ABSTRACT

MAPARI, SWAPNIL ASHOK. Simulation Modeling to Determine Shipment Strategies with Demand Evolution according to Product Life Cycle. (Under the direction of Dr. Anita Vila-Parrish).

We develop simulation models with Arena for inventory systems with one and two modes of supply, varying demand over the finite time horizon considering Product life cycle (PLC). We use OptQuest, an Arena tool, to minimize supply chain cost and find near optimal order quantities by fast mode and slow mode by varying different scenarios. We have assumed cost factors like holding cost, backorder cost and unit ordering cost which are important considerations when making decisions about inventory policies. The cost factors are different for different modes of supply, which help us to optimize the ordering quantities by fast and slow modes of supply with the objective of minimizing the total system cost. We have observed the effects of different initial inventory levels and different lead times of supply on ordering policies. Numerical experiments show that optimal solutions differ with different cases in consideration. While most of the research has focused on stationary demand and stationary cost factors, our models are able to change all the input factors like demand distribution, cost factors, initial inventory levels and lead time of supply to get better insights of changing inventory systems. Considering the demand evolution as well as the demand variability according to PLC, it is important to change the ordering policies to maintain the cost effectiveness of inventory system. This is particularly true for growth phase of PLC where demand variability is more compared to maturity phase. The results show that the split of total order quantities per mode of supply should change as the demand evolution takes place according to Product Life Cycle.

. Simulation Modeling to Determine Shipment Strategies with Demand Evolution according to Product Life Cycle

by

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DEDICATION

To Aai, Pappa and Piyush

BIOGRAPHY

Swapnil Mapari was born in December 1986 in Parbhani, India to Lata and Ashok Mapari. He completed his Bachelor's in Mechanical Engineering from College of Engineering Pune in 2008. One year later, in 2009, he joined the Master of Science program in the Edward P. Fitts Department of Industrial and Systems Engineering at North Carolina State University, Raleigh.

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Last but not the least; I remain indebted to my parents and my brother for always believing in me and supporting me through all the trouble that I keep getting myself into.

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CHAPTER 1: Introduction

1. 1 Introduction

Logistics and supply chain play a critical role in global technology. Supply chain management (SCM) is essential to company success and customer satisfaction. Whether dealing with day-to-day product flows or with an unexpected natural disaster, supply chain management (SCM) is an important tool to diagnose problems, creatively work around disruptions and figure out how to move essential products to customers as efficiently as possible [2]. SCM helps companies to develop their own core competencies to distinguish themselves in this very competitive world. SCM has allowed business go beyond solely having productivity advantage to also developing a value advantage [2]. As Martin Christopher states in his book, *Logistics and Supply Chain Management: Strategies for Reducing Cost and Improving Service*, “Productivity advantage gives a lower cost profile and the value advantage gives the product or offering a differential 'plus' over competitive offerings.”

Supplier-factory-Customer systems, involve huge numbers of suppliers, logistic platforms and sales points. When we consider such logistics networks, we need to deal with factors like analysis of network layout, item inventory management and allocation of optimal place for each type of item in storage area etc [1]. Such processes also involve a number of stochastic variables such as consumer demand forecasts, service levels provided by suppliers, lead times and out of stock occurrences. All these factors are very critical for the efficiency of supply chain network. Controlling and understanding how these different factors influence a company's SCM will be discussed further in subsequent sections.

1.2 Supply Chain and Inventory Management

Supply chain Management (SCM) is a vast subject to discuss, but we will narrow down the subject because our main area of concern is use of SCM in Inventory management. As complexity of supply chain grows, so does the demand for inventory management expertise. Supply chains increasingly span many organizations, and so operational control may be distributed across supply chain entities rather than centralized [3]. There are often multiple alternate shipment modes available between locations. Such structural complexities are compounded with factors like short product life cycles to make inventory management even more difficult. Supply chain practitioners require new, sophisticated tools, since simple single-location, stationary demand inventory models are not sufficient to deal with the complexities in these modern supply chains.

Companies should decide about which transportation modes to use for most cost effective and reliable delivery of products to customers. Each transportation mode has its own commercial and operational advantages and properties. Different modes can compete against one another in terms of cost, speed, accessibility, frequency, safety, comfort etc. Different geographical markets affect selection of mode of transport. If different markets are involved, modes will permit a continuity within the transport system, particularly if different scales are concerned, such as between national and international transportation. This requires an interconnection, where it is possible to transfer from one mode to the other. What is being transported also affects the selection of transportation mode. Some products are easy and reliable to handle on the contrary some are very fragile. That leads to using different modes of transport because carrying the products without damage is very essential for customer satisfaction. Two modes that offer a different level of service will tend to compete against one another. So competition in modes arises when there is an overlap in geography, transport and level of service. Cost is one of the most important considerations in the choice of mode of transport, because each mode has its own price and its own performance profile. The actual competition between the modes depends primarily upon the distance traveled, the quantities that have to be shipped and the value of the goods. For example a maritime transport might offer the lowest variable costs over short distances and for small bundles of goods but road transport is also very competitive. Since a critical factor is the terminal cost structure for each mode, where the costs of loading and unloading the unit impose fixed costs that are incurred independent of the distance traveled [4].

1.3 Product Life Cycle

Like human beings, products also have a life-cycle. Human beings pass through various stages from birth to death; it is a similar case with products. Product lifecycle management (PLCM) is the process of managing the entire lifecycle of a product from its conception, through design and manufacture, to service and disposal. Product life cycle management (PLCM) must be considered in order to manage profit of the firm as product goes through different phases of life cycle. Following Figure 1.1 represents different phases of Product life cycle (PLC) and its effect on product sales.

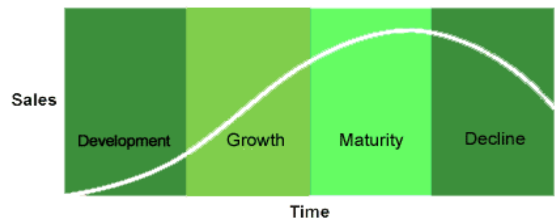

Figure 1.1 Product Life Cycle Phases (courses.cit.cornell.edu)

A new product progresses through a sequence of stages. The stages we consider are introduction, growth, maturity, and decline. This sequence is known as the product life cycle (PLC) and is associated with changes in the marketing situation, thus impacting the marketing strategy and the product mix [5]. The product sales can be plotted as a function of the life-cycle stages as shown in Figure 1.1. If we consider an example of computer systems, they are made up of both hardware and software components. The percentage of overall computer system cost spent on hardware has changed quite remarkably over the years [6]. The rising complexity of the market and the product increases the challenge in demand forecasting and subsequently inventory management during the PLC.

1.4 Use of Simulation Modeling

Another difficult aspect of inventory management is finding strategies that are practical to implement. Because of the number of stochastic factors in the process, we need to have different inventory policies for different scenarios. Factors like optimality and cost-effectiveness of given policy, compatibility with existing information technology, availability of supporting data and computational complexity put constraints on the selection of inventory strategies. So for this reason we need to have a tool that can represent different scenarios within quick period of time and help us to determine inventory management policies.

Simulation modeling is a good methodology to evaluate decisions within such inventory management. Simulation is the generation of an artificial history of the system and the observation of that artificial history to draw inferences about the operating characteristics of the real system. Simulation can be used to compare different scenarios of inventory system and consequently being used to optimize the simulation results to decide the proper inventory management policies for the system. A fundamental problem in supply chain modeling or inventory problems is performance evaluation. Simulation modeling is a very practical approach to explore the performance of large scale situations that exists in reality. We can evaluate the inventory problems prior to their implementation. Simulation modeling can be done using continuous simulation approach, where states vary continuously. The dynamic factors in production/inventory problems like production rates, sales rates, transportation times etc. are changed continuously. Simulation modeling can also be done using discrete event approach. In discrete event approach time is divided in periods of given length, that means time is incremented step by step within a given time bucket. At the end of each step a new step is calculated using the simulation equations.

The values for system performance measures obtained from the simulation model should be genuine reflections of the behavior of the system being modeled. Within a simulation model of a production system or inventory system, the number of objects and the number of events can become very large; as a result, the duration of a simulation experiment can become unacceptably long [7]. Therefore simplification may be necessary. Use of OptQuest makes it easy to optimize scenarios that a simulation model can handle. With the help of OptQuest we can try large numbers of input sets that allows us to analyze various scenarios in quick period of time [7]. We will talk in detail about OptQuest later in this paper.

1.5 Research Objectives

The main objectives of this research are to do the following:

Develop simulation models using Arena for inventory systems with

- i. One mode of supply
- ii. Two modes of supply: one fast mode and other slow mode
- iii. Varying demand over the horizon considering Product life cycle (PLC)

1. Use of OptQuest for above mentioned models to minimize supply chain cost and find near optimal amount of order quantities by fast mode and slow mode by varying different scenarios.

2. Comparison of the optimized order quantities obtained for different models to draw insights about how inventory policies and strategies change as a result of system characteristics.

1.6 Thesis Outline

Chapter 2 of the thesis discusses the related literature on this topic. The literature review covers previous work on inventory systems with one and two modes of transportation and also the use of simulation modeling in supply chain and inventory management. In Chapter 3, the use of OptQuest in Arena is discussed as well as different models built in Arena to represent various scenarios of inventory system. The comparison of all the results obtained from OptQuest is presented in Chapter 4. Finally Chapter 5 discusses the scope for future work and conclusions of the present work.

CHAPTER 2: Literature Review

2.1 Introduction

The primary objective of this thesis is to develop simulation models in Arena for inventory systems with two modes of supply and changing demand over the Product life cycle (PLC). This chapter looks at related literature on use of Markov decision process in finding optimal policies for inventory systems; study of inventory policies with two modes of supply (fast mode and slow mode of supply). This chapter also looks into effect of PLC on demand change and use of simulation modeling in inventory management.

2.2 Markov Decision Process

Markov decision process (MDP) is being used many times to find optimal inventory policies for different supply chain scenarios. So MDPs are useful for studying a wide range of optimization problems solved via dynamic programming. Today MDP is used in a variety of areas including robotics, automated control, economics and manufacturing.

Vila-Parrish et al. (2009) [8] considered a firm with a geographically distant supplier that simultaneously decides the order for each of two supply modes (e.g. air shipment mode and ocean shipment mode) on a periodic basis. Vila-Parrish et al. (2009) considers products that have changes in demand and demand variability over time representing the product lifecycle. They have developed a Markov Decision Process (MDP) which determines the optimal ordering quantities per mode under stochastic, non stationary demand. They have considered two cases. Case 1 is the general model which models demand evolution as an embedded Markov chain, and case 2 considers demand evolution is time dependent. They have specified demand evolution and demand characteristics according to the structure of Product Lifecycle (PLC). Optimal base stock policies, which are defined by two base stock levels are derived and are shown to be both state and time dependent for both cases. The results of their experiments showed that different strategies should change throughout and according to the product life cycle.

In 1986, Ding [9] used Markov Decision Process (MDP) methodologies to solve a multi stage stochastic production/inventory problem.MDP deal with sequential decision making in stochastic system. One of the purposes of his study is to develop a methodology which facilitates the solution of large scale problems, and to provide the computational results indicating the value of the approach. Also a representative set of multi stage stochastic demand production/inventory problems with different set up cost at each stage are solved using MDP methodology as a tool and the optimal solution are characterized and displayed. The results are compared with the approximate solution obtained by the Clark and Scarf procedures. This study found that the differences in solution values between two procedures (MDP & Clark and Scarf) grow noticeably as the number of stages of the problem increases.

2.3 Inventory Policies with Periodic Review and Two Modes of Supply

Use of two modes of transport is very common in supply chain; one is the fast mode and other is the slow one. At times faster mode is restricted to emergencies in case of demand requirements e.g. stockouts and slow mode is used in other normal demand conditions. We consider Periodic review systems where factors like demand requirement and current inventory level are updated on periodic basis as a result of ordering decisions. We now review some of the work regarding this area of study.

Sethi and Yan (2003) [10] studied periodic review inventory system with fast and slow delivery modes, fixed ordering cost and regular demand forecast updates. At the beginning of each period, on-hand inventory and demand information are updated. Also at the same time, decisions on how much to order using fast and slow delivery modes are made. Fast orders and slow orders are delivered at the end of the current period and at the end of the next period respectively. Fast orders are more expensive than slow ones. At the beginning of each period the inventory/backlog level is reviewed, and the forecast of the demand to be realized at the end of the period is updated. Also known at the time is the slow order that was issued in the previous period which will be delivered at the end of the current period. With this data in hand, the decisions regarding the amounts to be ordered this period by each mode are made. They found that the optimal policies for both fast and slow orders are of (s,S) type. They also found that the policy parameters exhibit a monotonic behavior with respect to forecast updates, increased demand implies higher order-up-to levels and reorder points.

Whitttemore and Saunders (1977) [11] addressed the problem of optimal ordering policies under stochastic demand when two supply options of air and surface transport are available with different costs and different delivery times. This paper's contribution is the derivation of formulas for optimal order quantity with conditions on the holding cost functions, linear ordering costs and backlogging. They have obtained some sufficient conditions to show when it is optimal to order nothing by air and others to show when it is optimal to order nothing by surface.

Chiang and Gutierrez (1998) [12] described a periodic review inventory system. Where they have compared emergency orders which have a shorter supply lead time but are subject to higher ordering cost compared to regular orders which can be placed on a continuous basis. They considered a periodic review system in which the order cycles are relatively long so that they are possibly larger than the supply lead times. Their study assumes that the difference between the regular and emergency supply lead times is less than the order-cycle length. This paper developed a dynamic programming model and derived a stopping rule to end the computation and obtain optimal operation parameters.

2.4 Considering Product Life Cycle (PLC) and Use of Simulation Modeling for Inventory Systems

The last thing we should study about is the effect of Product life cycle (PLC) on demand distributions in inventory systems. It is important to observe change in demand as product passes through growth, maturity and decline phases of its life. Also we should look into use of simulation modeling to understand its advantages and shortcomings.

Ahiska and King (2010) [13] investigates the optimal inventory policies over the life cycle of a remanufacturable product. They have considered a product which is produced by manufacturing or remanufacturing. They were able to find long-run optimal policies through Markov decision analysis and the optimal or near-optimal policy characterizations with practical structure are determined for every life cycle stage under several setup cost configurations. The effects of changes in the demand and return rates on the optimal inventory policies are investigated through these policies. Further, a performance comparison with a PULL strategy is provided. Finite horizon settings were also used to evaluate the performance of these long-run policies. Numerical examples were used to illustrate the importance of frequent policy revision over the product life cycle. They have found that appropriate policy structures over the product life cycle depend on the setup cost structure of the system. The optimal parameter values of the inventory policies are sensitive to changes in the demand and return rates and the cost of an inventory policy is sensitive to the changes in its parameters values. They have recommended revising the inventory policies over the product life cycle anytime a change in the rates occurs.

In 2000, Beyer and Ward [14] conducted an inventory management project at Hewlett-Packard Laboratories for HP's Network Server Division (NSD). They have considered a NSD manufacturing unit, which manufactures a major subassembly of network servers in Singapore and ships it to four distribution centers (DCs) worldwide, where the assembly is completed as per the customer specifications. They have considered two modes of supply (air and ocean) between factory and DCs and assume demand is stochastic and non-stationary at the DCs. The goal was to reduce NSD's supply chain costs by redistribution of inventory, by reducing overall supply chain inventory and by increasing the use of ocean shipments. They used a software tool to give the optimized results about the selection of transfer mode and also to optimize the cost of supply chain. The software tool uses the algorithm which is programmed using 'C' and runs on HPUX. Their results showed that they produced more effective inventory strategies than what NSD used before. Prior to the commencement of this project, NSD used simple single location, single supply mode, and stationary demand inventory models to determine the inventory targets. This new approach made significant impact over their inventory strategies.

This thesis is motivated by these above mentioned works. We focus on developing one and two modes of supply. These models will allow for changes in lead times for fast and slow modes of transfer; and will easily accommodate changes in values for holding cost, backorder cost, setup cost, unit ordering cost etc. Finally this model incorporates demand that changes over the horizon instead of using fixed demand. By developing this flexible model we can compare the inventory and ordering policies over a multitude of scenarios.

CHAPTER 3: OptQuest and Simulation Models

3.1 Introduction

Simulation modeling is used to predict system performance. Initially the use of this technique was limited to forecasting outcomes of changes made to equipment, processes or systems within a warehouse or manufacturing unit. Today simulation modeling has become much broader to encompass entire supply chain network their facilities, transportation modes and inventory systems. Significant research is being made in the field of using simulation modeling for inventory management in various scenarios. In this chapter we will discuss the use of simulation modeling in context of specific inventory systems under multiple/single modes of supply and the use of OptQuest tool in Arena.

3.2.1 What Is OptQuest?

OptQuest is used to find near optimal solutions within your simulation models which consequently helps to enhance the analysis capabilities of Arena. In most simulation models the ultimate goal is to determine the best values for a set of controls. One of the limitations of simulation models in general is that they can only evaluate the model for the controls that you have specified. Thus to evaluate performance of a process by using simulation model we must first select the specific control levels and then run a simulation to forecast the performance of that particular configuration. For finding an optimal solution for a simulation model without an appropriate tool, generally requires that we search in a heuristic or ad-hoc manner [15]. In this fashion we usually run a simulation for an initial set of decision variables, analyze the results, change one or more variables, re-run the simulation, and repeat this process until a satisfactory solution is obtained [15]. In most of the problems this process can be very tedious and time consuming and it is often not clear how to adjust the controls from one simulation to the next. OptQuest is able to overcome this limitation by automatically searching for optimal solutions within Arena simulation models. First a mathematical description of our optimization problem in OptQuest is formulated and then it searches for the values of controls that maximize or minimize a predefined objective function. We can find solutions that satisfy a wide variety of constraints by using OptQuest. Another benefit of OptQuest is the built-in nature of the optimization algorithms which we discuss in the following sections.

3.2.2 Use of Optquest / The OptQuest user interface

OptQuest treats the simulation model as a 'black box' (i.e., it observes only the Input and Output of the simulation model). Figure 3.1 is a generic representation of a simulation model.

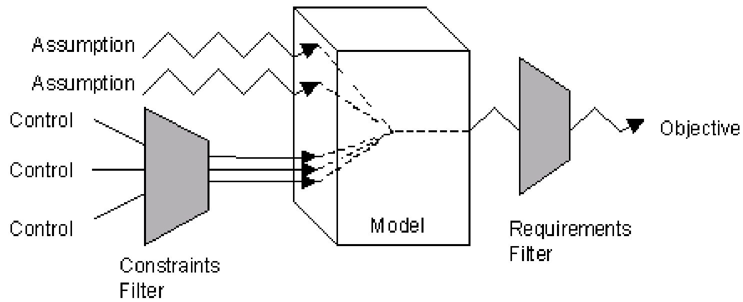

Figure 3.1 Generic representation of a simulation model
(http://www.rockwellautomation.com/support/)

OptQuest tries to find a candidate solution and if it does not fit the constraints then that solution is eliminated and candidates that are likely to yield improved objective function are explored. OptQuest allows the simulation analysts to explicitly define integer and linear constraints on the deterministic simulation inputs and the specification of boundaries on the random simulation outputs. OptQuest requires specifying lower, suggested, and upper values for the variables that are to be optimized. The suggested values determine the starting point. The selection of lower and upper values affects the efficiency and effectiveness of the search. The following are the steps to use OptQuest tool.

1. Before using OptQuest, you must first build an Arena model for your problem. This includes building a well-tested simulation model and defining the controls and responses that you are planning to use in optimization model. For example the models developed in this research defines variables indicating order quantities by fast mode and slow mode as controls, also total cost is defined as response variable. You should make sure the Arena model is working correctly and giving the expected results by

running several simulations. After defining the control variables and response statistics in Arena, you can begin the optimization process in OptQuest.

2. You should start with selecting the Controls that need to be optimized. The values of these Controls will change with each simulation until OptQuest finds values that yield the best possible value for the objective. For some cases you might fix the values of certain Controls and optimize the remaining. A tree-structured user interface of OptQuest for Arena is shown in Figure 3.2. That contents the optimization model components i.e. Controls, Responses, Constraints, Objectives, Suggested Solutions, and Options as nodes in the tree structure in the left-hand section. When we select any of the nodes its summary grid is displayed in the right-hand section. Modify upper bound, lower bound and suggested value of resource Controls by double clicking the row or selecting the named Control in the left-hand tree panel. Next, click on the Responses in the tree on the left to select the outputs of interest. Responses section includes the built in Arena costing outputs and all outputs we have defined [16].

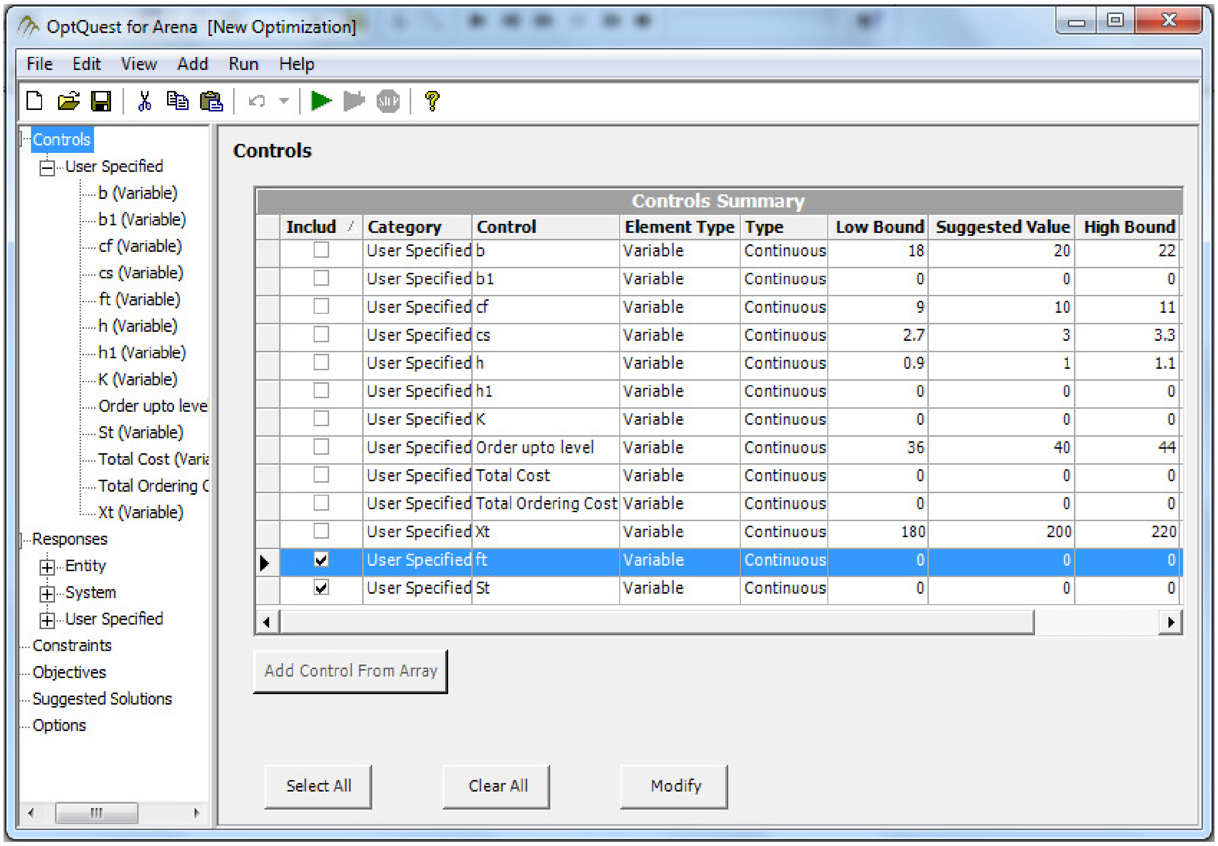

Figure 3.2 OptQuest User Interface

3. Next we should define constraints to limit the search for solution. A constraint defines a relationship among controls and/or responses. OptQuest allows you to add linear or non-linear constraints which are represented in terms of the controls that have been selected for optimization. OptQuest can evaluate linear constraints without running a simulation. To determine the feasibility of non-linear constraints it requires a simulation to be run [15]. Next we should define the goal of the optimization i.e. we need to define an objective function. We can define more than one objective using OptQuest but only one objective can be used for an optimization. The other objectives

are ignored and have no impact on the optimization. For example our objective function in this paper is to minimize total cost over a simulated product life cycle.

4. Next step is selecting optimization options. We should select the stop options to control how long the optimization will run. We can select more than one stop option, but the optimization will stop when the first stop condition is satisfied. Out of four options of Number of Simulations, Manual Stop, Automatic Stop, and Run Only Suggested Solutions at least one stop option must be selected. We also have to select a tolerance value which is useful when two solutions are equal. The default setting is 0.0001. We can specify the number of replications per simulation. This is the number of times that the model will be run in every simulation After setting all these options we can start optimizing the simulation model.

5. Figure 3.3 shows OptQuest window when optimization is complete. The top section of the displays shows the best values of objective function and Control variables that need to be optimized. The status column indicates whether the solution is feasible or infeasible. The bottom part of the optimization window displays a graph that plots the trajectory of the search for the best solution. When the optimization completes a Best Solutions node is added to the tree and the right-hand panel shows the top 25 solutions.

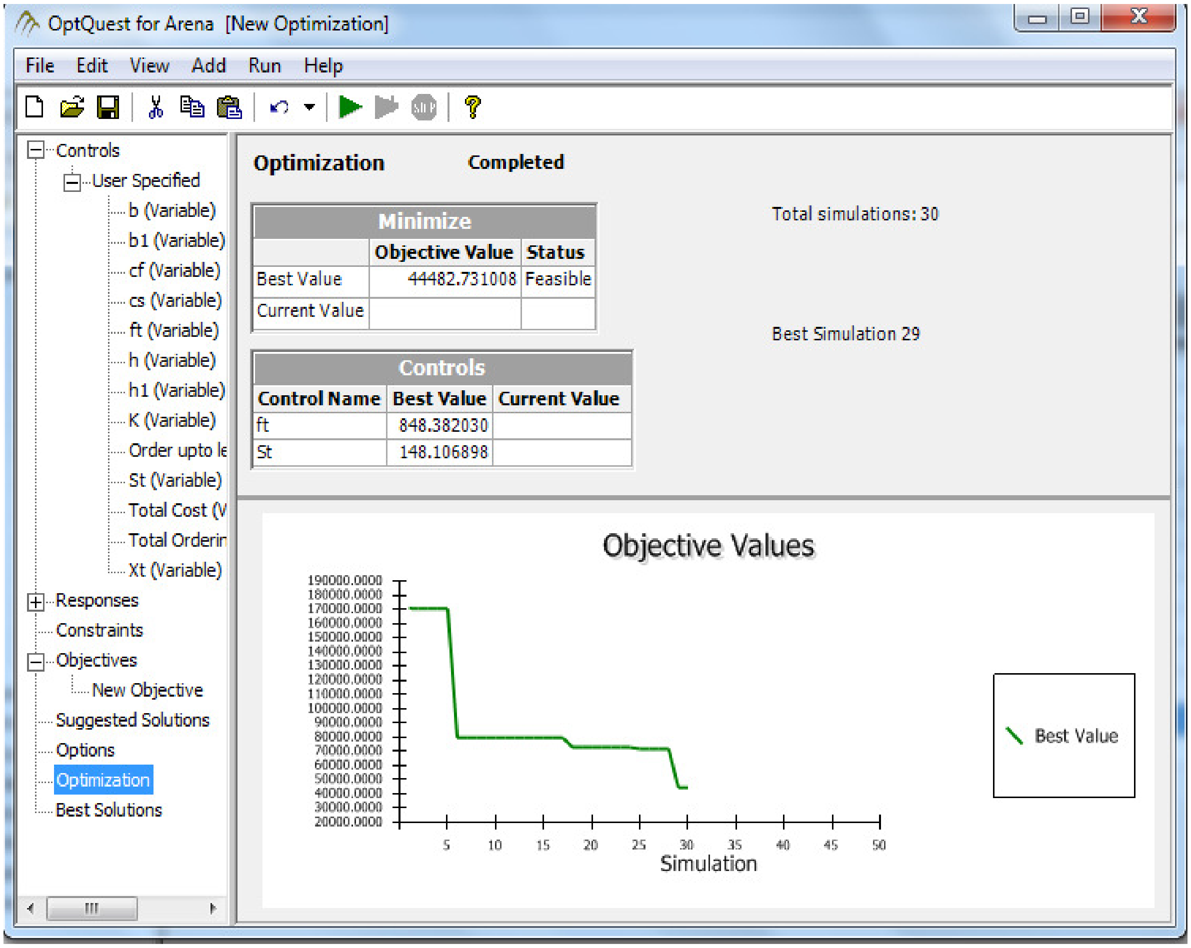

Figure 3.3 OptQuest Output Window

3.3 Arena Models

The first step in simulation modeling is to develop Arena models representing specific inventory systems under consideration for optimization. In this section we will discuss in detail about the logic being used to construct five different Arena models. Following are the necessary notations that are used throughout this paper.

t = {1,2,…,T} where T is the horizon of the inventory model

i_t = the demand state during period t

x_t = inventory level at the start of period t

d_t = the demand in period t

$\psi_k(.)$ = the conditional density function of d_t when $i_t = k$

f_t = the order quantity via the fast supply mode in period t

s_t = the order quantity via the slow supply mode in period t

O = the order up to level

l_f = the lead time of the fast supply mode

l_s = the lead time of the slow supply mode, $lf < ls$

c_f = the variable cost of the fast supply mode

c_s = the variable cost of the slow supply mode, $c_f > c_s$

κ = the setup cost

h_t = unit holding cost at time t

b_t = unit backorder cost at time t

The four models we are going to consider are as follows:

1. Model using only fast mode of supply and optimizing f_t
2. Model using only slow mode of supply and optimizing s_t
3. Model using both modes of supply and optimizing f_t & s_t for constant demand over time horizon
4. Model using both modes of supply and optimizing f_t & s_t for changing demand over time horizon

3.3.1 Arena Model 1

The first model we are going to consider is the simplest of all. In this model we will consider a simple inventory system with one supplier, one factory and with only fast mode of supply and consequently trying to optimize f_t. The demand is constant over the entire time horizon. The time horizon is finite. The best way to describe the model logic is to consider each module and its use. The following Figure 3.4 shows the schematic for this model and module logic being used to construct it

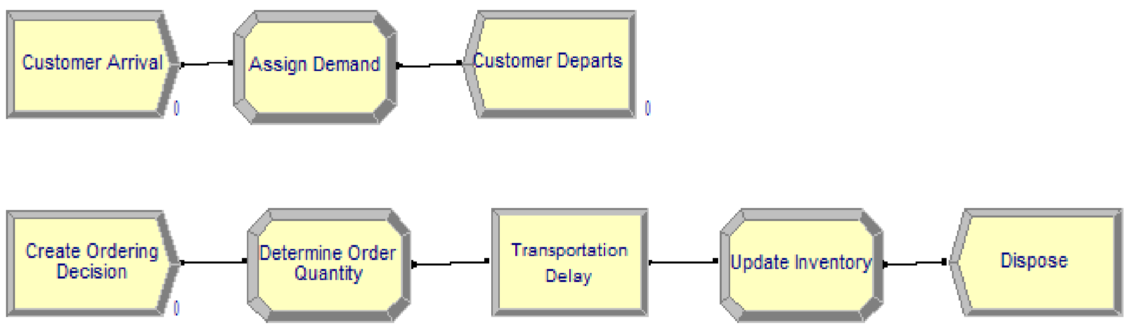

Figure 3.4 Model 1 (Use of Only One Mode of Supply)

The first part of the figure represents demand generation. The first create module signifies customer arrival and is used to define customer inter-arrival time. The entity type defined here is called the *customer.* The assign module next to it generates demand and decrements the customer demand quantity from the inventory level. The dispose module indicates customer departure.

The second part of the figure updates the inventory level after the order quantity is decided and orders arrive. The logic starts with the Create module. We want the first creation to be at time 0 since our system calls for an inventory evaluation at the beginning of the run. In this model, the create module generates a signal to make decisions about ordering quantities. The entity type defined by this module is called the *Inventory Evaluator*. The assign module next to it is used to determine the order quantity by fast mode of supply (f_t); also this module defines and calculates total cost of ordering. The delay module adds a transportation delay before ordered quantity arrives which for now we assume to be zero. One more assign module is defined to update the inventory level by adding the amount being ordered. And finally the decision signal departs through the dispose module.

Every time an order is placed there is fixed setup cost incurred of K regardless of the order quantity. Also there is unit cost of order for fast mode (c_f) for every item being ordered. If no order is placed there is no ordering cost, not even the fixed cost of K. Whenever there are items actually physically in inventory (i.e $x_t > 0$), a holding cost h_t is incurred per item per day. Whenever we are in backlog (i.e $x_t < 0$), a shortage cost of b_t per item per day is incurred. The following equations shows the change in inventory after f_t is ordered and received and demand d_t is realized.

$$x_{t+1} = x_t + f_t - d_t \tag{3.1}$$

$$Total\ Ordering\ Cost = \sum_0^T c_f f_t + Total\ Holding\ Cost + Total\ Shortage\ Cost \tag{3.2}$$

$$Total\ Holding\ Cost = \sum_0^T h_t \mathrm{MX}(\mathrm{x_t}, 0) \tag{3.2a}$$

$$Total\ Shortage\ Cost = \sum_0^T b_t \mathrm{MX}(-\mathrm{x_t}, 0) \tag{3.2b}$$

We have used OptQuest to find optimized values of the order quantity (f_t) and total ordering cost (Eq.3.2) for different sets of cost values, demand and Inventory level. The OptQuest results are discussed in chapter 4.

3.4.2 Arena Model 2

In this model we will consider an inventory system with one supplier, one factory and two modes of supply (i.e. fast mode and slow mode). The fast mode of supply is used only when the inventory level drops below zero thus it is seen as an emergency mode of transportation. Further, it is assumed that the amount ordered by fast mode is just enough to bring the inventory level back to zero. Here we will try to optimize the order quantity by slow mode (s_t). Again, the demand is constant over the entire time horizon of 90 days. Since we are using two modes of supply, we can see the change in model logic compared to Model 1 in following Figure 3.5. The main difference between model 1 and 2 is the addition of decide module to select the required mode of supply.

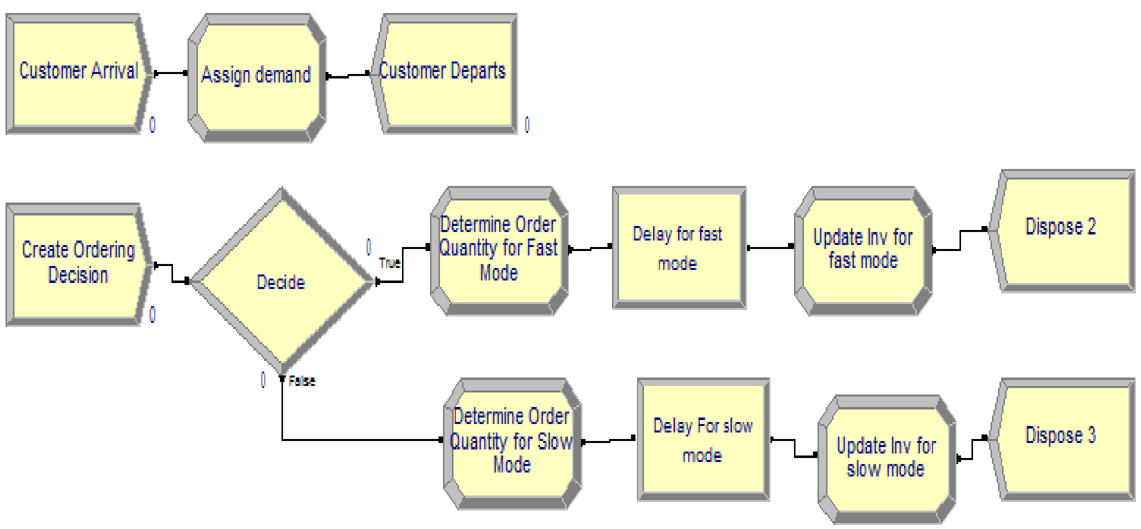

Figure 3.5 Model 2 (Use Two Modes of Supply)

As we can see the first part of diagram which is used to represent the demand generation, is same as in Model 1. The objective of second section of the model is also same as in Model 1, i.e. update the inventory level as a result of ordering decisions and deliveries. The create module is again used to initiate the decision signal. The decide module which is unique to this model is used to define a criterion which helps to select which mode of supply will be used depending on inventory level. The first branch is followed if $x_t < 0$, is true, indicating we have to place an order now with the fast mode of transfer, which has shorter delivery lag compared to slow mode of transfer. If the condition is false the second branch is used to place an order with slow mode of transfer.

Once we decide the correct mode of supply the entity, termed the *Inventory Evaluator,* moves to the respective assign module, which determines the order quantity and it also computes the ordering cost incurred. The delay module adds the delivery lag depending on the slow or fast mode of transfer. The next assign module updates the inventory level by adding the respective ordered quantity. And the entity *Inventory Evaluator* leaves the system with dispose module. If the fast mode is used the inventory balancing and costs are calculated as follows:

$$x_{t+1} = x_t + f_t - d_t \tag{3.3}$$

$$Total\ Ordering\ Cost = \sum_{o}^{T} c_f f_t + Total\ Holding\ Cost + Total\ Shortage\ Cost \tag{3.4}$$

For slow mode of supply we substitute s_t for f_t in Eq. 3.3 and 3.4

$$x_{t+1} = x_t + f_t - d_t \tag{3.5}$$

$$Total\ Ordering\ Cost = \sum_0^T c_f f_t + Total\ Holding\ Cost + Total\ Shortage\ Cost \tag{3.6}$$

$$Total\ Holding\ Cost = \sum_0^T h_t \mathrm{MX}(\mathrm{x_t}, 0) \tag{3.6a}$$

$$Total\ Shortage\ Cost = \sum_0^T b_t \mathrm{MX}(-\mathrm{x_t}, 0) \tag{3.6b}$$

3.4.3 Arena Model 3 & 4

Model 3 and 4 are very similar; the only difference is demand variation. Model 3 assumes constant demand over the time horizon, whereas Model 4 has changing demand over the time horizon. So we will describe Model 3 and 4 in the same section. Unlike model 2, here we will try to optimize both f_t and s_t.

In these models we will allow for the simultaneous use of both fast and slow modes of supply. The fast mode is used only when the inventory level drops below zero. Here we will try to optimize both f_t and s_t over a finite time horizon of 90 days. As mentioned before the demand is constant for Model 3 and it is varying for Model 4. We will look into timeline of events which will help us to understand the model logic.

The order quantity by fast mode of supply (f_t) and order quantity by slow mode of supply (s_t) are two important decisions to be made periodically in inventory system. These two decisions are dependent on inventory level (x_t) and demand (d_t). To illustrate, when these decisions are made we will consider a representative timeline of events when ls = 1and lf = 0. This timeline is shown in following Figure 3.6.

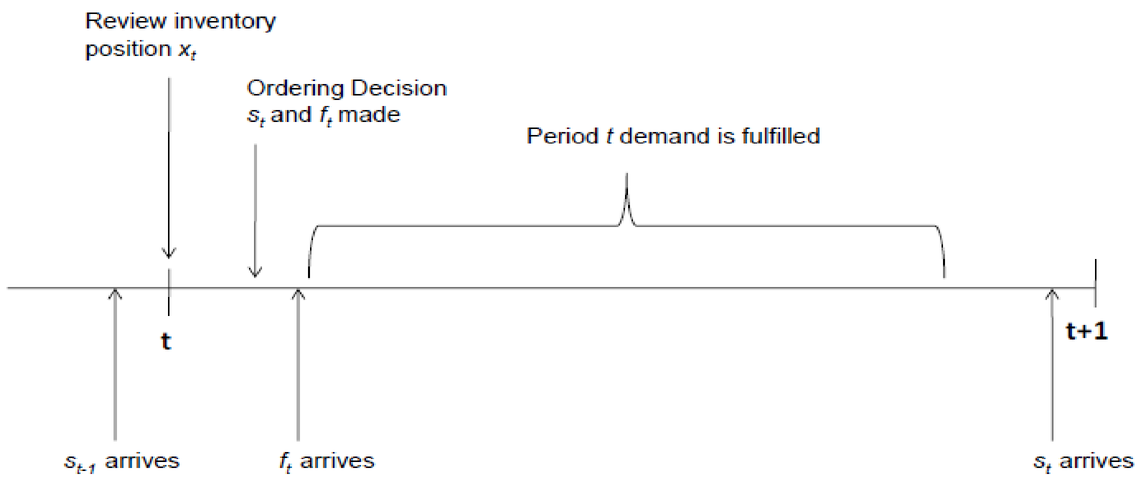

Figure 3.6 Timeline of events when *ls* = 1and *lf* = 0 (Vila-Parrish 2009) [8]

As we can see in Figure 3.6, the state is observed at the beginning of period t, to place orders by one or both supply modes. Since $lf = 0$, the order quantity by fast mode arrives immediately. Then respective demand d_t is fulfilled before the end of period t. Unsatisfied demand is fully backlogged. The schematic of this model is shown in Figure 3.7.

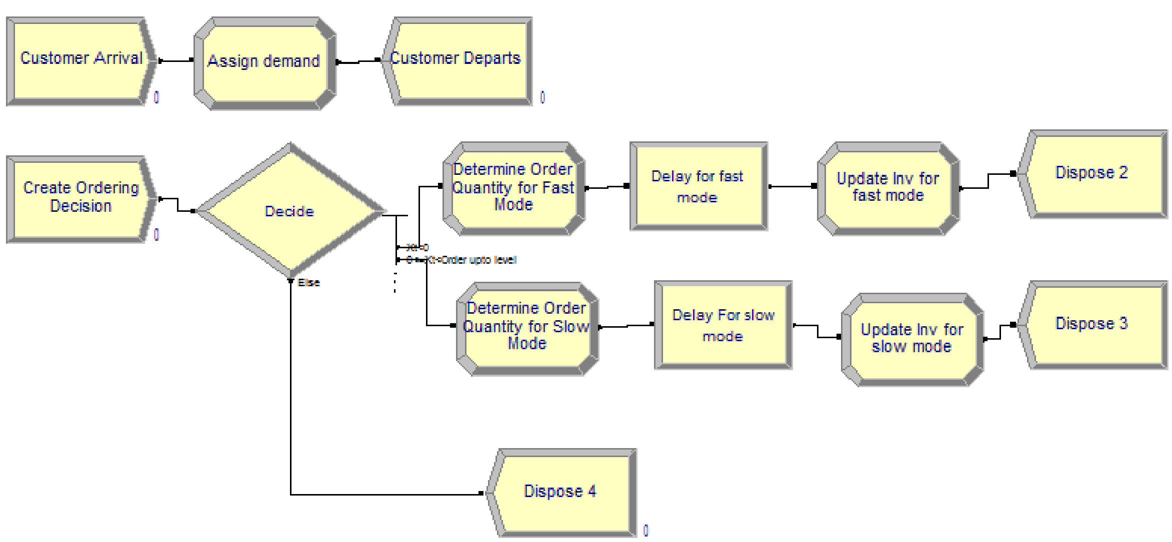

Figure 3.7: Model 3/ Model 4

The first part indicating demand generation is similar to the previous models. As we can see in Figure 8 the main difference is the decide module. First branch is of type 'If' with condition $x_t < 0$, which, if true, indicates we have to place an order now with the fast mode of transfer, which has shorter delivery lag compared to slow mode of transfer. The second branch is of type 'If' again with condition $x_t < O$ (where O is the order up to level), which, if true, indicates that we need to place an order with slow mode of transfer. And the third branch is of type 'Else' indicating the possibility of no order being placed. The rest of the logic work same as Model 2. The equations representing Model 3 and 4 are shown below.

$$x_{t+1} = x_t + f_t + s_t - d_t \tag{3.7}$$

$$Total\ Ordering\ Cost =$$

$$\sum_0^T c_f f_t + \sum_0^T c_s s_t + Total\ Holding\ Cost + Total\ Shortage\ Cost \tag{3.8}$$

$$Total\ Holding\ Cost = \sum_0^T h_t \mathrm{MX}(\mathrm{x_t}, 0) \tag{3.8a}$$

$$Total\ Shortage\ Cost = \sum_0^T b_t \mathrm{MX}(-\mathrm{x_t}, 0) \tag{3.8b}$$

CHAPTER 4: OptQuest Results

4.1 Introduction

The objective of our simulation models is to minimize the total system cost and find near optimal values of ordering quantities when one or more mode of supply are present. In section 3.3 of previous chapter we have discussed how five different arena models have been developed to represent different supply chain systems. To analyze the nature of each system, we will discuss each model one by one. The input parameters of OptQuest like demand distribution, initial inventory level, and lead times are varied to get the results indicating near optimal ordering quantities, which will help us to understand the dynamics of each inventory system in detail.

4.2 Demand Distributions

We are interested in exploring how demand distribution and demand variability impact the optimal cost and order quantities in our models. We will use the uniform probability distribution and the normal probability distribution to represent different demand patterns in our models.

In the following Table 4.1 and 4.2 the parameters of the demand distributions are mentioned. Each distribution has the same mean (92) and varied degrees of freedom. The mean of every demand distribution is kept constant, for the sake of simplicity while comparing the results under different constraints.

Table 4.1 Uniform Distribution

No.	1	2	3
Demand	UNIF(51,133)	UNIF(67,117)	UNIF(80,114)
Mean	92	92	92
CV	0.25	0.15	0.1

Table 4.2 Normal Distribution

No.	1	2	3
Demand	NORM(92,41)	NORM(92,25)	NORM(92,12)
CV	0.445	0.271	0.13

In the following section we describe the results of our one mode of supply model

4.3 Model 1 Results–One Mode of Supply

In this model we will consider a simple inventory system with one supplier, one factory and with only fast mode of supply and consequently trying to optimize f_t. The following results are distinguished according to demand distribution being used and input factors being varied. The common parameters being used in model 1 are listed below in Table 4.3.

Table 4.3 Baseline Parameters

x_t	0
k	0
h	1
b	20
c_f	10
l_f	0

4.3.1 Optimizing f_t -Change In Demand Distribution

Ignoring demand variation will lead to excess inventory or negative inventory. Thus, our interest is in studying the effect of demand variation on optimal order quantities. Table 4.4 and 4.5 describe the results according to each demand distribution. Each of the demand distribution has a mean of 92 and coefficient of Variation (CVs) decreases from demand distribution number 1 to 3.

Table 4.4 Model 1, Uniform Distribution, Change In Demand Distribution

Demand Distribution	UNIF(51,133)	UNIF(67,117)	UNIF(80,114)
f_t	126	104	98
Total Cost	92402	86154	79943

Table 4.5 Model 1, Normal Distribution, Change In Demand Distribution

Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	102	89	74
Total Cost	84422	67125	47801

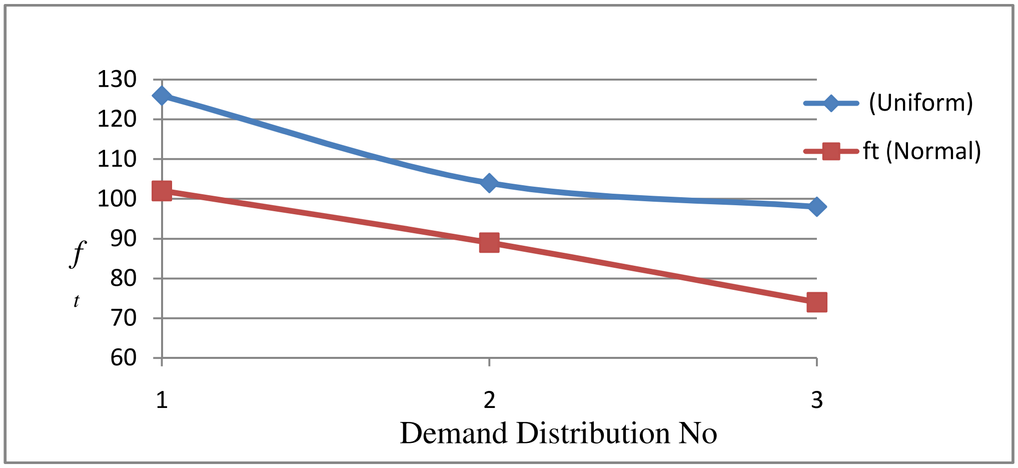

Figure 4.1 Model 1, Optimize f_t, Change in Demand Distribution

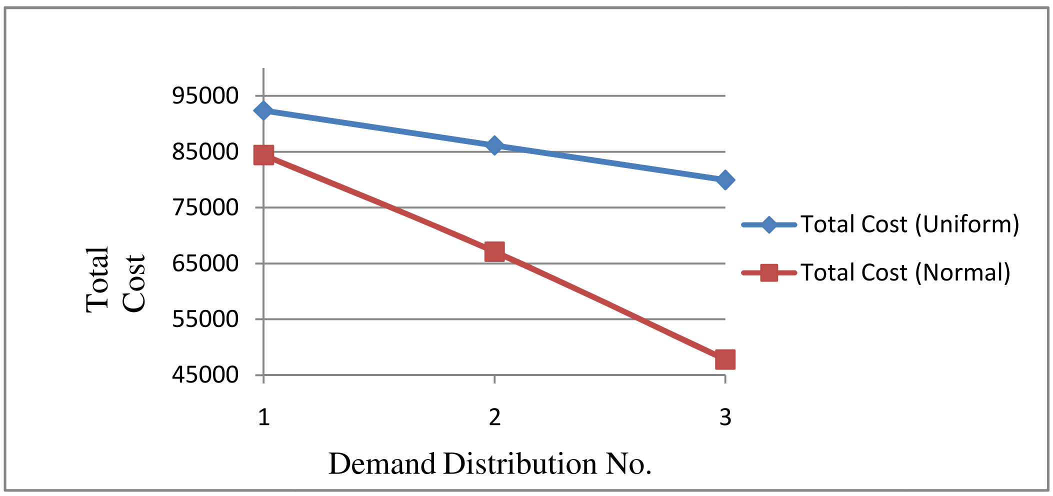

Figure 4.2 Model 1, Total Cost, Change in Demand Distribution

The first set of experiment shows how variation in demand impacts the optimized values of f_t. As we decrease the gap between maximum and minimum limit of uniform distribution the order quantity (f_t) decreases. In the case of normal distribution, when coefficient of variation (CV) decreases the order quantity (f_t) decreases. The results show that demand (i.e. Uniform versus Normal) distributions that have less central tendency leads to vague prediction of realized demand, which results in increase of order quantity.

4.3.2 Optimizing f_t -Change in Initial Inventory Level

Keeping large amount of initial inventory can avoid further ordering, but production facilities may face unexpected failures or sudden decrease in demand, which makes this an inefficient option. While we do not incorporate these events, we are interested in exploring how different amounts of initial inventory can lead to different ordering policies. Initial inventory level can be a very important factor to define the starting conditions of any inventory system. Here we will observe its effect on ordering quantities.

Table 4.6 Model 1, Uniform Distribution, Change in Initial Inventory Level

x_t	100	150	200
Demand Distribution	UNIF(67,117)	UNIF(67,117)	UNIF(67,117)
f_t	95	91	81
Total Cost	75447	74337	73228

Table 4.7 Model 1, Normal Distribution, Change in Initial Inventory Level

x_t	100	150	200
Demand Distribution	NORM(92,25)	NORM(92,25)	NORM(92,25)
f_t	81	73	69
Total Cost	53730	47761	45920

As we can see from results below an increase in initial inventory level leads to decrease in order quantity. More initial inventory helps to fulfill the demand for longer time without any additional ordering. Also we can observe that the decrease in order quantity is not significant, indicating the effect of initial inventory lasts for only the beginning of time horizon which is considered to be 90 days in this model.

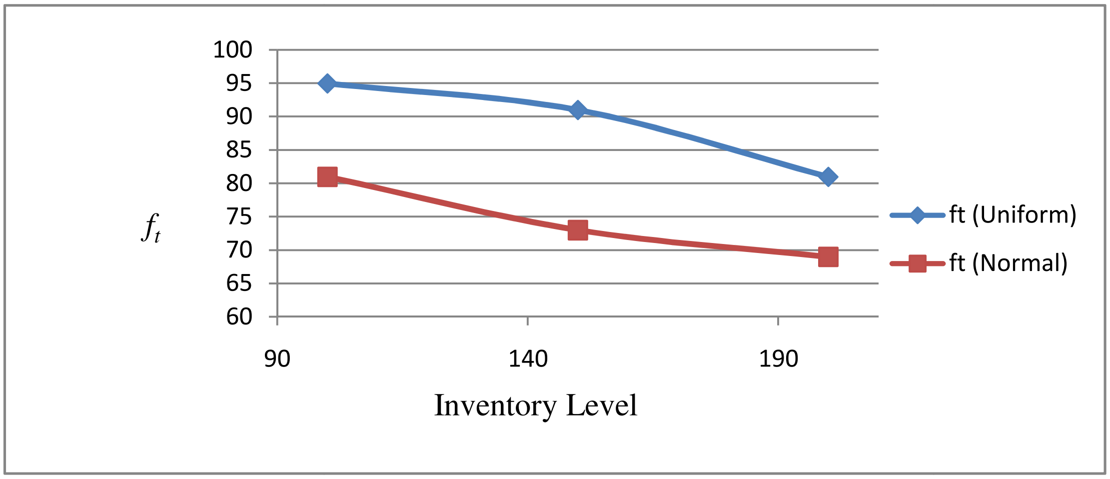

Figure 4.3 Model 1, Optimize f_t, Change in Initial Inventory Level

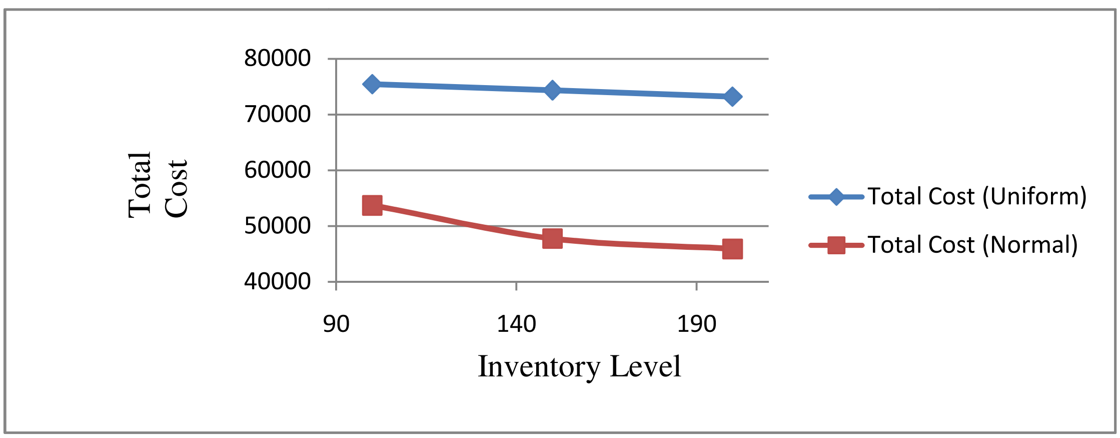

Figure 4.4 Model 1, Total Cost, Change in Initial Inventory Level

Next we will study the effect of change in lead time of transportation on ordering quantities.

4.3.3 Optimizing f_t : Change in Lead Time:

Factors like type of transportation distance of transportation, and failures in transportation results in variation of lead time of supply, that is why effect of lead time plays important role in studying inventory systems. An increase in lead time leads to aggregating the demand.

Table 4.8 Model 1, Uniform Distribution, Change in Lead Time

Demand Distribition	UNIF(67,117)	UNIF(67,117)	UNIF(67,117)
l_f	1	2	3
f_t	112	127	143
Total Cost	89874	92874	102716

Table 4.9 Model 1, Normal Distribution, Change in Lead Time

Demand Distribution	NORM(92,25)	NORM(92,25)	NORM(92,25)
l_f	1	2	3
f_t	103	114	133
Total Cost	77940	78105	83570

We can see in below graphs that amount of order quantity increases with increase in lead time. Increase in lead time leads to aggregating the demand, that is the reason why there is increase in order quantities and consequently the total cost.

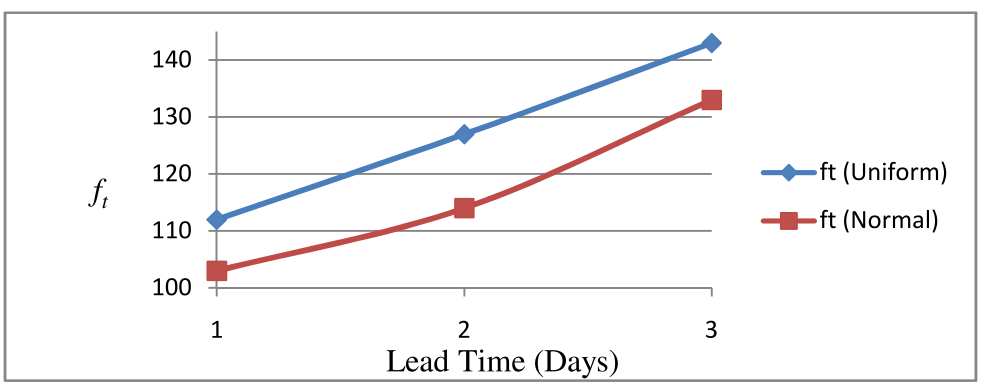

Figure 4.5 Model 1, Optimize f_t, Change in Lead time

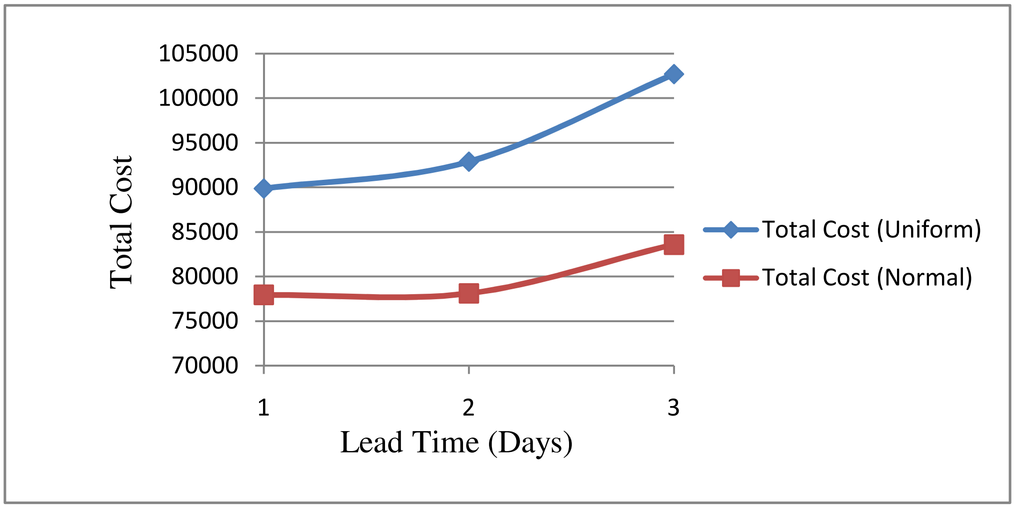

Figure 4.6 Model 1, Total Cost, Change in Lead time

.Next we will discuss the results of the model with two modes of supply.

4.4 Model 2 Results-Two Modes of Supply

In this model we tend our single source model to consider an inventory system with one supplier, one factory and two modes of supply (i.e. fast mode and slow mode). We assume the fast mode of supply is used only when the inventory level drops below zero. In the literature this is termed as an emergency supplier order. It is assumed that the amount ordered by fast mode is just enough to bring the inventory level back to zero. Here also the results are distinguished according to the demand distribution being used and the input factor being varied. The common factors used in this model are listed below.

Table 4.10 Baseline Parameters Model 2

x_t	0
k	0
h	1
b	20
c_s	3
c_f	10
l_f	0
l_s	1

4.4.1 Optimizing s_t-Change In Demand Distribution

As before, we change the demand distribution using uniform and normal distribution to find the near optimal values of ordering quantities (s_t) is shown in Table 4.11 and 4.12

Table 4.11 Model 2, Uniform Distribution, Change In Demand Distribution

Demand Distribution	UNIF(51,133)	UNIF(67,117)	UNIF(80,114)
s_t	146	129	122
Total Cost	41456	37506	37042

Table 4.12 Model 2, Normal Distribution, Change In Demand Distribution

Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
s_t	106	102	94
Total Cost	21681	18323	14984

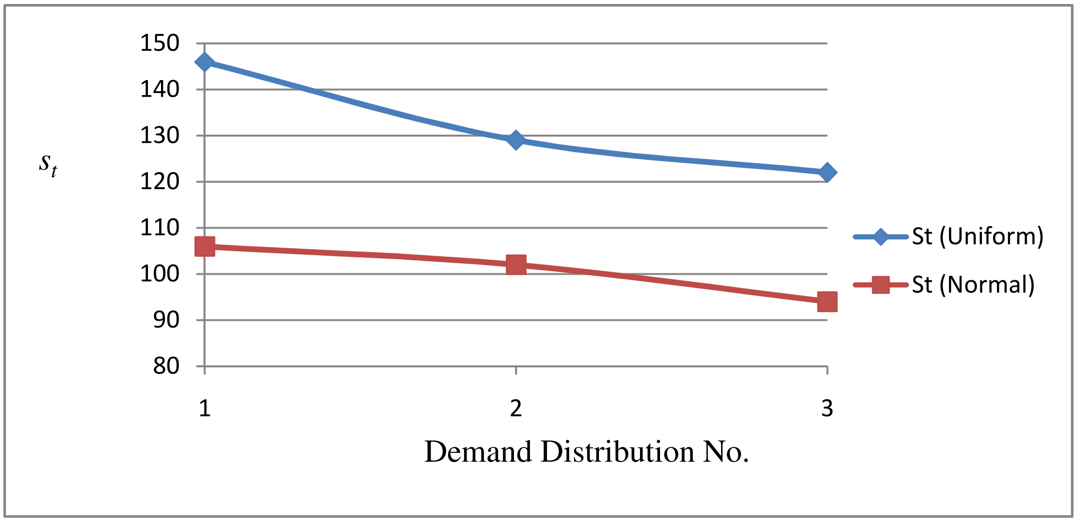

Figure 4.7 Model 1, Optimize s_t, Change in Demand Distribution

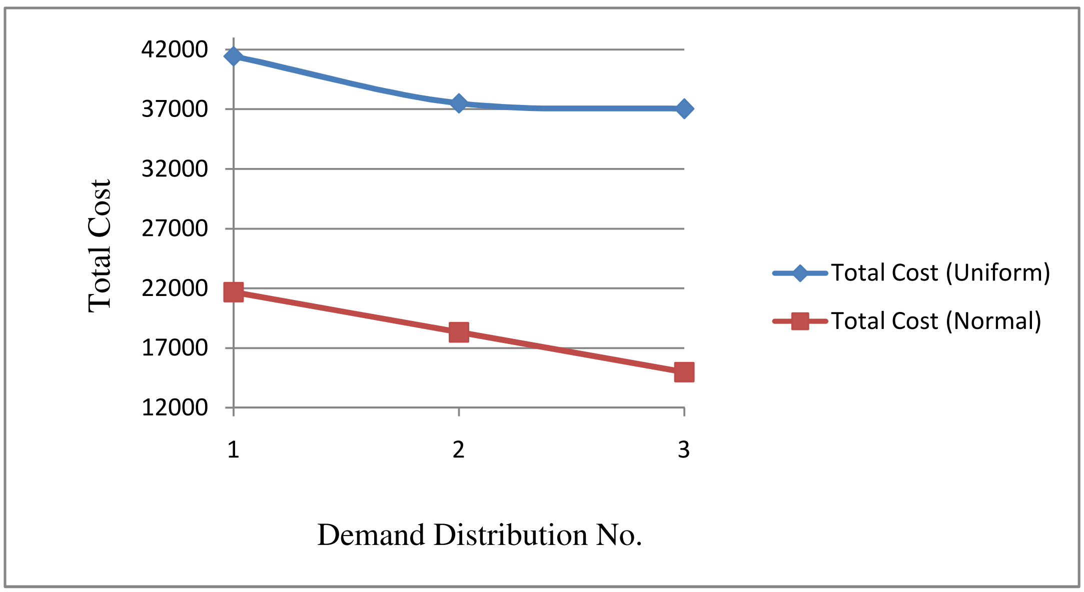

Figure 4.8 Model 1, Total Cost, Change in Demand Distribution

Change in demand size has the same effect on order quantity (s_t) as in model 1. Narrowing the gap between maximum and minimum limit of uniform distribution and decreasing the coefficient of variation (CV) in the normal distribution results in a decrease in the order quantity. The decrease in order quantity (s_t) in model 2 is less steep compared to decreasing in order quantity (f_t) in model 1 (Figure 4.1 and 4.2), because in model 2 negative inventory is brought to zero with the help of fast mode of supply with no lead time. Use of fast mode compensates for some amount of demand variation.

4.4.2 Optimizing s_t-Change in Initial Inventory Level

In model 2 we use the fast mode of supply in an emergency to bring the negative inventory level to zero. Keeping inventory level in the positive range avoids the use of fast mode, and that is why initial inventory level plays an important role in determining the optimal order quantities in model 2. As we can see from the results below an increase in initial inventory level leads to decrease in order quantity (s_t). The results are very similar compared to model 1.

Table 4.13 Model 2, Uniform Distribution, Change in Initial Inventory Level

x_t	100	150	200
Demand Distribution	UNIF(67,117)	UNIF(67,117)	UNIF(67,117)
s_t	128	108	103
Total Cost	37043	31820	27604

Table 4.14 Model 2, Normal Distribution, Change in Initial Inventory Level

x_t	100	150	200
Demand Distribution	NORM(92,25)	NORM(92,25)	NORM(92,25)
s_t	102	83	72
Total Cost	20627	17830	16404

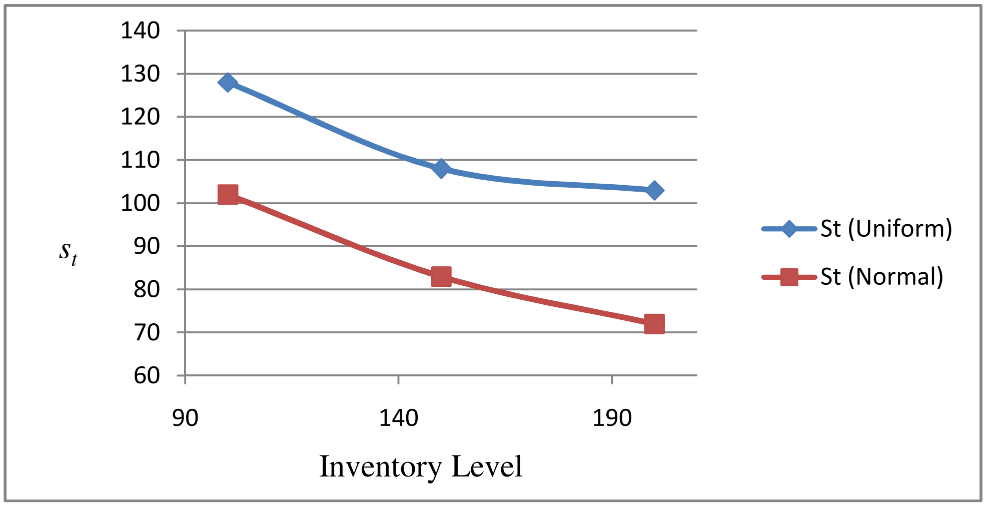

Figure 4.9 Model 1, Optimize s_t, Change in Initial Inventory Level

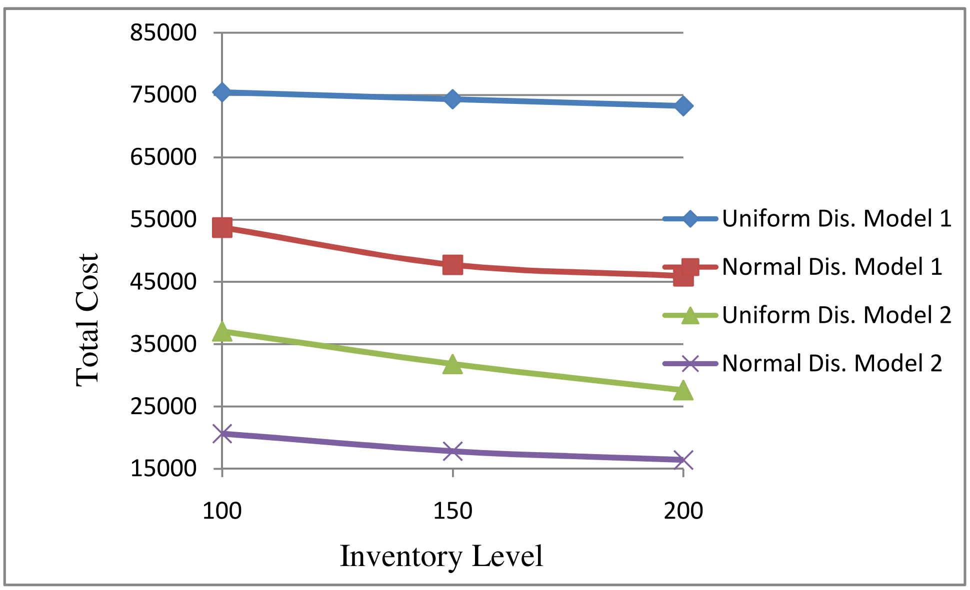

Figure 4.10 Model 1 v/s Model 2, Total Cost, Change in Initial Inventory Level

As we can see in Figure 4.10 shows the comparison of total cost in model 1 and 2. Total costs in model 1 are much higher than model 2. Unit ordering cost for fast mode is higher than unit ordering cost for slow mode. So we should use fast mode of supply only in case of emergency demand requirements. It is very important to maintain proper mix of order quantities by fast and slow mode to make the ordering policies cost effective.

4.4.3 Optimizing s_t-Change in Lead Time

Next we will study the effect of change in lead time of the slow mode of supply on the ordering quantity (s_t). The lead time of fast mode of supply is kept constant at zero indicating it is used as emergency option only. The change in total cost caused by a increasing lead time is also plotted in Figure 4.12

Table 4.15 Model 2, Uniform Distribution, Change in Lead Time

Demand Distribution	UNIF(67,117)	UNIF(67,117)	UNIF(67,117)
l_f	0	0	0
l_s	1	2	3
s_t	130	149	161
Total Cost	39104	45935	47848

Table 4.16 Model 2, Normal Distribution, Change in Lead Time

Demand Distribution	NORM(92,25)	NORM(92,25)	NORM(92,25)
l_f	0	0	0
l_s	1	2	3
s_t	99	127	144
Total Cost	22943	29702	33681

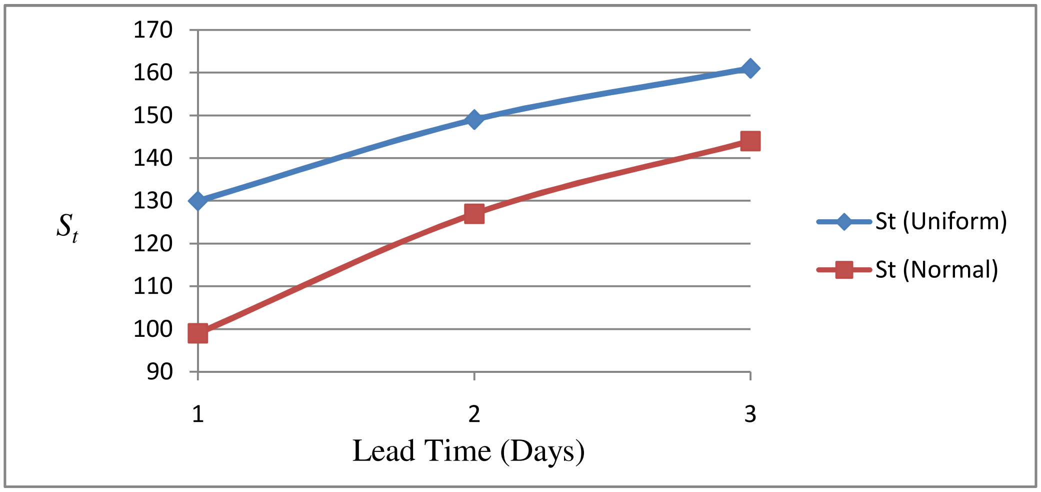

Figure 4.11 Model 1, Optimize f_t, Change in Lead time

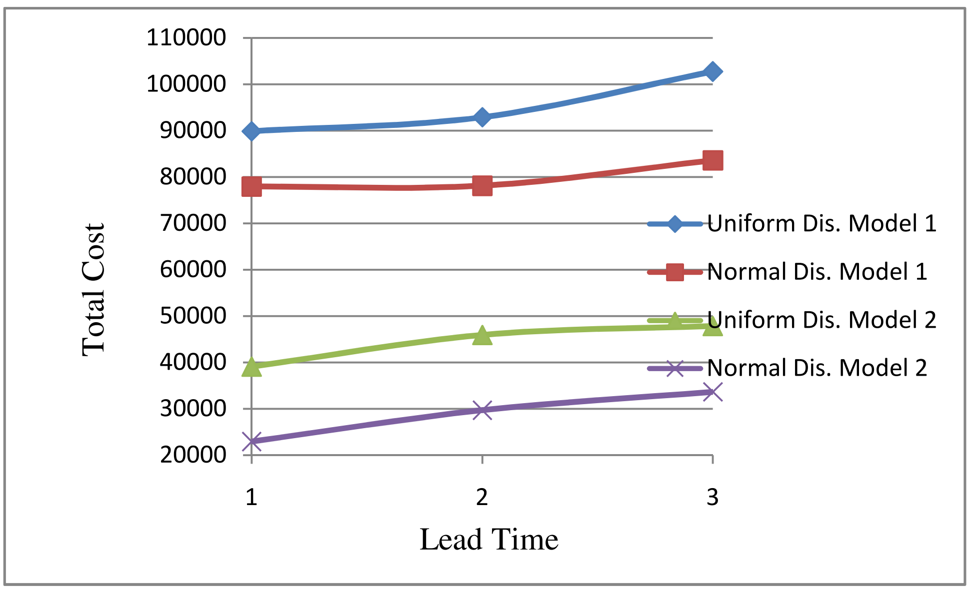

Figure 4.12 Model 1 v/s Model 2, Total Cost, Change in Lead time

We can see in above graphs that amount of order quantity (s_t) increases with increase in lead time like in model 1. Also the increasing graph of order quantity (s_t) in model 2 (Figure 4.11) is less steep compared to increasing graph of order quantity (f_t) in model 1 (Figure 4.5 and

4.6), because in model 2 negative inventory level generated by aggregated demand is brought to zero with the help of fast mode of supply with no lead time.

4.5 Model 3 Results-Two Modes of Supply-Constant Demand Over Horizon

Model 3 uses both fast and slow modes of supply. However, the fast mode is not used only to bring the inventory back to zero like in model 2, but it is determined (i.e., it is a decision variable) simultaneously with the slow mode of supply. Here we will try to optimize both order quantities f_t and s_t over a finite time horizon of 90 days. Optimizing f_t and s_t together will help us to analyze what fraction of the total shipment quantity is being ordered by slow mode and what fraction is being ordered by fast mode, when the factors like demand distribution, initial inventory level and lead time of transportation are varied. The common factors with their values used in this model are listed in Table 4.17

Table 4.17 Baseline Parameters for Model 3

$\boldsymbol{x_t}$	100
$\boldsymbol{k}$	0
$\boldsymbol{h}$	1
$\boldsymbol{b}$	20
$\boldsymbol{c_s}$	3
$\boldsymbol{c_f}$	10
$\boldsymbol{l_f}$	0
$\boldsymbol{l_s}$	1

4.5.1 Optimize f_t and s_t-Change in Demand Distribution

Similar to our previous analysis we begin with changes in demand distribution. Following Tables 4.18 and 4.19 show the changes in demand distribution and results of optimized f_t and s_t.

Table 4.18 Model 3, Uniform Distribution, Change in Demand Distribution

Demand Distribution	UNIF(51,133)	UNIF(67,117)	UNIF(80,114)
f_t	143	157	164
S_t	96	117	148
Total Cost	32257	37702	40193

Table 4.19 Model 3, Normal Distribution, Change in Demand Distribution

Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	127	134	153
S_t	82	108	142
Total Cost	29572	33045	38948

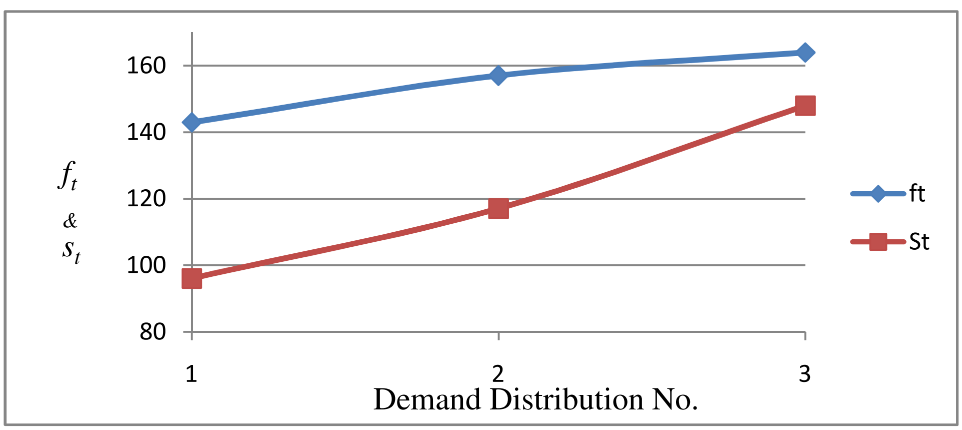

Figure 4.13 Model 3, Uniform Distribution, Optimized f_t & s_t, Change in Demand Distribution

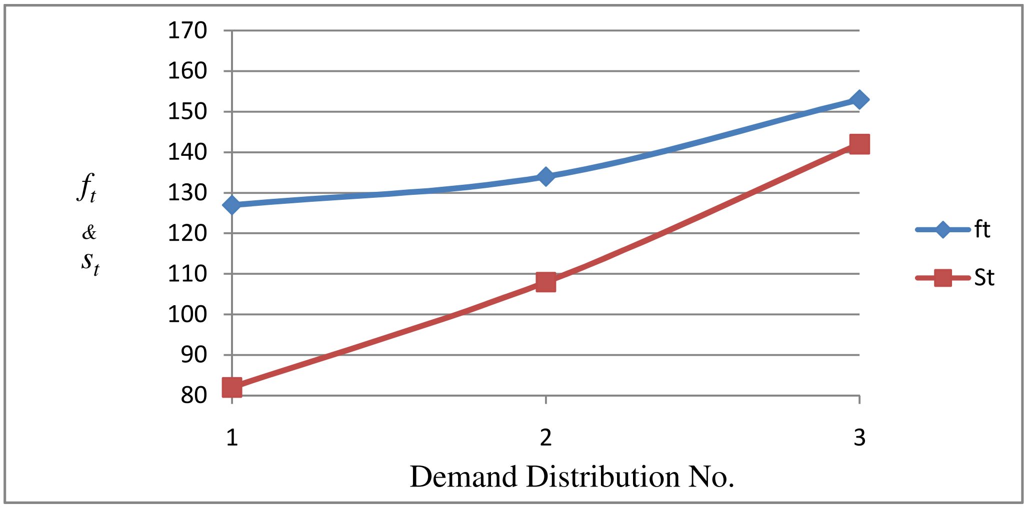

Figure 4.14 Model 3, Normal Distribution, Optimized f_t & s_t, Change in demand Distribution

The change in demand distribution is made to represent the phase changes of Product Life Cycle (PLC). The initial phase of PLC corresponds to demand distributions with higher coefficient of variation (CV). The optimal solutions are dependent on the variability and shape of demand in the corresponding PLC phase. As product moves from growth phase to maturity phase the CV of demand distribution reduces. The result shows that, as the CV of demand distribution decreases the order quantities f_t and s_t increases. Also the fraction of the total shipment quantity order by the slow mode increases.. During the growth phase of high variability optimal solutions emphasizes ordering by fast mode of supply. As the product moves towards maturity phase more volume is ordered by cheaper, slower mode of supply to gain the cost advantage. The order quantities f_t and s_t with uniform demand distribution are observed to be more compare to the order quantities f_t and s_t with normal distribution. The reason behind this is the vague nature of uniform distribution compared to normal distribution.

4.5.2 Optimize f_t and s_t-Change in Initial Inventory level

The effect of change in demand distribution on optimized order quantities is studied with different amount of initial inventory. Following Table 4.20 shows the values of f_t, s_t and total cost with different initial inventory level

Table 4.20 Model 3, Change in Demand Distribution at Different Initial Inventory Level

X_t	500	500	500
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	111	132	141
S_t	89	114	137
Total Cost	22305	24968	28946

X_t	1000	1000	1000
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	107	119	134
S_t	95	102	129
Total Cost	21835	24271	27012

X_t	2500	2500	2500
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	98	112	133
S_t	102	110	129
Total Cost	18743	21593	24741

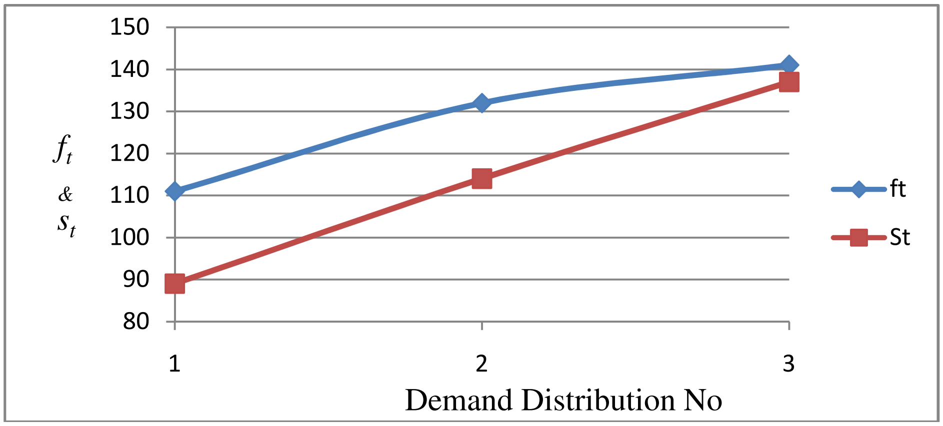

Figure 4.15 Model 3, Change in Demand Distribution at Initial Inventory Level of 500

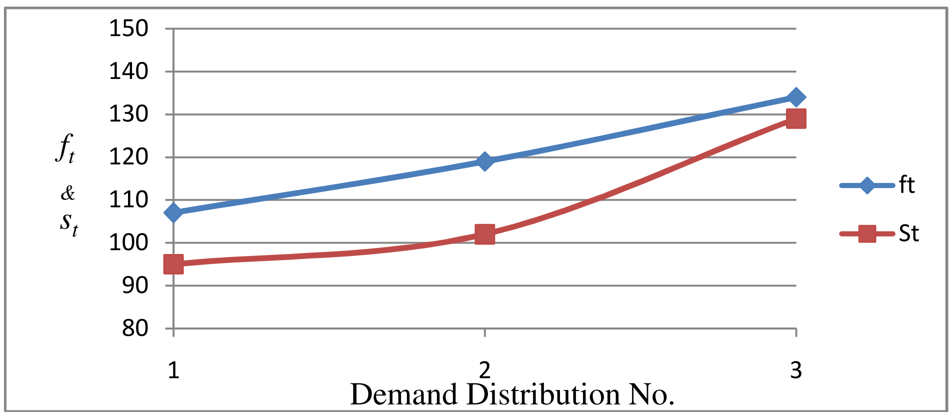

Figure 4.16 Model 3, Change in Demand Distribution at Initial Inventory Level of 1000

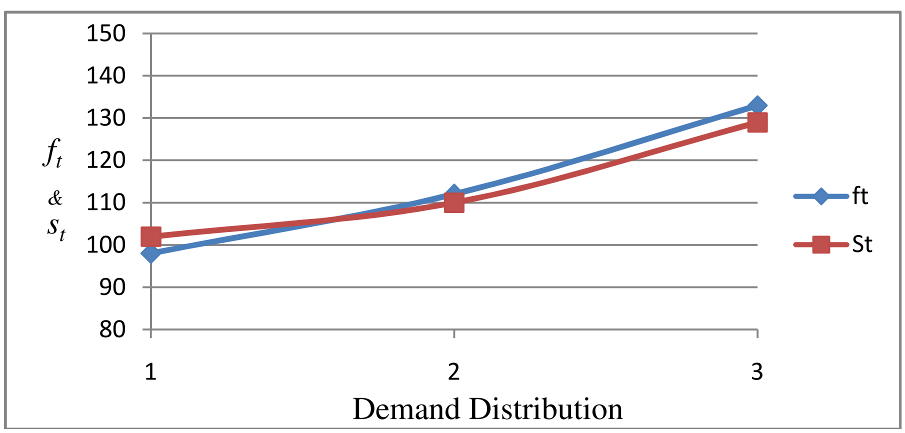

Figure 4.17 Model 3, Change in Demand Distribution at Initial Inventory Level of 2500

We can see from the results that, as the initial inventory level increases the fraction of total shipment quantity ordered by slow mode increases while the fraction ordered by fast mode decreases. This effect is predominantly observed at the beginning of the total time horizon. We can observe that, at initial inventory level of 2500 the ordering quantity s_t becomes more than ordering quantity f_t. This indicates that carrying more inventory on hand decreases the probability that you will need additional products immediately by fast mode to fulfill demand.

4.5.3 Optimize f_t and s_t-Change in Lead Time

The effect of change in demand distribution on optimized order quantities is observed with different amount of lead time for slow mode of supply. The lead time for fast mode of supply is kept constant at zero. Following Table 4.21 shows the values of f_t, s_t and total cost with different lead time.

The result indicates that as the lead time of slow mode of supply increases the order quantities f_t and s_t both increases. A decrease in CV of demand distribution leads to more volume being ordered by slow mode of supply. The moment when ordering quantity s_t becomes more than ordering f_t indicates the shift of PLC phase from growth to maturity, the CV has decreased to a critical point. We observe that an increase in lead time of slow supply modes forces the phase shift to occur early. An increase in lead time is also accompanied by an increase in total cost, which is due to an increase in total ordering quantity. So we can conclude that, it is important to understand the point of phase shifts to accordingly change the ordering policy and supplier strategy. If we use the optimal ordering policy for the maturity phase throughout the lifecycle or if we use the optimal ordering policy of growth phase throughout the horizon we may have periods of excess inventory or shortages.

Table 4.21 Model 3, Change in Demand Distribution at Different Lead Time

l_f	0	0	0
l_s	2	2	2
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	135	151	172
S_t	84	130	154
Total Cost	33842	36734	37023

l_f	0	0	0
l_s	4	4	4
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	142	164	185
S_t	91	138	189
Total Cost	35515	37782	41945

l_f	0	0	0
l_s	7	7	7
Demand Distribution	NORM(92,41)	NORM(92,25)	NORM(92,12)
f_t	144	171	188
S_t	103	147	197
Total Cost	38676	40835	44190

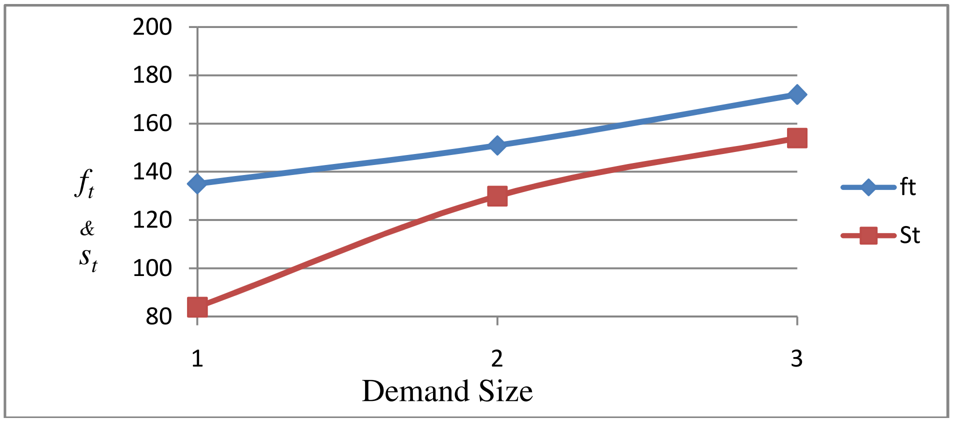

Figure 4.18 Model 3, Change in Demand Distribution at Lead Time of 2 Days

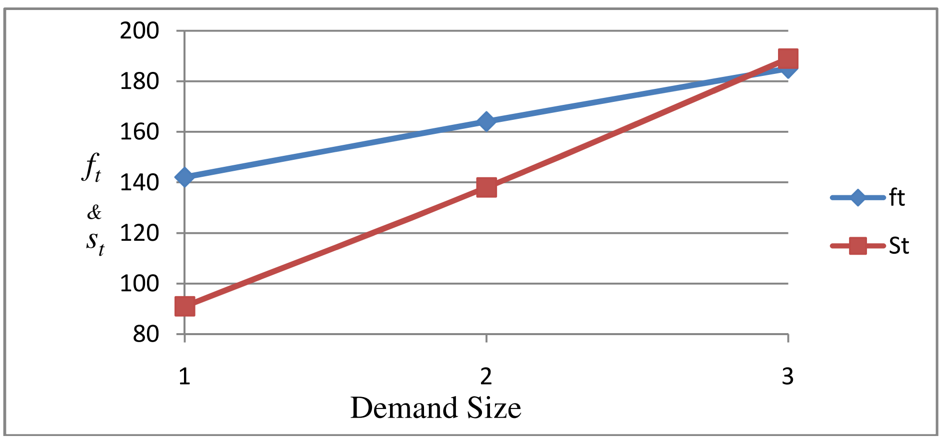

Figure 4.19 Model 3, Change in Demand Distribution at Lead Time of 4 Days

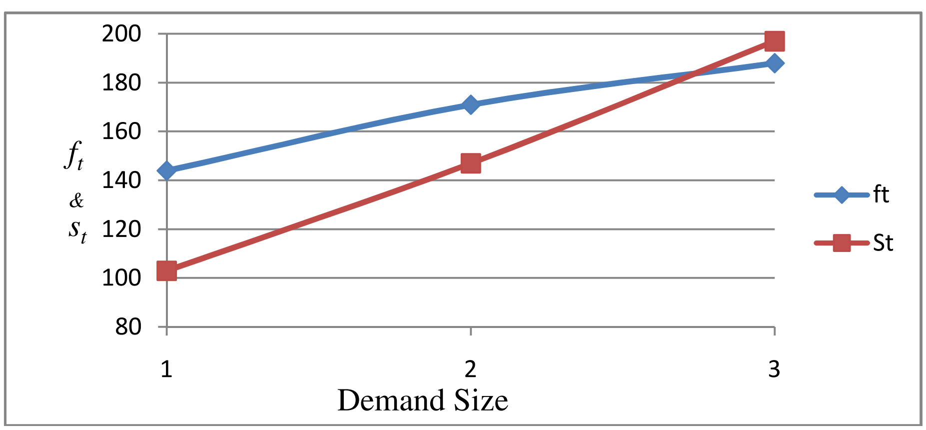

Figure 4.20 Model 3, Change in Demand Distribution at Lead Time of 7 Days

Next we will discuss the results of model 4, where demand is changing over the time horizon.

4.6 Model 4 Results-Two Modes of Supply-Changing Demand Over Horizon

As stated before model 4 is similar to model 3, the only difference is the implementation of the demand distributions. Recall that model 3 had constant demand over the time horizon, while model 4 in contrast has changing demand over the finite time horizon of 90 days. We are going to use new sets of demand distribution in this model to represent different phases of Product Life Cycle (PLC). The Table 4.22 and 4.23 shows the parameters of new demand sets.

Table 4.22 Demand Distribution Set 1 (For Growth Phase)

No.	1	2	3
Demand Dis.	NORM(92,36)	NORM(92,41)	NORM(92,46)
CV	0.39	0.445	0.5

Table 4.23 Demand Distribution Set 2 (For Maturity Phase)

No.	1	2	3
Demand Dis.	NORM(92,7)	NORM(92,12)	NORM(92,18)
CV	0.07	0.13	0.19

Demand set 1 has higher values of CVs to represent growth phase of PLC, while demand set 2 has lower values of CVs to represent maturity phase of PLC. The Table 4.24 lists the values of common parameters that are being used in this model.

Table 4.24 Baseline Parameters for Model 4

X_t	100
k	0
h	1
b	20
c_s	3
c_f	10
l_f	0
l_s	1

Here we will try to observe the effects of demand set 1 and 2 on optimized values of ordering quantities f_t and s_t under different circumstances of initial inventory level and lead time of transportation.

4.6.1 Optimize f_t and s_t- For Different Demand Distribution Sets

First we will discuss the effects of the predefined demand sets indicating two different phases of the PLC is studied here. The values of the optimized order quantities are shown below according to each distribution. The demand distributions are used in the same order as in Table 4.22 and 4.23.

Table 4.25 Model 4, Demand Distribution Set 1

Demand Distribution	NORM(92,46)	NORM(92,41)	NORM(92,36)
f_t	121	127	156
S_t	77	82	123
Total Cost	26190	29942	32743

Table 4.26 Model 4, Demand Distribution Set 2

Demand Distribution	NORM(92,18)	NORM(92,12)	NORM(92,7)
f_t	143	153	165
S_t	111	142	173
Total Cost	29511	33629	35824

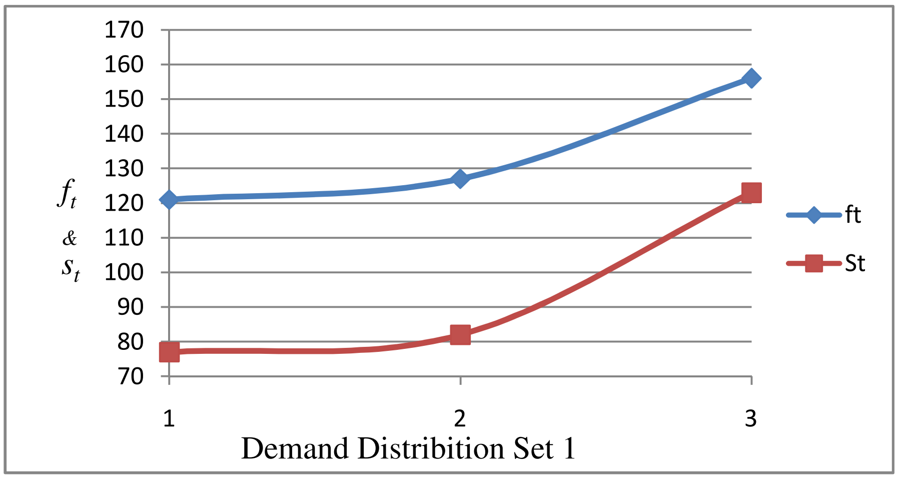

Figure 4.21 Model 4, Optimized f_t and s_t, For Demand Distribution Set 1

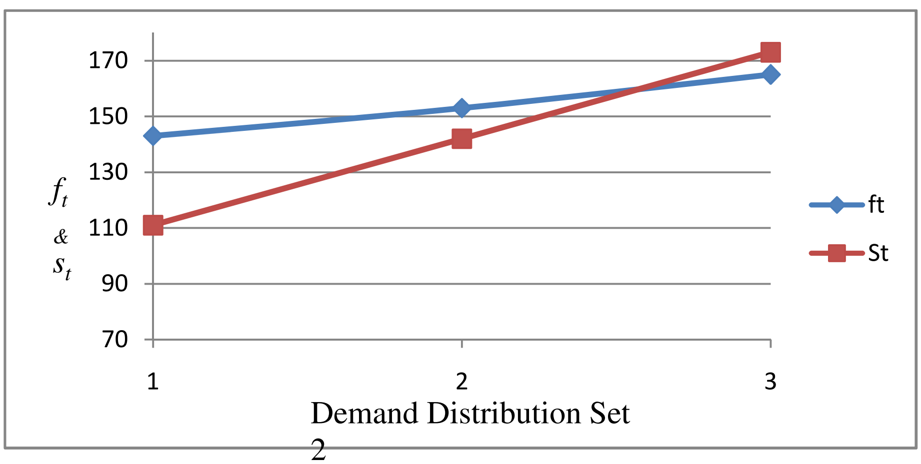

Figure 4.22 Model 4, Optimized f_t and s_t, For Demand Distribution Set 2

From the results we observe when there is change in PLC phase occurs, it is important to make changes in ordering policies to maintain the cost effectiveness. Keeping the ordering policy constant may result in to excess inventory or negative inventory. The result shows that ordering quantities f_t and s_t are larger with demand distribution set 1 compared to demand distribution set 2. When demand set 2 is used, the optimal order quantities by slow mode represents larger fraction of total shipping quantity (f_t + s_t). Results show that increase in optimal ordering quantities by fast mode is gradual in both demand sets 1 and 2, but increase in order quantities by slow mode is significant, this is because of decrease in variability of demand distribution.

4.6.2 Optimize f_t and s_t- For Different Demand Distribution Sets, With Different Values of Initial Inventory

Next we show effect of different initial inventory level on ordering quantities with demand sets 1 and 2. The first results assumes an initial inventory of 1000 units.

Table 4.27 Model 4, Demand Distribution Set 1, Initial Inventory level 1000

X_t	1000	1000	1000
Demand Distribution	NORM(92,46)	NORM(92,41)	NORM(92,36)
f_t	114	122	151
S_t	98	96	128
Total Cost	25490	26832	30027

Table 4.28 Model 4, Demand Distribution Set 2, Initial Inventory level 1000

X_t	1000	1000	1000
Demand Distribution	NORM(92,18)	NORM(92,12)	NORM(92,7)
f_t	135	141	158
S_t	121	123	167
Total Cost	26438	29856	33516

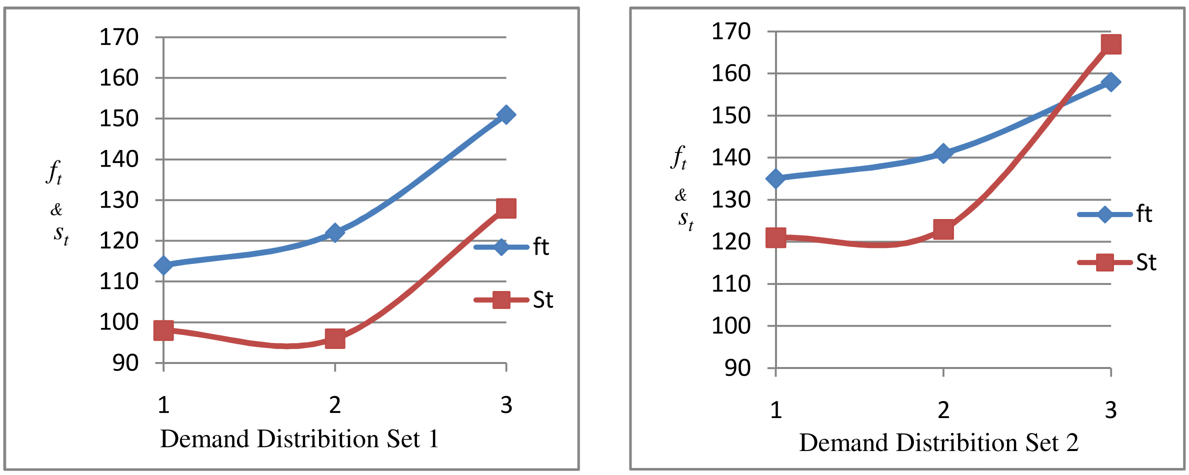

Figure 4.23 Model 4, Optimized f_t & s_t, Demand Distribution Set 1 &2, Initial Inventory 1000

To elaborate the effect of initial inventory level, we will assume one more set of experiments with increased initial inventory of 4000 units. The readings and graph for this set of experiment is shown below.

Table 4.29 Model 4, Demand Distribution Set 1, Initial Inventory level 4000

X_t	4000	4000	4000
Demand Distribution	NORM(92,46)	NORM(92,41)	NORM(92,36)
f_t	106	117	147
S_t	110	102	133
Total Cost	25120	26076	29318

Table 4.30 Model 4, Demand Distribution Set 2, Initial Inventory level 4000

X_t	4000	4000	4000
Demand Distribution	NORM(92,18)	NORM(92,12)	NORM(92,7)
f_t	128	138	157
S_t	130	129	162
Total Cost	25347	28548	32179

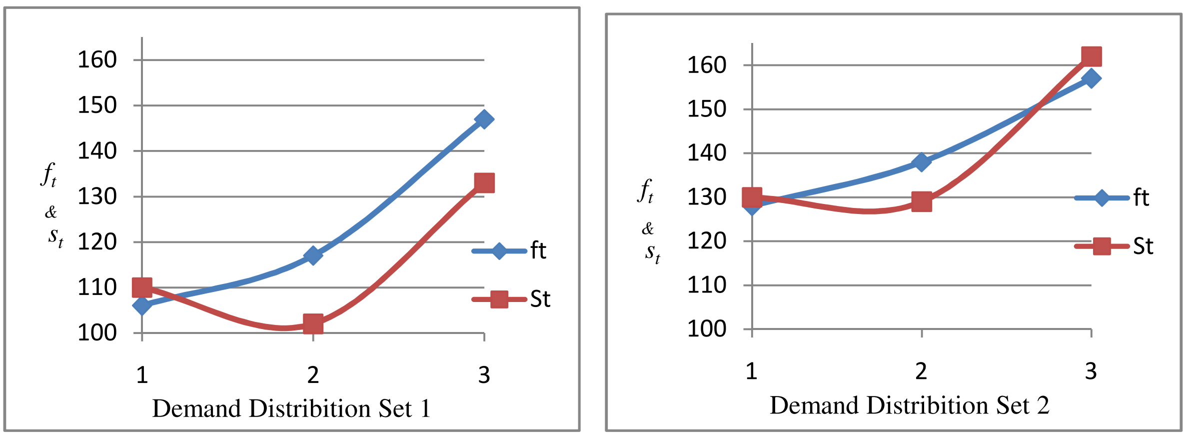

Figure 4.24 Model 4, Optimized f_t & s_t, Demand Distribution Set 1 &2, Initial Inventory 4000

The result shows that ordering quantities with an initial inventory of 4000 units are smaller compared to ordering quantities with initial inventory of 1000 units. With 4000 units of initial inventory the optimal order quantities by slow mode of transport has a larger fraction in total shipment quantity compared to initial inventory of 1000 units. This phenomenon is significantly observed at the beginning of the total time horizon. Thus, the amount of initial inventory plays different roles in different phases of PLC. For instance, during the growth phase we observe that the ordering quantity by the fast mode of supply is greater. So, having significant amount of initial inventory in growth phase saves more ordering cost compared to maturity phase where emphasis is on ordering by the slow mode.

4.6.3 Optimize f_t and s_t- For Different Demand Distribution Sets, With Different Values of Lead Time

Demand variability is different in growth and maturity phases of PLC, so the impact of lead time will be different on optimal order quantities with demand sets 1 and 2.

Table 4.31 Model 4, Demand Distribution Set 1, Lead Time 5

l_s	5	5	5
Demand Distribution	NORM(92,46)	NORM(92,41)	NORM(92,36)
f_t	139	154	170
S_t	101	127	158
Total Cost	30732	32805	35520

Table 4.32 Model 4, Demand Distribution Set 2, Lead Time 5

l_s	5	5	5
Demand Distribution	NORM(92,18)	NORM(92,12)	NORM(92,7)
f_t	152	169	186
S_t	115	153	179
Total Cost	34627	36731	39942

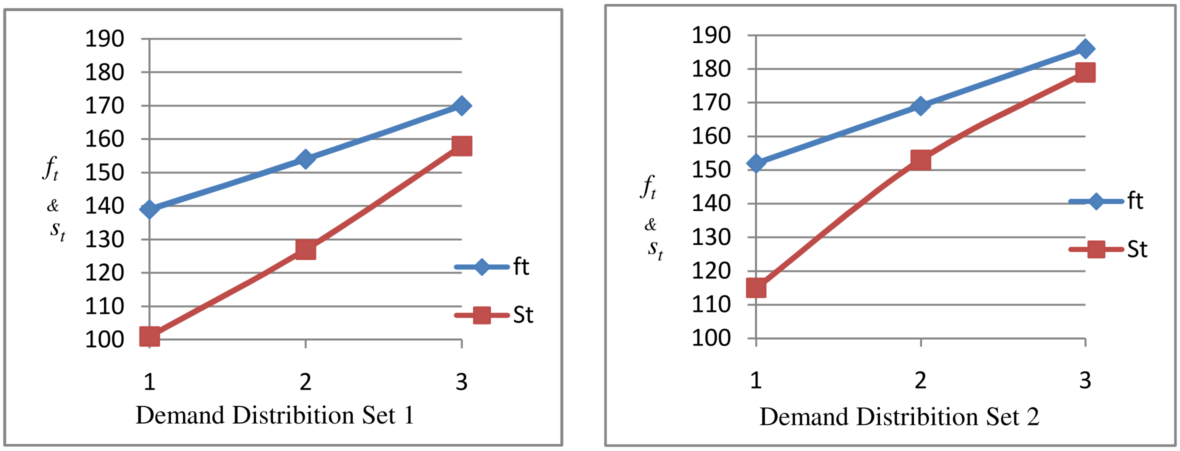

Figure 4.25 Model 4, Optimized f_t & s_t, Demand Distribution Set 1 &2, Lead Time 5 Days

The first set of experiments assumes a lead time of slow mode of supply as 5 days. While the second set of experiments assumes a lead time of 8 days. The lead time of fast mode of supply is kept constant at zero.

Table 4.33 Model 4, Demand Distribution Set 1, Lead Time 8 days

l_f	0	0	0
l_s	8	8	8
Demand Dis.	NORM(92,46)	NORM(92,41)	NORM(92,36)
f_t	146	161	175
S_t	108	137	173
Total Cost	32629	33715	37284

Table 4.34 Model 4, Demand Distribution Set 2, Lead Time 8 days

l_f	0	0	0
l_s	8	8	8
Demand Dis.	NORM(92,18)	NORM(92,12)	NORM(92,7)
f_t	160	172	187
S_t	124	158	195
Total Cost	38720	42104	43826

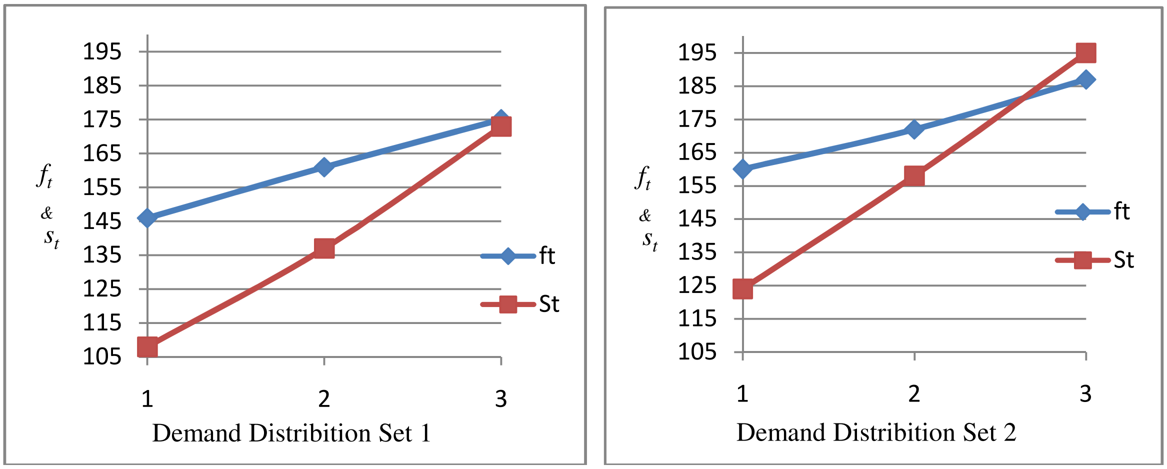

Figure 4.26 Model 4, Optimized f_t & s_t, Demand Distribution Set 1 &2, Lead Time 8 Days

The result shows that increase in lead time leads to increase in order quantities and consequently increasing the total cost. Use of fast mode of supply becomes more significant as we move from demand set 1 to demand set 2, this effect becomes more and more prominent with an increase in lead time of supply. There are similarities between the results of model 3 and model 4, like ordering quantities by fast mode see steady and gradual change, while ordering quantities by slow mode varies greatly.

CHAPTER 5: Conclusion and Future Work

5.1 Conclusion

This thesis explains the developing of simulation models using Arena for inventory systems with one and two modes of supply. We find near optimal solutions for ordering quantities under changing demand according to the concepts of Product Life Cycle (PLC). We have used OptQuest, an Arena tool, to minimize supply chain cost and find near optimal order quantities by fast and slow mode by varying different scenarios. We have compared the optimized order quantities for different models to draw insights about how inventory policies and strategies change as a result of system characteristics.

We have considered four models to represent various scenarios of inventory system. Model 1: uses only fast mode of supply and optimizes f_t. Model 2: uses only slow mode of supply and optimize s_t. Model 3: uses both modes of supply and optimizing f_t and s_t for constant demand over time horizon. Model 4: uses both modes of supply and optimizing f_t and s_t for changing demand over time horizon. We have assumed cost factors like holding cost, backorder cost and unit ordering cost which are important considerations when making decisions about inventory policies. The cost factors are different for different modes of supply, which help us to optimize the ordering quantities f_t and s_t with the objective of minimizing the total system cost. We have observed the effects of different initial inventory level and different lead times of supply on ordering policies. Numerical experiments show that optimal solutions differ with different cases in consideration. While most of the research has focused on stationary demand and stationary cost factors, our models are able to change all the input factors like demand distribution, cost factors, initial inventory levels and lead time of supply to get better insights of changing inventory systems.

Considering the demand evolution as well as the demand variability according to PLC, it is important to change the ordering policies to maintain the cost effectiveness of inventory system. This is particularly true for growth phase of PLC where demand variability is more compared to maturity phase. The results show that the split of total order quantities per mode of supply should change as the demand evolution takes place according to Product Life Cycle.

5.2 Future Work

We have used discrete simulation modeling in this paper, so the change in demand and reviewing of inventory level occurs on intermittent basis. But when we consider practical environment in inventory systems, the demand evolution is continuous, also it needs to review the inventory system on continuous basis. Potential areas of future work include use of continuous simulation programming to get closer to practical scenarios.

5.2.1 Arena Model 5- Two Modes of Supply-Changing Demand over Time Horizon of 10 Periods

This is the last model we have tried on experimental basis. The basic motivation behind this model is finding optimized values of order quantities for each time period in consideration separately. This type of model requires large number of variables to be defined. OptQuest is not able to handle these many variables properly, and we can find some discrepancies in the results. The details of this model with discrete simulation modeling and OptQuest results are discussed below.

In this last model we will consider both fast and slow modes of supply. Here the time horizon is of 10 periods. The demand is varying over time horizon. The variables $f_{t_1}, f_{t_2,\ldots,} f_{t_{10}}$ are defined to indicate order quantities by fast mode for period1, period2,….,period10 respectively. The variables $s_{t_1}, s_{t_2,\ldots,} s_{t_{10}}$ are defined to indicate order quantities by slow mode for period1, period2,….,period10 respectively. In this model we will try to optimize all the twenty variables for ordering quantities. The construction logic for this model is same as Model 3 and 4 (Chapter 3.4.3), which is why the schematic of this model is also same as Model 3 and 4 (Chapter 3.4.3). The only difference that we need to look into is the cost equation. Since we are using twenty variables two indicate order quantities for each period, the cost equation is changed, and it is shown below.

$$Total\ Ordering\ Cost = c_f f_{t_1} + c_f f_{t_2} + c_f f_{t_3} + \cdots + c_f f_{t_{10}} + c_s s_{t_1} + c_s s_{t_2} + c_s s_{t_1} + c_s s_{t_2} + c_s s_{t_3} + \cdots + c_s s_{t_{10}} + Total\ Holding\ Cost + Total\ Shortage\ Cost \tag{5.1}$$

$$Total\ Holding\ Cost = \textstyle\sum_0^{10} h_t \mathrm{MX}(\mathrm{x_t}, 0) \tag{5.2a}$$

$$Total\ Shortage\ Cost = \textstyle\sum_0^{10} b_t \mathrm{MX}(-\mathrm{x_t}, 0) \tag{5.2b}$$

Now we have seen the construction and logic for each of the five models under consideration. The next thing is to use OptQuest to minimize the total ordering cost and find optimal order quantities.

The demand distribution is changing over the time horizon. For first three periods demand distribution is NORM (92,41), from period 4 to 6 it is NORM (92,25) and for period 7 to 10 it is NORM (92,12).

Table 5.1 Period wise Demand Distributions-Model 5

No.	1	2	3
Period	1-3	4-6	7-10
Demand	NORM(92,41)	NORM(92,25)	NORM(92,12)
CV	0.445	0.271	0.13

Following Table 5.2 shows the values of common factors used in model 5.

Table 5.2 Baseline Parameters Model 5

x_t	0
k	0
h	1
b	20
c_s	3
c_f	10
l_f	0
l_s	1

Next we discuss the effect of demand change, initial inventory level and lead time on optimal order quantities in each period by fast and slow modes of supply. Table 5.3 shows optimal order quantities when demand is varied, Table 5.4 shows optimal order quantities when initial inventory of 300 units is assumed, and Table 5.5 shows optimal order quantities when we assume 3 days of lead time for the slow mode of supply. The graphs of order quantities over the time horizon of 10 periods are also shown.

Table 5.3 Model 5, Optimal f_t & s_t, Changing Demand Distribition

Period	1	2	3	4	5	6	7	8	9	10
f_t	122	122	121	134	141	142	148	149	158	158
S_t	68	82	81	98	102	104	104	116	123	122

Table 5.4 Model 5-Optimal f_t & s_t-Changing Demand Distributions-Initial Inventory of 300

Period	1	2	3	4	5	6	7	8	9	10
f_t	73	78	106	126	137	136	143	144	153	153
S_t	62	62	66	89	97	105	102	111	118	119

Table 5.5 Model 5-Optimal f_t & s_t-Changing Demand Distributions-Lead Time of 3 Days

Period	1	2	3	4	5	6	7	8	9	10
f_t	131	130	142	146	145	152	152	159	165	171
S_t	76	83	97	105	105	112	108	115	144	161

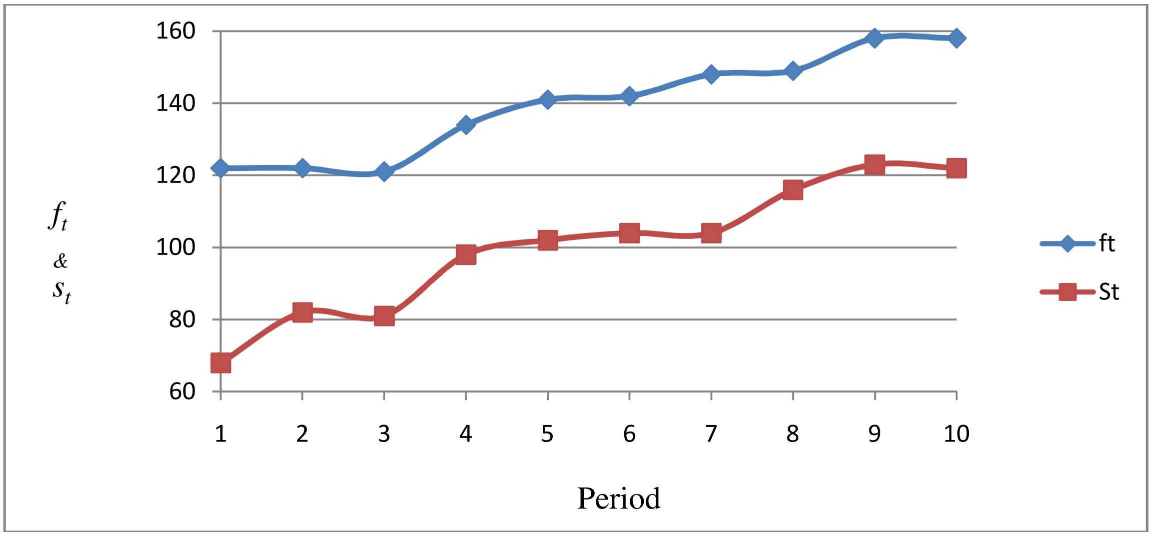

Figure 5.1 Model 5, Optimized f_t & s_t for 10 periods, Changing Demand

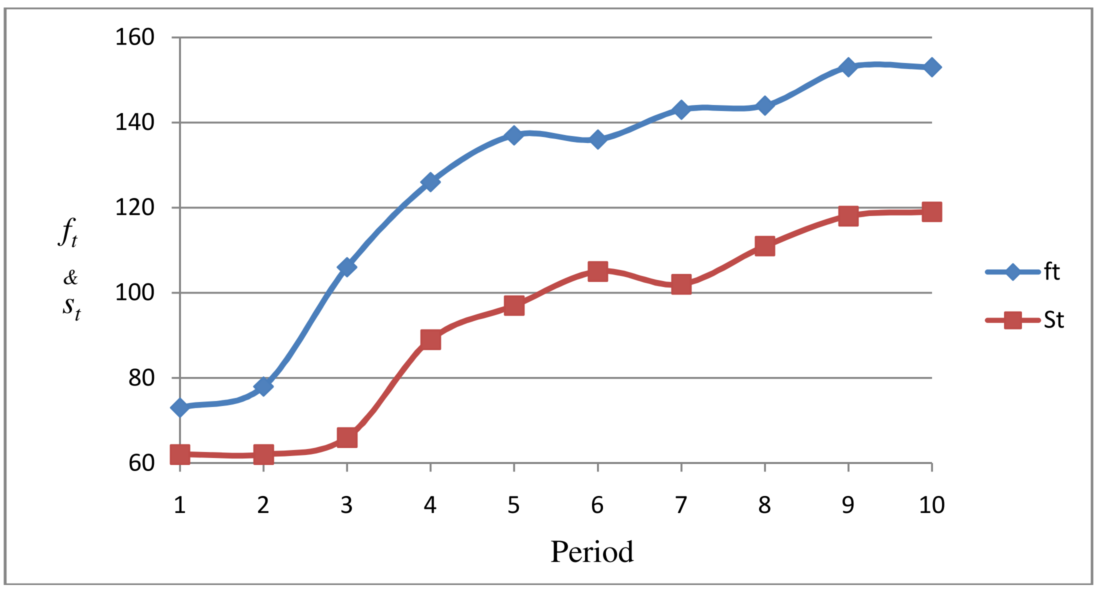

Figure 5.2 Model 5, Optimized f_t & s_t for 10 periods, Changing Demand, Initial Inventory 300

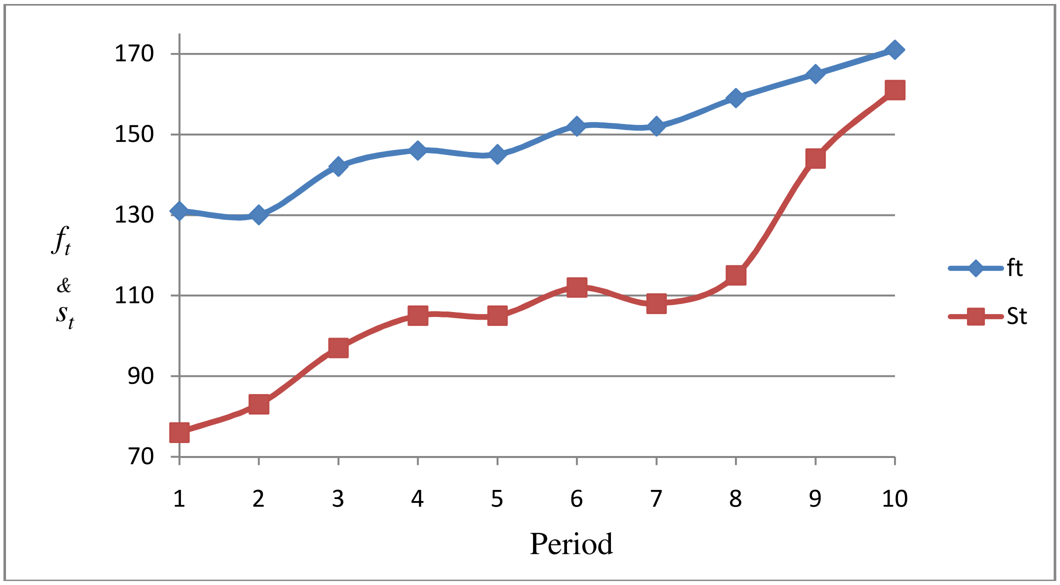

Figure 5.3 Model 5, Optimized f_t & s_t for 10 periods, Changing Demand, Lead Time 3 Days

The results show that, though there are small ups and downs in the graphs of ordering quantities f_t & s_t, the broader view of the trends shows an increase in the order quantities as variability of demand distribution decreases from period 1 to period 10. Additionally initial inventory and increases in lead time shows similar effects on order quantities as discussed in model 3 and 4 (Chapter 4.5 and 4.6) . The Rate of increase of order quantities by the slow mode is greater compared to rate of increase of the order quantities by fast mode. Using a smaller time horizon of 10 periods to represent the same demand change that occurs during PLC, and trying to find order quantities for each period, illustrates the required change in ordering policies as product moves from growth to maturity phase of PLC.

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