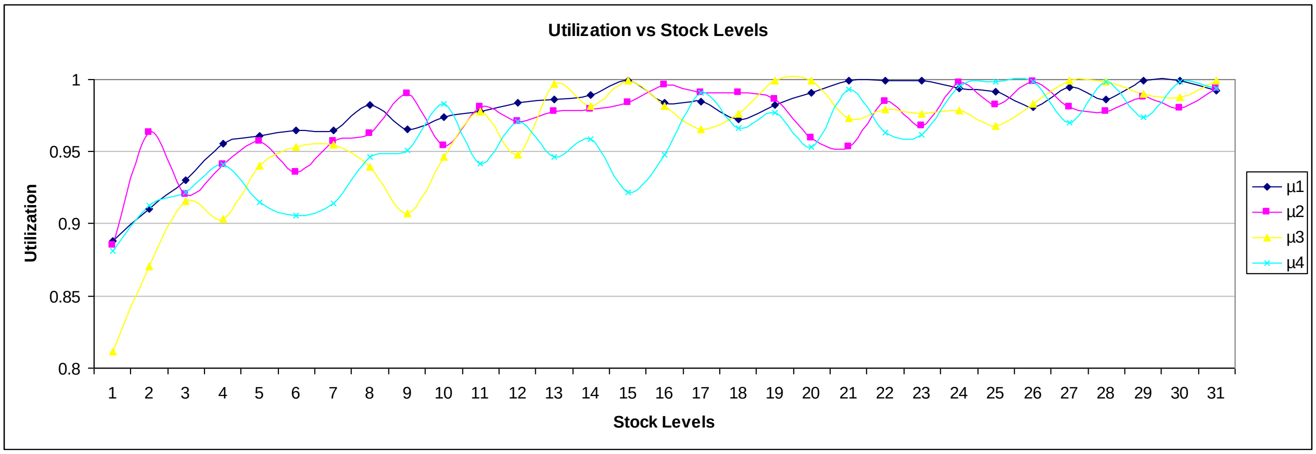


Figure 16. Stage Utilization vs. Stock Levels

4.1.3.Effect of Increasing Stock Levels over Customer Demand Fill Rate

Initially because of the low stock levels the customer demand fill rate is around 85%.However increasing the level of stock increases the Fill rate to only to certain point which is approximately 96% because as the WIP increases the assembly cycle time also increases. Thus it hampers the throughput and eventually the Fill rate of the system.

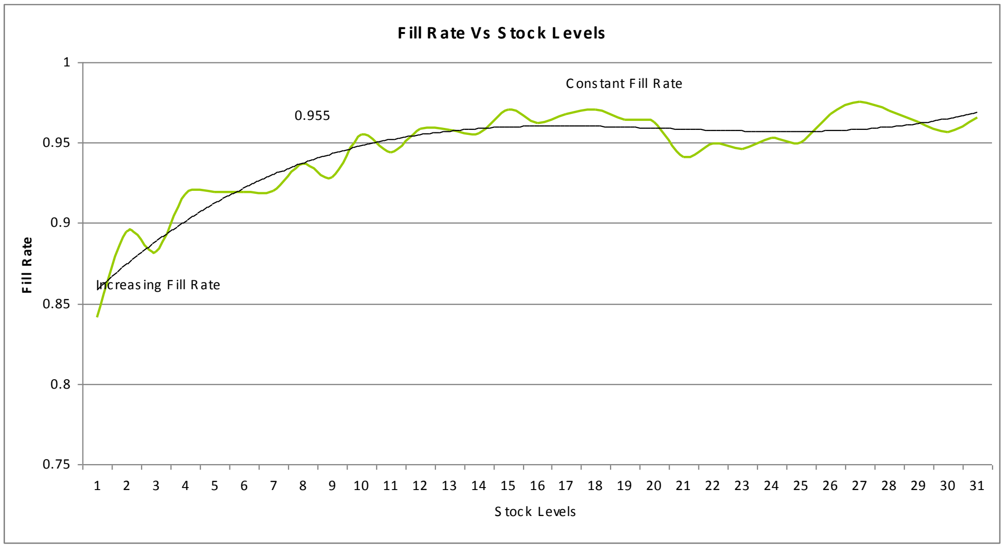


Figure 17. Fill Rate vs. Stock Levels

4.1.4 Effect of Increasing Stock levels on the Bottleneck Percentage and Bottleneck Shiftiness

Referring to the base stock levels from Case 1 the bottleneck percentages for all the stages is near 25% and the Shiftiness measure is at 0.9. As we progressively increase the base stock levels the shiftiness measure decreases gradually as seen in Figure19.This can also been seen in Figure 18 as Stage 1 and Stage 3 have higher bottleneck percentage while Stage 4 and stage2 gradually decrease.

In case 11 which is where the Fill rate starts to get flat the bottleneck Shiftiness parameter decreases but with high variability. In Figure 18 the bottleneck percentage after case 11 for all the Stage except stage 4 have high variability. Here the Stage 1 progressively becomes the major bottleneck with the increase in base stock levels.

The reason for the high variability of the bottleneck percentage is, as the base stock levels increase, the stages have to keep up and process as many parts to fill the base stock levels. In other words, the diminishing effect of the capacity of the stages to fulfill the base stock level is pronounced as the base stock levels increase. The key insight with this observation is that by increasing the base stock levels after the Fill Rate hits a plateau the bottleneck shiftiness would decrease with very high variability.

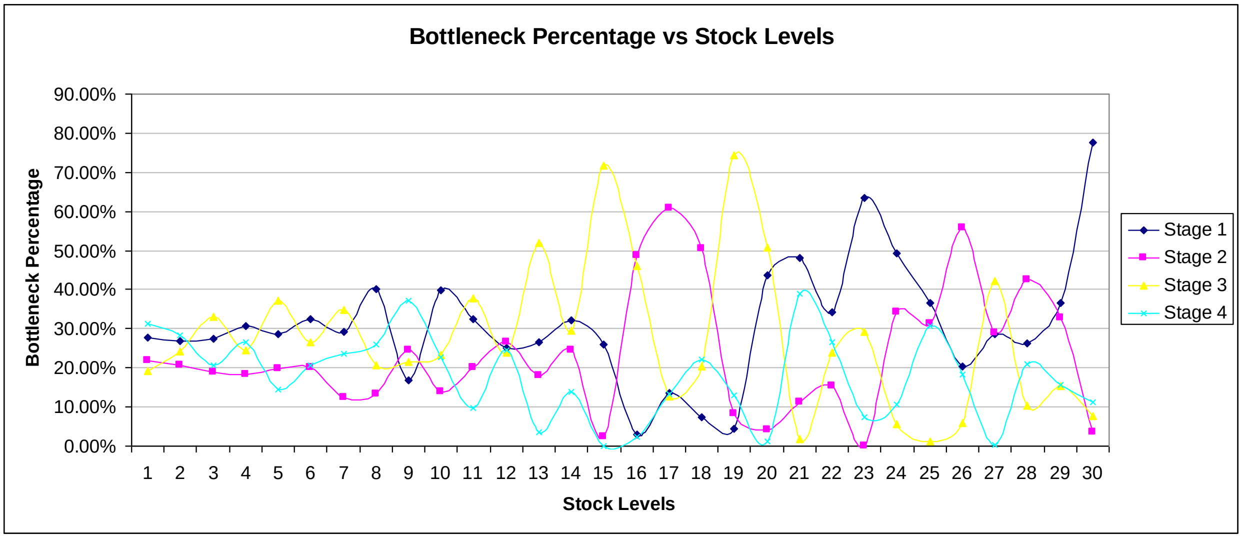


Figure 18. Stage Bottleneck Percentages vs. Stock Levels

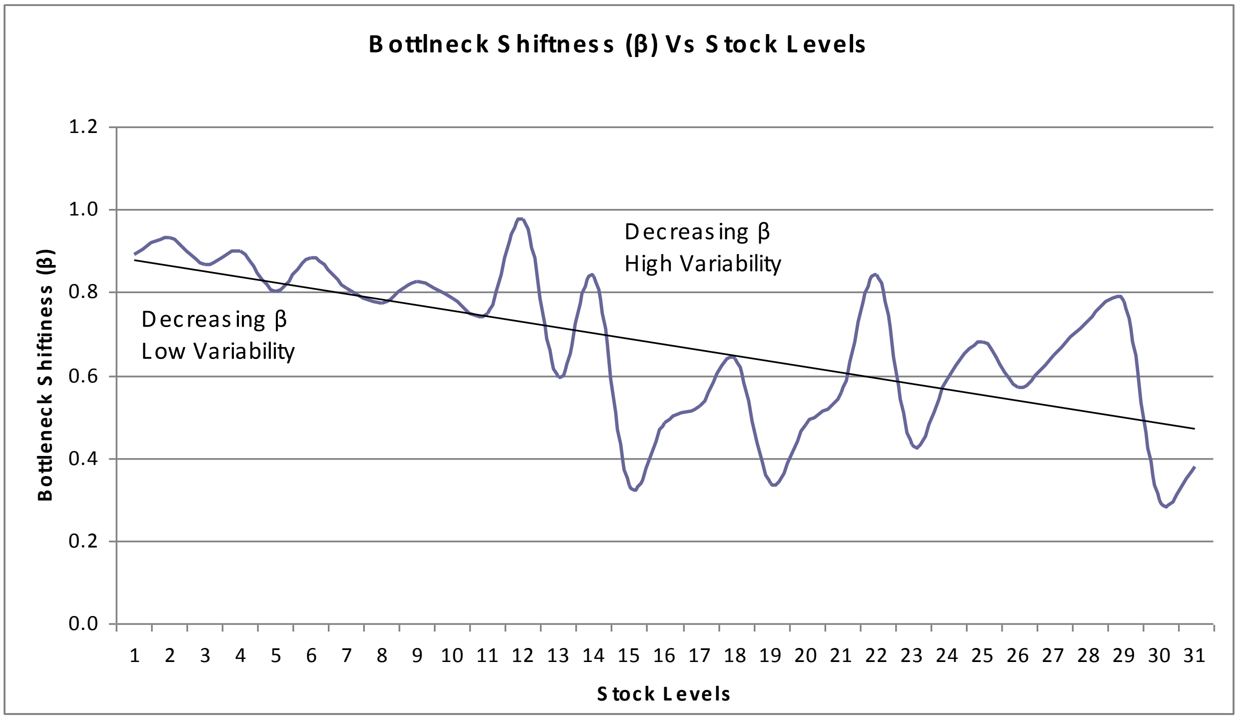


Figure 19. Bottleneck Shiftiness Measure Vs Stock Levels

4.2 Effect of Coefficient of Variation of Demand on Bottleneck Shiftiness Parameter

To study the effect of C.V variation of demand on the bottleneck shiftiness parameter, the C.V of demand was varied at two levels low and medium. For the C.V of demand level set, the stock levels are computed to achieve a maximum achievable fill rate. This experiment was also tested for the three different models Model 100, 90 and 80 having progressively decreasing bottleneck shiftiness.

4.2.1 Low C.V of Demand Vs the Bottleneck Shiftiness Measure for Model 100, 90 and 80

Low Coefficient of Variation is ratio of Standard deviation and Mean whose value lies between 0 and 0.33. Here the Mean Demand is set at 3 and SD at 0.25 thus CV is 0.083. Table 4 shows the simulation output of the different models tested under the Low C.V of Demand Level. Here for each Model the base stock levels were computed to achieve a Fill Rate. Every Model for a constant Fill Rate has a ***Point of Minimum Shiftiness*** for particular Base stock level combination. Figure 20 illustrates the Point of Minimum Shiftiness for Low C.V of Demand for the different models. The key insight by analyzing the different case studies shown in Table 4 is that for the drop in bottleneck shiftiness is drastic in the case of a highly biased model for increasing combinations of stock levels to achieve the same Fill rate as seen in Model 80.For Model 80 the drop in the bottleneck shiftiness parameter is approximately 80.3% to value of 0.11. As in the case of Model 90 the drop in the bottleneck shiftiness parameter is approximately 30% to a value of 0.47.The prominence of this effect is less in the case of Model 100 which has the drop in bottleneck shiftiness parameter of approximately 19.6% to value of 0.78.Thus this also shows that the effect of variation of stock levels in more pronounced for a supply chain structure that has low variation in the movement of the bottleneck.

4.2.2 Medium C.V of Demand Vs the Bottleneck Shiftiness Measure for Model 100, 90 and 80

Medium Coefficient of Variation is ratio of Standard deviation and Mean whose value lies between 0.33 and 1. Here the Mean Demand is set at 3 and SD at 2.5 thus CV 0.833. Table 5 shows the simulation output of the different models tested under the Medium C.V of Demand Level. After analyzing the case studies shown in Table 5 and comparing that with the Low variability of Demand the effect of decrease in Fill Rate levels is observed. Thus for the same the Model the maximum attainable Fill rate drops. After computing the combinations of stock levels .the occurrence of a Point of Minimum Shiftiness can also be observed. Figure 21 shows the effect of medium coefficient of variation of demand on the stage bottleneck shiftiness. For Model 100 the drop in the bottleneck shiftiness parameter by varying the different base stock levels is approximately 16.7% to value of 0.65. Model 90 shows a drastic drop as compared to previous with a drop of 80% to value of 0.13. Similarly Model 80 shows a drop in the bottleneck shiftiness parameter of approximately 68% to value of 0.11. The key insight by comparing the bottleneck shiftiness effect for Low and the medium coefficient of variation of Demand is that as the C.V. of Demand increases the drop in bottleneck shiftiness parameter is more pronounced for the Model achieving a constant Fill Rate.

TABLE 5 CASE STUDY SIMULATION OUTPUT FOR LOW C.V. OF DEMAND

		Demand			Base Stock							Utilization				Fill Rate	Assembly Time	Bottleneck Percentage				Shiftiness Ratio
Case	*Model*	Mean	σ	C.V	S1	S2	S3	S4	S5	S6	STotal	μ1	μ2	μ3	μ4	Mean	Mean	Stage1	Stage2	Stage3	Stage4	β
1	100	3	0.25	0.08	14	15	16	14	15	16	90	0.9618	0.9622	0.9415	0.9636	0.95	61.01	24.49%	26.96%	25.19%	23.36%	0.97
2	100	3	0.25	0.08	16	16	17	16	16	17	98	0.967	0.9812	0.9627	0.9598	0.95	65.70	19.09%	25.32%	23.36%	32.22%	0.89
3	100	3	0.25	0.08	17	17	18	17	17	18	104	0.9498	0.9792	0.9625	0.9543	0.95	69.30	10.63%	33.69%	22.49%	33.19%	0.78
4	100	3	0.25	0.08	18	18	18	18	18	18	108	0.9787	0.9746	0.9652	0.9547	0.96	71.90	20.33%	40.39%	22.59%	16.69%	0.79
5	100	3	0.25	0.08	19	19	19	19	19	19	114	0.9611	0.97	0.9801	0.9491	0.96	76.29	27.36%	26.89%	29.29%	16.46%	0.88
6	90	3	0.25	0.08	19	18	19	19	18	19	112	0.9878	0.932	0.9603	0.9733	0.94	73.1256	43.89%	3.43%	29.19%	23.49%	0.67
7	90	3	0.25	0.08	19	19	19	19	19	19	114	0.9956	0.9105	0.9423	0.9851	0.94	73.25	61.08%	5.10%	23.86%	9.96%	0.49
8	90	3	0.25	0.08	19	19	20	19	19	20	116	0.9857	0.922	0.9473	0.9774	0.94	75.72	2.47%	1.67%	50.78%	45.08%	0.47
9	90	3	0.25	0.08	21	21	21	21	21	21	126	0.9931	0.9064	0.9864	0.982	0.95	77.75	61.15%	3.20%	28.76%	6.90%	0.47
10	90	3	0.25	0.08	21	20	21	21	21	21	125	0.9929	0.9291	0.9571	0.9756	0.95	80.62	49.55%	7.00%	11.70%	31.76%	0.61
11	90	3	0.25	0.08	27	23	26	27	26	26	155	0.9887	0.9485	0.9782	0.9727	0.96	97.75	32.89%	9.13%	19.59%	38.39%	0.74
12	80	3	0.25	0.08	21	21	21	19	19	19	120	0.9908	0.8551	0.9144	0.983	0.90	80.04	46.55%	1.00%	11.50%	40.95%	0.56
13	80	3	0.25	0.08	21	21	21	20	20	20	123	0.9971	0.8376	0.9143	0.9916	0.91	79.78	61.28%	1.50%	0.00%	37.22%	0.41
14	80	3	0.25	0.08	22	21	22	22	21	21	129	0.999	0.8357	0.9165	0.9958	0.90	82.73	91.87%	0.83%	0.43%	6.86%	0.11
15	80	3	0.25	0.08	25	23	24	25	25	24	146	0.9946	0.8355	0.907	0.9965	0.90	95.02	30.72%	0.33%	3.10%	65.84%	0.39

TABLE 4 CASE STUDY SIMULATION OUTPUT FOR MEDIUM C.V. OF DEMAND

		Demand			Base Stock							Utilization				Fill Rate	Assembly Time	Bottleneck Percentage				Shiftiness Ratio
Case	*Model*	Mean	σ	C.V	S1	S2	S3	S4	S5	S6	STotal	μ1	μ2	μ3	μ4	Mean	Mean	Stage1	Stage2	Stage3	Stage4	β
1	100	3	2.5	0.83	20	20	20	19	19	19	117	0.9571	0.9575	0.9539	0.941	0.95	81.39	7.50%	32.36%	36.45%	23.69%	0.74
2	100	3	2.5	0.83	21	21	21	21	21	21	126	0.9477	0.9565	0.9523	0.9256	0.94	87.93	23.89%	18.79%	40.75%	16.56%	0.78
3	100	3	2.5	0.83	22	22	22	22	22	22	132	0.9643	0.9447	0.9231	0.9296	0.95	90.23	39.32%	15.29%	15.36%	30.02%	0.76
4	100	3	2.5	0.83	25	25	25	25	25	25	150	0.9669	0.9509	0.9609	0.9519	0.95	99.79	3.70%	31.39%	44.45%	20.46%	0.65
5	100	3	2.5	0.83	26	26	26	25	25	25	153	0.9661	0.9663	0.9731	0.9416	0.94	104.23	14.70%	17.09%	33.32%	34.89%	0.79
6	100	3	2.5	0.83	26	26	26	26	26	26	156	0.9872	0.9531	0.9446	0.9532	0.95	100.42	19.16%	30.82%	20.33%	29.69%	0.88
7	90	3	2.5	0.83	29	29	29	29	29	29	174	0.9945	0.9235	0.9281	0.9807	0.93	109.74	48.38%	5.03%	19.79%	26.79%	0.64
8	90	3	2.5	0.83	30	30	30	30	30	30	180	0.999	0.9175	0.9653	0.9796	0.93	108.15	62.08%	2.50%	34.99%	0.43%	0.41
9	90	3	2.5	0.83	32	32	32	32	32	32	192	0.999	0.9295	0.9827	0.9823	0.94	116.46	76.87%	1.10%	12.66%	9.36%	0.30
10	90	3	2.5	0.83	33	32	33	33	32	33	196	0.999	0.9109	0.9303	0.9884	0.94	118.68	90.37%	2.00%	1.87%	5.76%	0.13
11	90	3	2.5	0.83	34	32	33	34	32	33	198	0.999	0.89	0.9783	0.9791	0.94	114.99	81.04%	0.40%	17.96%	0.60%	0.23
12	80	3	2.5	0.83	29	29	29	29	29	29	174	0.9953	0.8479	0.8825	0.9935	0.91	107.95	65.71%	2.23%	12.20%	19.86%	0.44
13	80	3	2.5	0.83	30	30	30	30	30	30	180	0.9953	0.8104	0.9395	0.9901	0.92	106.83	78.91%	3.87%	10.43%	6.80%	0.28
14	80	3	2.5	0.83	32	32	32	32	32	32	192	0.9922	0.8533	0.9199	0.9975	0.91	114.67	89.34%	0.30%	1.50%	8.86%	0.14
15	80	3	2.5	0.83	33	33	33	33	33	33	198	0.9989	0.8547	0.9471	0.9981	0.91	115.65	65.18%	0.00%	31.79%	3.03%	0.39
16	80	3	2.5	0.83	33	33	35	33	33	35	202	0.9914	0.8019	0.9361	0.9925	0.91	120.41	55.71%	1.70%	15.03%	27.56%	0.54

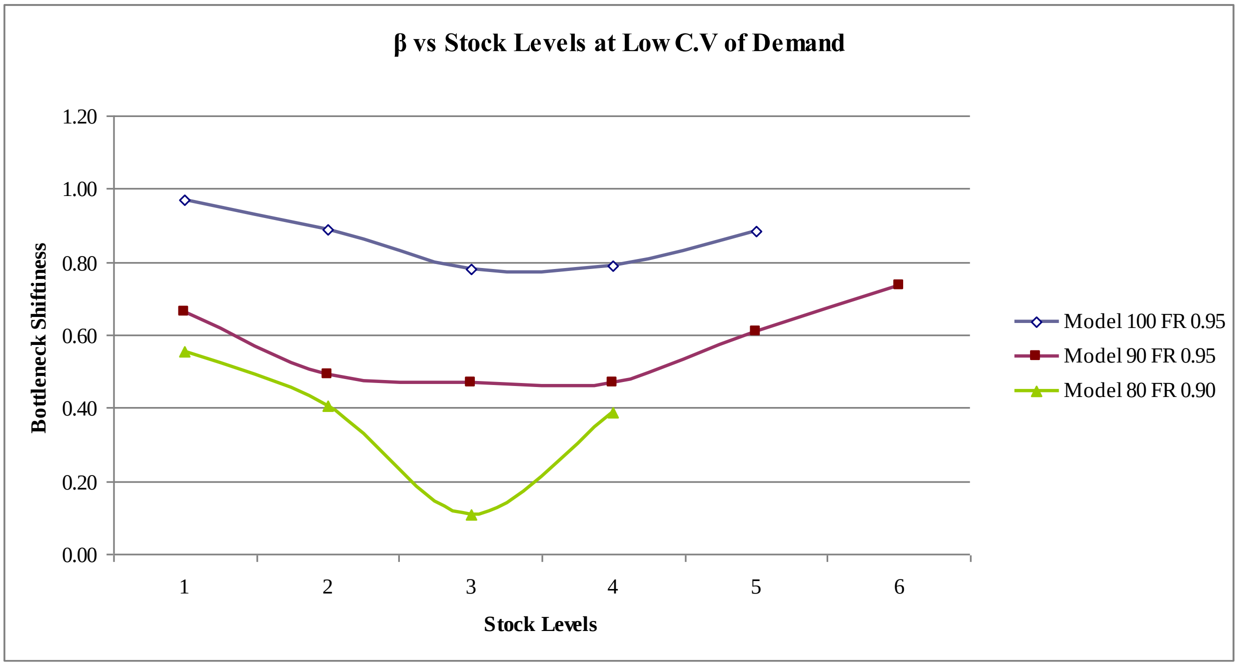


Figure 20. Low Variability of Demand Vs β

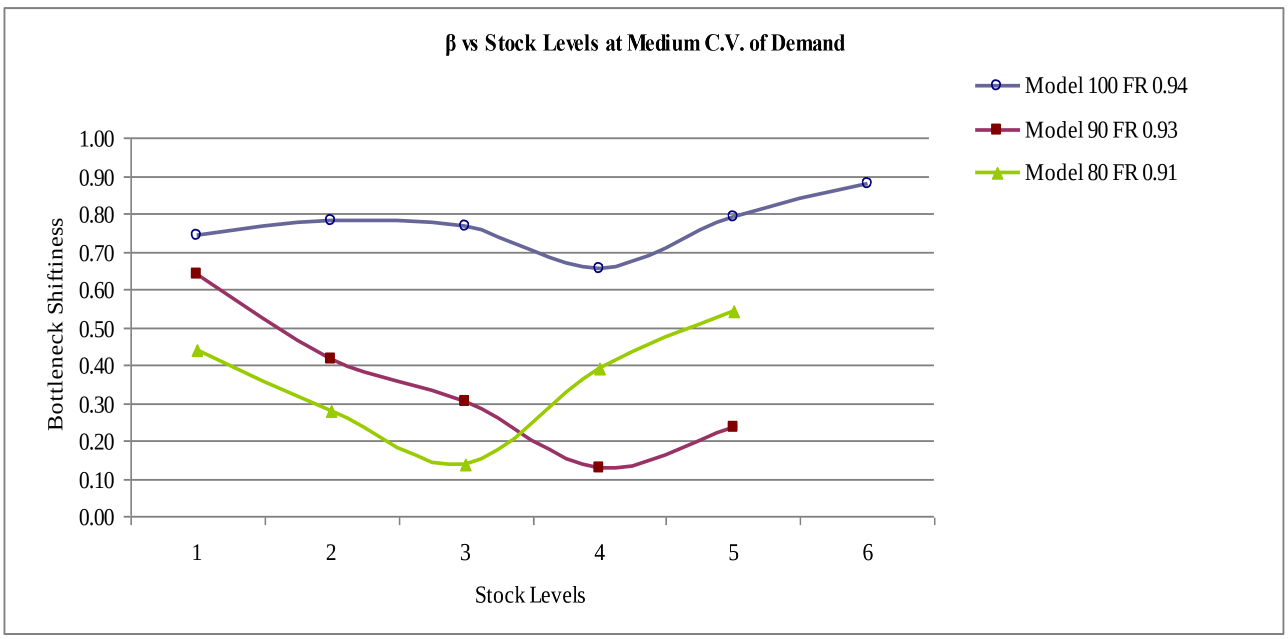


Figure 21. Medium Variability of Demand Vs β

CHAPTER V

CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusions

According to simulation results obtained for the different scenarios run, we can clearly see the influence of the varying base stock levels at the different stages for a 3 part 4 stage assembly processes. These experiments have attempted to develop a trend in the variation of base stock levels and the bottleneck shiftiness parameter. We can generalize these findings to the following conclusions.

- In a supply chain network for a fixed capacitated environment the increase amount of stock levels at the different stages decreases the ability of the bottleneck stage to move. However as we know that the as we continue to the increase the amount of WIP in the assembly the lead times to the customer increase.
- Increase in the base stock levels increase the fill rate to the customer only to the level of capacity. Beyond which an increase decreases / keeps the fill rate constant
- Increasing the base stock levels beyond the point of constant fill rate decreases the predictability of the decrease in movement of the bottleneck stages. This is also a key insight to TOC as buffering a bottleneck stage beyond a certain point might not to be advantageous if it does not improve the fill rate.
- For every supply chain there is an optimal combination of base stock levels across the different stages to subject to a required customer fill rate.
- Even though a base stock combination results in a lower inventory stock subject to a desired customer fill rate it does not result in the decreased movement of stage bottlenecks.

- A particular supply chain structure cannot be optimized for both minimum safety stock and minimum movement of stage bottleneck simultaneously.

5.2 Future Research

The simulation results conducted above has resulted in establishing a platform to research development to develop an analytical model to establish the safety stock factor needed to take into account the bottleneck shifting phenomenon. Furthermore the following areas of research tremendously benefit from the insights highlighted in the previous section.

- Simulation models can be modified to segregate the safety stock levels and the pipeline inventory to analyze the effect of safety stock levels on the shiftiness phenomenon
- Other measures for bottleneck shiftiness can be used in the simulation method and a comparative study can be developed.
- A key insight can be seen from Figure 20 and 21 that base stock levels and shiftiness can never minimize simultaneously. Thus models can be developed to have a trade off between the ability to control bottlenecks and the amount of stock
- The simulation model can be further developed to by incorporating inventory costs .This model can be used to obtain derivatives to be used in optimization of safety stock positioning.

REFERENCES

LIST OF REFERENCES

[1] Simpson, K.F., "In-process inventories," *Operations Research*, Vol. 6, 1958, pp.863–873.

[2] Minner, S., "Strategic safety stocks in supply chains", *Springer, Berlin Heidelberg New York*, 2000.

[3] Graves, S.C., Willems, S.P., "Supply chain design: Safety stock placement and supply chain configuration," In: De Kok, A.G., Graves, S.C (eds*) Supply chain management: Design, coordination and operation*,2003, North-Holland, Amsterdam.

[4] Graves S.C., "Safety stocks in manufacturing systems," *Journal of Manufacturing and Operations Management*, Vol 1, 1988, pp.67–101.

[5] Clark A.J., Scarf H., "Optimal policies for a multi-echelon inventory problem," *Management Science*, Vol 6, 1960,pp.475–490.

[6] Sitompul, Carles, Aghezzaf, El-Houssaine, Dullaert, Wout and Van Landeghem, Hendrik "Safety stock placement problem in capacitated supply chains," *International Journal of Production Research*, Vol 1,2007, pp. 1 – 19.

[7] Glasserman, P. and Tayur, S., "The stability of a capacitated, multi echelon production inventory system under a base-stock policy," *Operations Research*, Vol 42, 1994, pp.913–925.

[8] Glasserman, P., and Tayur, S., "Sensitivity Analysis for Base-stock levels in Multiechelon Production-inventory Systems," *Management Science*, Vol 41, 1995, pp. 263-281.

[9] Inderfurth, K. and Minner, S., "Safety stock in multi-stage inventory systems under different service measures," *European Journal of Operation Research*, Vol 106, 1998, pp. 57–73.

[10] Graves, S.C. and Willems, S.P., "Optimizing strategic safety stock placement in supply chains," Manfucturing and Service Operation Mangement, Vol 2, 2000, pp. 68–83.

[11] Orcun,S., Cetinkaya, S., Uzsoy,R., "Determining safety stocks in the presence of workload dependent lead times," *Proceeding from the 39th Winter Simulation conference*, 2007,pp.1691-1698.

[12] Eppen, G. and R. K. Martin , "Determining Safety Stock in the Presence of Stochastic Lead Times," *Management Science*, Vol 34, 1988,pp.1380-1390.

[13] Hadley, G. and T. M. Whitin (1963), “Analysis of Inventory Systems,” Englewood Cliffs, NJ, Prentice-Hall. Hopp,W. and M. L. Spearman (2001). *Factory Physics*. Boston,Irwin

[14] Karmarkar, U. S. "Capacity Loading and Release Planning with Work-in-Progress (WIP) and Leadtimes," *Journal of Manufacturing and Operations Management*, Vol 2, 1989, pp.105-123.

[15] Orcun, S., R. Uzsoy and Kempf, K.G., “Using System Dynamics Simulations to Compare Capacity Models for Production Planning,” *Proceeding from the 38th Winter Simulation conference*, 2006,pp.1855-1862.

[16] Steffen Klosterhalfen and Stefan Minner “Comparison of stochastic and guaranteed service approaches to safety stock optimization in supply chains,” *Operation Research Proceedings*, 2006, pp. 485- 490.

[17] Liu, L., X. Liu and Yao, D.D., "Analysis and Optimization of Multi-stage Inventory Queues." *Management Science,* Vol 50, 2004, pp.365-380.

[18] Roser,C., Nakono,M., Tanaka, M., “Shifting Bottleneck detection,” *Proceedings from the Winter Simulation Conference*, 2002, Vol 2, pp.1079-1086.

[19] Roser,C.,Nakono,M.,Tanaka, M.(2003) “Buffer Allocation model based on single simulation” ,*Proceedings from the Winter Simulation Conference*

[20] Fisher, M., “What Is the Right Supply Chain for Your Product,” *Harvard Business Review*, Vol 75/2, 1997, pp.105-116.

[21] Ettl, M., G. E. Feigin, G. Y. Lin and Yao, D.D., “A Supply Network Model with Base-Stock Control and Service Requirements,” *IBM Technical Report (RC 20473)*, 1996.