The PennsylvaniaStateUniversity

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USING DISCRETE EVENT SIMULATION TO IMPROVE BLOOD SUPPLY CHAIN

A Thesis in

Industrial Engineering

by

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ABSTRACT

Blood Supply chain is a very complicated and interesting problem as it's a costly commodity and its wastage is undesirable. Blood is a perishable commodity i.e. has a fixed shelf life with a unique medical value. In case of blood all the components of blood are perishable with different lifetimes. This thesis deals with minimizing the shortage and wastage of blood units by maintaining an optimal amount of safety stock in the system.

In this thesis, various critical parameters that affect the blood supply chain like Lead time, Safety stock level and Hold time were studied and an optimal safety stock level was obtained for each blood type. The safety stock level was focused on minimizing the blood shortage and wastage. This thesis also compares three issuing policies Last in First out, First in Last out and Expiry first. The performance of all three of the policies was evaluated based on the shortage and wastage of blood units. The thesis uses simulation as a tool to compares the effect of future increase in demand, Lead time and inter-arrival time. The system was observed for variation in safety stock level as the demand, lead time and inter-arrival time increased while other parameters were constant.

From the simulation results it was found out that Expiry first always outperformed the FIFO and LIFO policies. It was noted that Lead Time has critical influence in system performance. The lesser the lead time the effect of other parameters in the system is significantly low. The increase in lead time makes the system more vulnerable when other parameters change.

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Chapter 1

Introduction

1.1 Motivation and Background

Blood is a living tissue of unique medical value to the human body. The components of blood like white cells, red cells are perishable except plasma. We usually consider a perishable inventory as a system in which units in stock have a common deterministic lifetime. In case of blood all the components of blood are perishable with different lifetimes. Each have lifetimes varying from 6 hours (white cells) to 21 (recently extended to 35) days for red blood cells (Prastacos, 1984). Blood is collected in units of one pint per donor at collection sites such as a Regional Blood Center or a Hospital Blood Bank. When collected it undergoes a series of typing and screening tests, and may be separated into components. It is then shipped to a Hospital Blood Bank where it is available to satisfy the demands for transfusions to patients.

Hospital blood bank must be able to determine the optimal issuing and ordering policies for the various types of blood groups in order to meet the demands of the patients at the hospital. There are many factors affecting the ordering and issuing policies for blood. The most important factors are

1. The Supply of blood is stochastic.
2. The Demand of blood is stochastic.
3. Much of the blood demanded is not used and returned back to inventory.

4. The demand for a blood can be satisfied from a more recent rather than an older inventory.
5. Blood is perishable commodity and can deteriorate to a lower freshness category on a step function basis.
6. Approximately 50 percent of all units of blood requested by physicians, "cross- matched" for compatibility with the blood of prospective patients, and reserved are eventually found not to be required for the patient in question and are returned to the "unassigned" inventory.

These characteristics make Blood supply chain a very complicated and interesting problem. This research helps to find solution for a complex stochastic, multi-product perishable inventory problem. Since this is very difficult to be solved analytically using approaches like dynamic programming, queuing theory and Markov chains (closed form solution not possible) simulation was used as a tool to solve the above problem. Using statistical analysis various trends and seasonality of the blood demand are observed.

1.2 Problem Description

The hospital places an order to the RBB (Redcross blood bank). Redcross blood bank issues the required blood to the hospital based on the availability. In the hospital blood is tested for infections and for confirming the blood type. Successful blood is then stored in the hospitals storage as unassigned inventory. This unassigned blood is used to meet the scheduled as well as the unscheduled demands of the doctors. The requested blood is cross-matched and if it matches the patient it is placed in the assigned inventory. All the assigned unused blood becomes unassigned subsequently and is sent back to hospitals blood bank. Since there is an uncertainty in the demand of the blood from the hospital, the subsequent replenishment from Red Cross too is uncertain. Even when the required blood arrives from Red Cross there is uncertainty if the blood would pass cross match. These uncertainties make the model complex to work with.

1.3 Objectives

The objectives of this thesis are as follows

1. To model the blood supply chain in the hospital as a discrete event simulation model.
2. Come up with optimal amount of safety stock for various blood types, crossmatch release period and ordering frequency so that wastages and shortages of the blood group can be kept to the minimum.
3. To highlight how process driven approach of Discrete Event simulation can be used to solve complex stochastic, multi product perishable inventory problem.

1.4 Methodology

The thesis focuses on building a simulation model that is similar to the actual process and policies followed in the hospital thereby mimicking the actual system. This model is written as a process interaction approach than compared to the traditional event driven approach used in most research. This involves finding the optimal level of safety stock levels for various blood types, cross match release period and lead time so that it reduces the wastage and shortage simultaneously. Appropriate issuing policy for the blood bank was also focused.

1.5 Organization

The thesis is organized as follows. Following the introduction is chapter 2 which focuses on overview of the literature review, chapter 3 discusses the problem definition. Chapter 4 presents the simulation development comprehensively while chapter 5 discusses the results and analysis of the simulation. Finally in Chapter 6 conclusions are presented.

Chapter 2

Literature Review

This section reviews the literature for the optimal ordering policies in blood supply chain and is divided into two parts. The first part gives an introduction to the basic forecasting techniques that could be used to predict the demand. The second section presents a detailed review of literature on various works done to improve blood supply chain for a blood bank.

2.1 Ordering Policies

The two important aspects of ordering policies are basically how much to order and when to order. The two most commonly used ordering policies are

- Periodic review policy - The inventory level is checked periodically (such as once a month) and an order is placed at that time if necessary. The risk period is equal to the time until the next review plus the replenishment lead time.
- Continuous review policy - The inventory level is being check continuously and orders can be placed immediately, so the risk period is just the replenishment lead time.

It is to be noted that the ordering quantities of both the policies are equivalent if the demand and lead time are deterministic but differ when they are random.

Ford Whitman was the first to work on finding the optimal order quantity and developed a model called the Economic Order Quantity (EOQ) model also known as lot sized model or Wilson's formula. The aim of the model is to find the optimal quantity of products to be ordered, given constant demand, cost of ordering and holding Inventory so that the annual operating cost is minimized.

The optimal order quantity EOQ and time between orders can be given using the formulas given below. The derivation of the optimal quantity can be found in Ravindran, Solberg and Phillips (1987).

$$\boxed{EOQ = \sqrt{\frac{2 \times D \times S}{H}}} \quad \boxed{T = \sqrt{\frac{2 \times S}{D \times H}}}$$

D = Annual demand (units)

S = Cost per order ($)

C = Cost per unit ($)

I = Holding cost (%)

H = Holding cost ($) = I x C

There have been numerous modifications to the EOQ model for varying scenarios lead time, back order, price discounts etc. There have also been performances measures tied to the model like service levels, fill rates, etc which are used to calculate the safety stock to be carried and to determine order-up-to-levels and reorder points. Models were also developed to identify optimal order quantities for multi-echelon systems and systems with time-varying demand.

Nahmias (1975) and Fries (1975a) have dealt with problem of determining optimal policies for items with fixed lifetime. Nahmias developed a single decision model and extended to the case where a sequence of ordering decisions had to be made. He shows that the change in ordering quantity is more sensitive to new inventory on hand than on older stock. In the case of backlogging, the order quantity is the optimal order quantity plus the amount backlogged. Fries's model had a cost function that included the costs for holding and shortages, and considered only the number of expected outdates in the current period. Fries assumed no backlogging and that an emergency procurement would be made to satisfy all shortages.

A dynamic programming approach was used to obtain minimum expected discounted cost function. In Fries' model, the optimal policy for lifetime more than two periods and length of horizon greater than or equal to two periods is of the form: Order up-to a level whenever total inventory level drops below a certain level, i.e. (s, S) policy. The decision to order or not depends on whether or not the total inventory is less than a critical number (re-order point), and it does not depend on the age distribution of inventory or on the number of periods till the end horizon. However, the decision on how much to order depends on both the age distribution and the number of periods till the end horizon. Cohen (1979) has computed stationary distribution of total inventory for two period lifetime problem and thereby derived the optimal critical number policy.

2.2 Forecasting techniques

Planning the future blood collection efforts must be based on forecasts of transfusion demand. Auturo (2004) discusses three forecasting methods to plan for the future demand. He compares Autoregressive Integrated Moving Average (ARIMA), Holts-Winters Family of exponential smoothing models and neural network based method in predicting the demand. It was seen from the results that over a one year time horizon period ARIMA and exponential smoothing are fairly accurate but if the time horizon changes to two years it is seen that exponential smoothing usually outperforms other forecasting methods.

Frankfurter et al (1974) discuss a computerized short term forecasting system which helps the hospital in coming up with adaptive inventory planning information used to warn them against potentially or high blood inventory levels. They implemented Exponential smoothing and were able to produce satisfactory forecast for short term of two weeks. It was also found that a potential benefit of 50 to 60% can be attained if the system was implemented.

Chen et al (2008) discuss a neural network based forecasting method to plan for the future demand. They deployed an artificial neural network model (feed-forward multilayer perceptrons) to come up with a forecast with due considerations for external factors. It was seen that it consistently outperformed the time series forecasting models like ARIMA and moving average.

2.3 Simulation for Blood supply chain

Rytila et al (2006) aim to improve blood supply chain by simulation modeling. This was accomplished by varying parameters like the age of incoming units, financial loss caused by the outdated blood units, length of the blood reservation and cross match release period. Simulation modeling can be used to make complex systems with uncertainties into a more comprehensible and efficient system. This can help decision makers in taking tough and risky decisions regarding inventory policies. This is more useful in healthcare since scarce resources can be allocated better.

Katsailaki et al (2007) discuss about the use of Discrete Event Simulation in the Blood supply chain for the events between the regional Red Cross and the hospital. Simulation was chosen as the most appropriate method for modeling the system since both supply and demand are stochastic, the system was itself stochastic since every part of the supply chain has uncertainty and the processes and outcomes are time driven as discrete events. Discrete-event simulation was used to determine ordering policies leading to reductions in shortages and wastage, increased service levels, improved safety procedures and reduced costs, by employing better system coordination. They modeled the system with demand as lognormal distribution, a crossmatch release period of five days and a LIFO issuing policy.

William Pierskallat et al (1972) discuss the use of stochastic approaches used in the inventory control with FIFO (First In First Out) and LIFO (Last in First Out) blood issuing policies. The blood inventory considered here is grouped into categories according to shelf age (expiry date). Demand occurs for each of the blood types, and may be satisfied by inventory units from that category or from any "younger" blood types. It is shown for most of the objective functions considered that the optimal policy is to issue the oldest unit which will satisfy the demand. Thus we find that the issuing policy of blood from the hospital blood bank plays a very important role in the expiry of blood. We intend to vary the FIFO, LIFO and oldest unit first inventory policies to check the performance of the hospital.

Prastacos et al (1984) review Operations Research contributions to blood inventory management theory and practice. They discuss the statistical analysis of the demand and usage data since both these parameters are stochastic. They stress the importance of parameters like crossmatch release period, crossmatch to transfusion ratio and age of the incoming units on the shortage and wastage of the blood units. This paper stresses the importance of age of incoming units and its implications on the wastage of blood.

Ronald et al (1982) discuss the effects of operational policies on regional blood center. This was accomplished by changing the inventory policies i.e. changing the initial inventory of the system but maintaining the same distribution policy, changing the number of delivery vehicles, changing the age constraints on hospitals inventory. The result of this experimental policy considered reduced expirations significantly. The policies which showed increased expirations showed no overall improvement in the system's ability to respond to community needs. This gives us the percentage of blood units actually used i.e. transfusion to crossmatch ratio. Usually around 50% of the reserved units are used. These are critical parameters needed in the simulation of the supply chain.

Graves et al (1982) looked at building a similarity between perishable inventories and queuing models. By implementing queuing analysis models, the random nature of supply and demand can be modeled accurately and the computational difficulty encountered in keeping track of the age levels of blood can be eliminated. In this model, replenishment of items correspond to blood entrance in the queue, requests for demand correspond to the service process and customer impatience corresponds to the lifetime of blood.

Nandakumar et al (1993) developed near-myopic heuristics for the fixed life perishability problems formulated by Nahmias and Fries. They derived upper and lower bounds for the order quantities by viewing the problem under the framework of the newsvendor problem. They compare the performance of the weighted average of their upper and lower bounds against two of Nahmia’s approximations. While all the approximations performed very well, the bounds developed by Nandakumar and Morton were found to be easier to compute.

Chapter 3

Problem Definition and Methodology

3.1 Problem Description

Blood is a perishable inventory with a unique medical value. We usually consider a perishable inventory as a system in which units in stock have a common deterministic lifetime. In case of blood all the components of blood are perishable with different lifetimes. Usually the whole blood units have a life time of 28 days. The Blood units are collected in units of one pint from the donor at collection sites like Red Cross, Regional Blood Center or even from a Hospital Blood Bank. The blood so collected is first screened for infection and may be separated into components as needed. It is then shipped to a Hospital Blood Bank where it is available to satisfy demands for transfusions to patients.

The blood from the Regional Blood Center is first tested to retype its blood group. Thus verified donor unit is given a barcode. The Hospital Blood Bank operates as an inventory location, storing and issuing the appropriate blood units to satisfy transfusion requests. During the course of a day the Blood Bank receives random number of transfusion requests for each blood type, each request for random number of units. Once a request for a patient is received, the appropriate numbers of units of that type are removed from free inventory and, upon successful cross-match they are placed on reserve inventory for this particular patient.

Cross Matching is a process of testing that is performed to determine the compatibility of a donated unit of blood with its intended recipient. This is done by collecting the blood sample from the recipient and testing it for the compatibility with the donor blood. When the blood sample of recipient is compatible with the donor blood, the patient information is tagged with the donor unit. Thus the donor unit now has information of its intended recipient. Any units that are not transfused (usually within a day or two) are returned to free inventory.

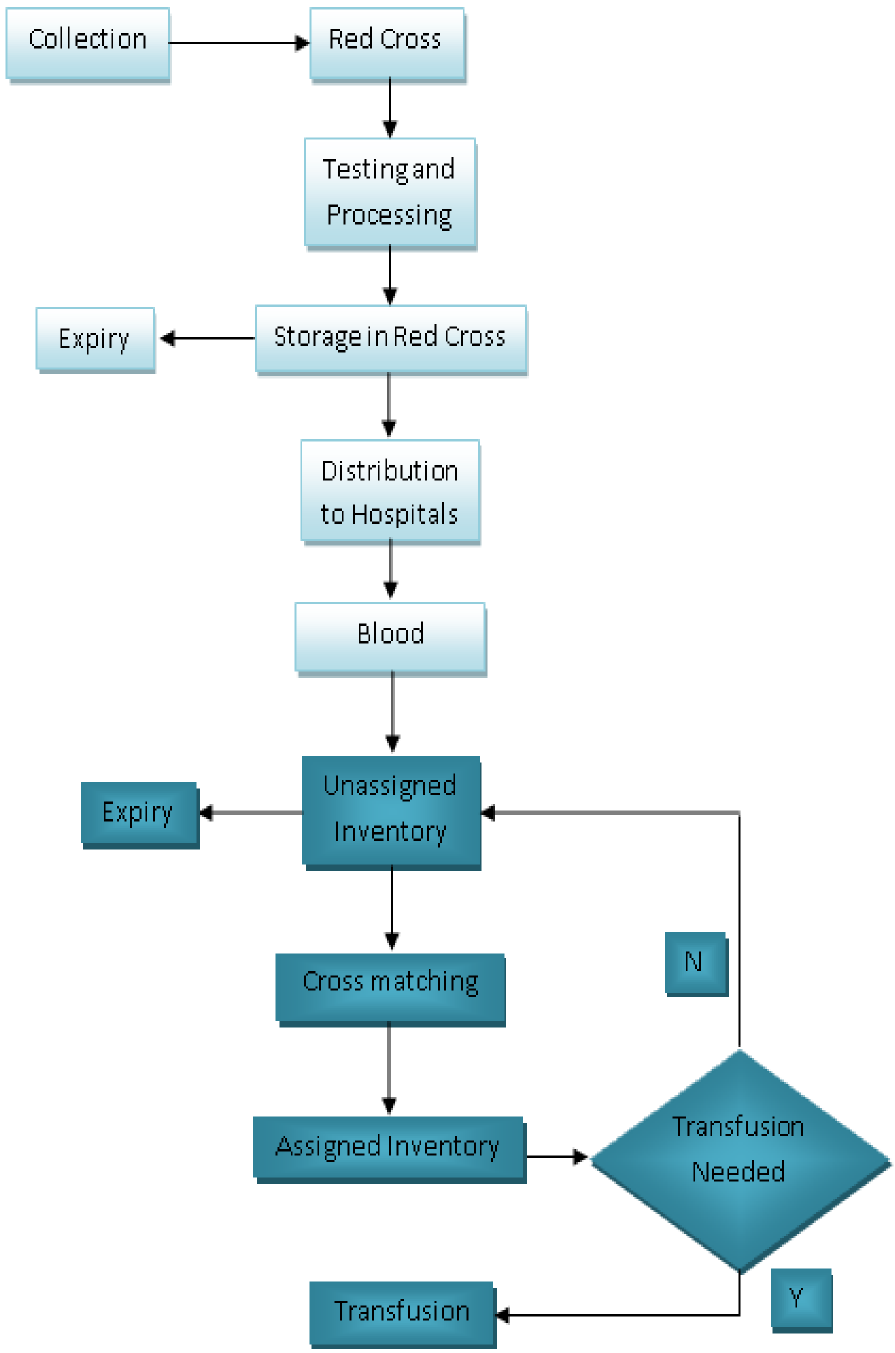

Figure 3.1 Problem Description

Elapsed between the patient's operation and the return of the unused units back to free inventory is called cross-match release period. For identification purposes the blood sample from the recipient contains a barcode with complete details of the patient. Since there is an uncertainty in the demand of the blood from the hospital, the subsequent replenishment from the Red Cross too is uncertain. Even when the required blood arrives from Red Cross there is uncertainty if the blood would pass cross match. These uncertainties make the model complex to work with.

3.2 Problem Definition

Blood inventory control has always been a challenging problem to solve due to the amount of complexity involved. The properties of blood bank inventory control system making it complex are

1. The Supply of blood is stochastic.
2. The Demand of blood is stochastic.
3. Much of the blood demanded is not used and returned back to inventory.
4. The demand for a blood can be satisfied from a fresher rather than an older one.
5. Blood is perishable commodity and can deteriorate to a lower freshness category on a step function basis.
6. Approximately 50 percent of all units of blood requested by physicians, "cross- matched" for compatibility with the blood of prospective patients, and reserved are eventually found not to be required for the patient in question and are returned to the "unassigned" inventory.

Due to these reasons it is necessary that blood inventory must be maintained properly else it may lead to serious shortages or wastages. In either case it will have detrimental effect on the patient.

So the scope of the project is to examine minimize the shortage and wastage by varying

1. Issuing Policies (FIFO, LIFO)
2. Cross-match release period.
3. Transfusion to cross-match ratio.

And come up with optima level of safety level of stock.

3.2.1 Data Sets

We collected data pertaining to

1. Demand data for 13 months (number of units per day).
2. Supply sent by RBB for the same 13 months (number of units per day).
3. Order upto level of each of the 23 products being used.

The demand was stochastic, but the supply was more uniformly distributed when compared to the demand. It was seen that the demand for the major blood units like O+, A+ had more demand during May to November of the year and it gradually almost decreased to one half during the following six months.

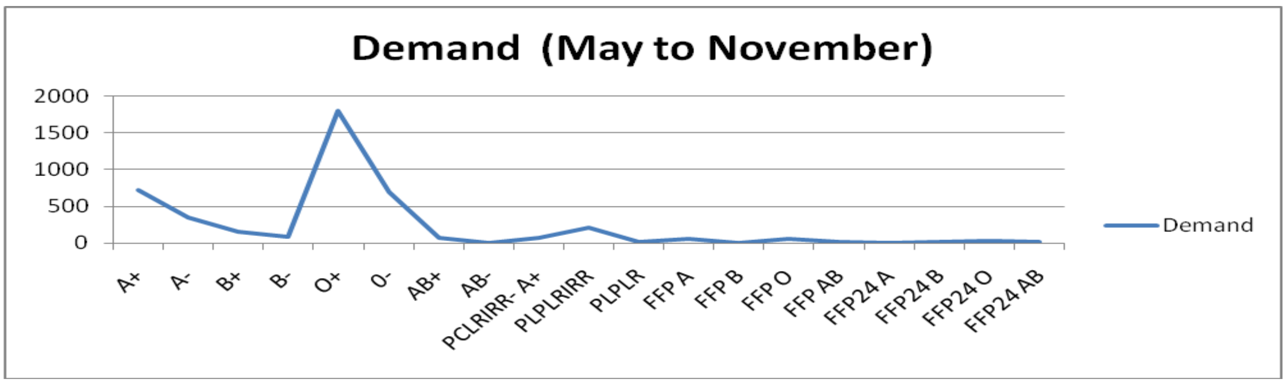

Figure 3.2 Demand variations for the initial six months

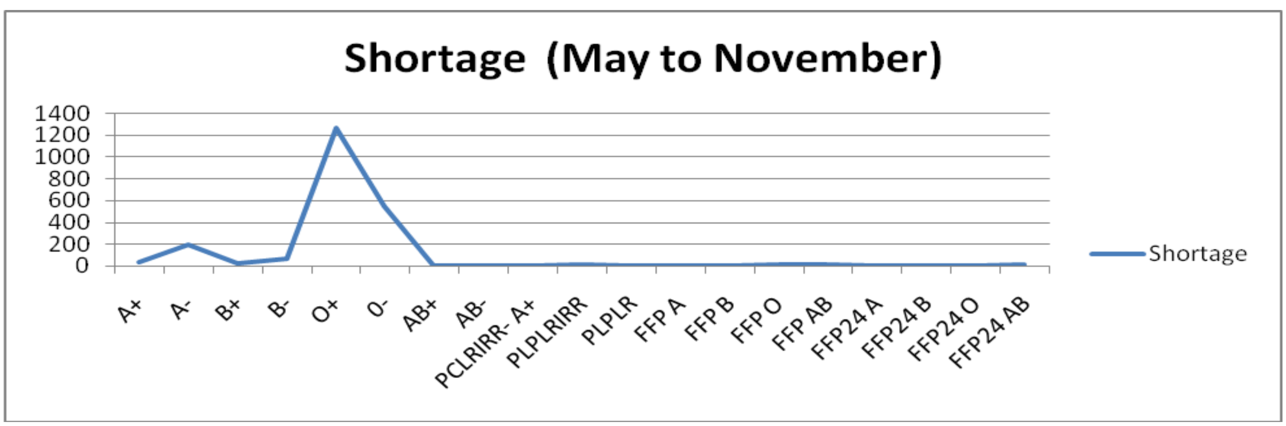

Figure 3.3 Shortage variations for the initial six months

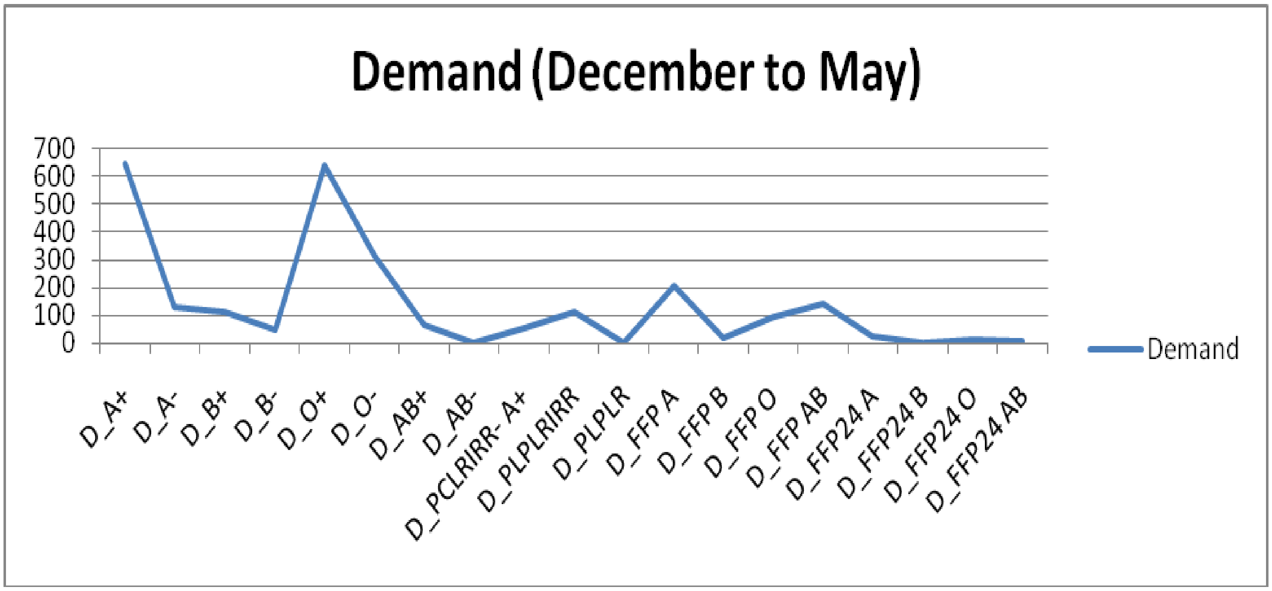

Figure 3.4 Demand variations for the final six months

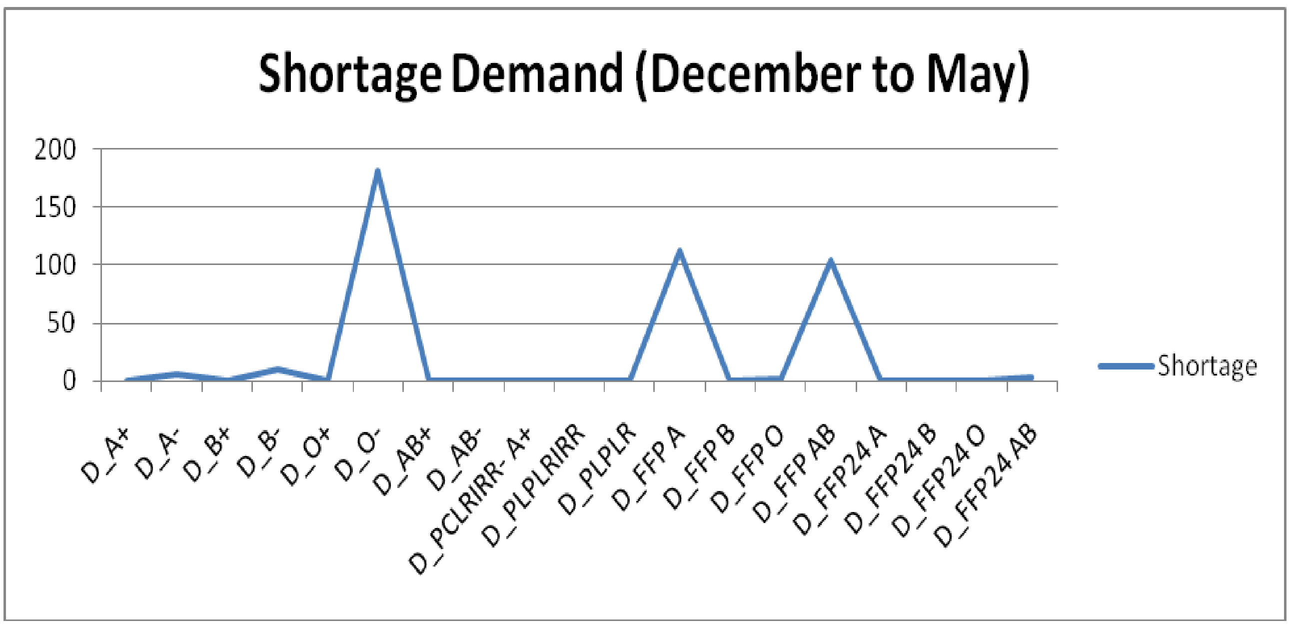

Figure 3.5 Shortage variations for the final six months

3.2.2 Variables

Table 3.1 Description of Variables

Variables	Description
Holding time or Cross match release period	The amount of time the blood unit can wait to be transfused to the patient.
Lead Time	The amount of elapsed from the time it was ordered to the time it was received.
Order Time	The frequency of ordering the blood.
Life Time	The average life time of a blood unit
Demand	The average demand of the blood unit.
Patient Inter-arrival	The rate at which patients arrive to the Hospital.
Fraction used	The Fraction of the Blood units used after successful cross-match.
Fill rate	The Fraction of Demand fulfilled by the Red Cross Blood bank

It must be noted that among these variables the following variables can be controlled in the simulation.

- Hold Time
- Lead time
- Safety Stock level
- Patient Inter-arrival Time

3.3 Process driven approach

Unlike the most common approach for simulation which is event driven approach found in most programming languages, AUTOMOD uses a Process driven approach. The process driven approach follow an entity's life-cycle as it moves through the system and the simulation software converts the process-interaction approach to event scheduling. Whereas in even driven approach is defining the events of the model and writing the logic for each event. Process driven approach is more suitable for supply chain simulation.

Chapter 4

Simulation Development

4.1 Introduction

The problem statement described in the previous chapter was developed into a simulation model using AUTOMOD. Rytila and Spens (2006) have already worked on a discrete event simulation model of a blood supply chain, varied parameters like age of the blood, cross match release period and proved that dynamics of the supply chain was more easily understood by medical practice. Katsailaki and Brailsford (2007) used simul8 as the discrete event simulation software to come up with first simulation model incorporating blood types with different shelf lives, mismatching and cross-match release period. By adopting their recommendations it was found that a large cost savings could be obtained eventually.

4.2 Description of the Base Model

Blood supply chain is a non-terminating system and does not start empty and idle. There are basically five events in the model which are for patient load – arrival (Figure 1) and departure (Figure 2) and three for blood load- being ordered (Figure 3), order arrival (Figure 4) and expiry (Figure 5).

A patient arrival follows a poison distribution. A patient on arriving is assigned a blood type and demand. The requested quantity is put on hold for that patient. If there happens to be shortage then the shortage is computed, then patient is scheduled for departure. The patient departs at the scheduled time and when he does, he returns the unused assigned blood back to the inventory.

An order is placed every 24 hours, amount to be ordered is obtained from the function F_ordering_policy. The fraction of the order is then received by the hospital (assuming fill rate varies between (0.5, 0.25)), where it is stacked in the hospital inventory and expiry is scheduled. At the time of expiry loads are pulled out of the order list at that time.

Table 4.1 Base model variables

<table>
<tr><th>Variables</th><th>Initial Value in the Base model</th><th>Description</th></tr>
<tr><td>V_SSL(7)</td><td><table><tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td></tr><tr><td>26</td><td>8</td><td>7</td><td>2</td><td>27</td><td>8</td><td>4</td></tr></table></td><td>Safety Level of stock for seven types of blood</td></tr>
<tr><td>V_bloodtypes</td><td>7</td><td></td></tr>
<tr><td>V_hold</td><td>2 X 24 hours</td><td>Cross-match release period</td></tr>
<tr><td>V_leadtime</td><td>7 hours</td><td></td></tr>
<tr><td>V_ordertime</td><td>24 hours</td><td></td></tr>
<tr><td>V_lifetime_mean</td><td>11 x 24 hours</td><td>Age of the incoming inventory</td></tr>
<tr><td>V_lifetime_sd</td><td>9 x 24 hours</td><td></td></tr>
<tr><td>V_demand_mean</td><td>2.9767</td><td rowspan="2">Lognormal Distribution</td></tr>
<tr><td>V_demand_sd</td><td>0.4723</td></tr>
<tr><td>V_patient_interarrival</td><td>10 hours</td><td>Poisson Distribution</td></tr>
<tr><td>V_frac_used_mean</td><td>0.37</td><td>Transfusion to cross-match ratio</td></tr>
<tr><td>V_frac_used_sd</td><td>0.10</td><td></td></tr>
<tr><td>V_fill_rate_mean</td><td>0.75</td><td rowspan="2">Uniform Distribution</td></tr>
<tr><td>V_fill_rate_sd</td><td>0.25</td></tr>
</table>

4.2.1 Patient Arrival

The patient arrival process is the first process in the simulation model. The load (Patient) to this process is derived from the model initialization function. As soon as the first patient arrives in the model, the arrival of the next patient is scheduled according to the inter-arrival time. Once the patient arrives a blood type is assigned to the patient based on the blood distribution in a population.

Table 4.2- Blood Group Distribution

TYPES	RATIOS
O +	38.40%
O -	7.70%
A +	32.30%
A -	6.50%
B +	9.40%
B -	1.70%
AB +	3.20%

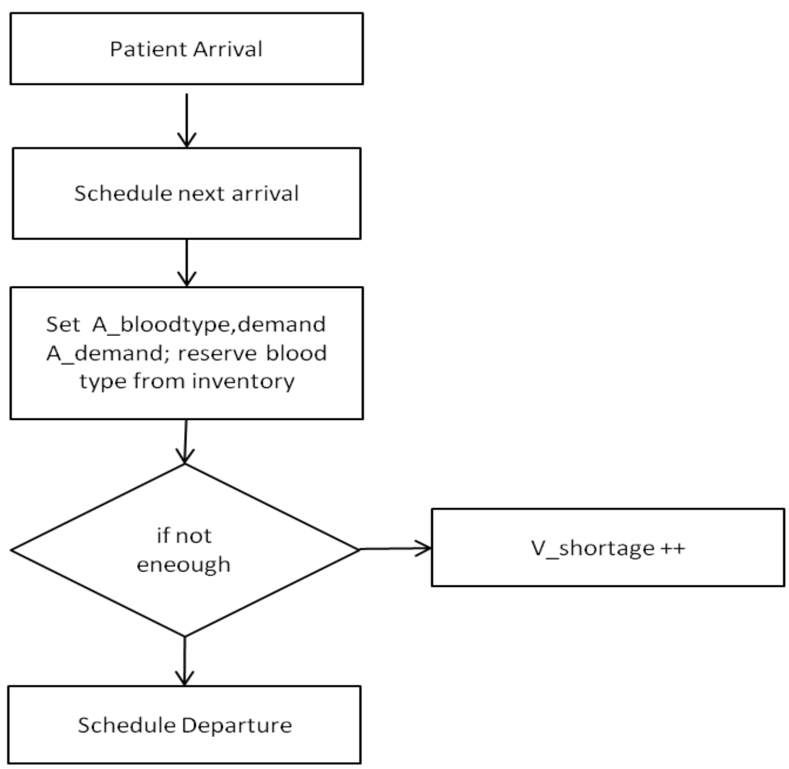

Figure 4.1: Flow chart - Patient Arrival

The demand of the blood is assigned and the requested quantity is put on hold for that patient. The shortage was computed in case of shortage and scheduled for departure. A patient departs at the scheduled time and when he does, he returns the unused assigned blood back to the inventory.

4.2.2 Patient Departure

The patient departure event is triggers after the blood is consumed or after the patient does not consume the allotted blood within the holding time. If the patient does not consume the blood then the blood units are sent to the unassigned inventory and the patient entity is sent to die.

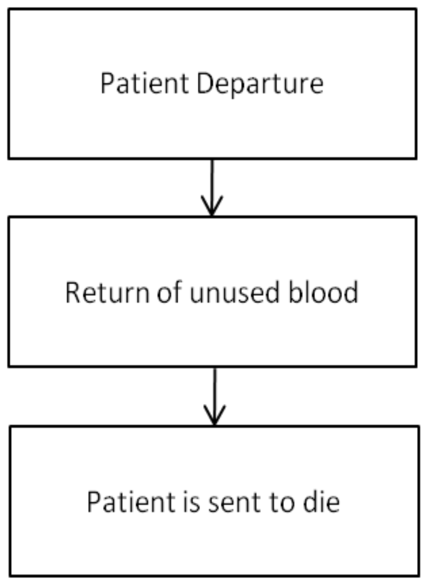

Figure 4.2: Flow chart- Patient Departure

4.2.4 Order placing

Order is placed everyday based on the current level of inventory and the doctor's demand for the day. Whenever an order needs to be placed we compute the required number of blood units by a function F_Ordering_Policy. This function compares the current level of inventory with the safety stock level needed and calculates the blood units needed for every blood group. Once the number of blood units is calculated then order is placed to the Red Cross and scheduled for a delivery in 7 hours. Since the lead time for the delivery is less it makes the model very robust to change in other values. Since an order can be realized in a less time, the effect of other parameters is masked.

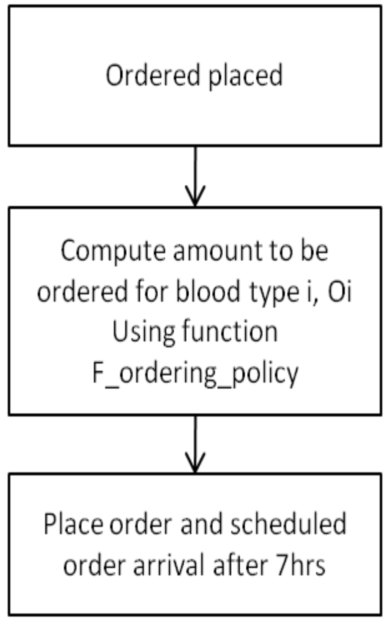

Figure 4.3: Flow chart-Order placing

4.2.3 Order Arrival

When the order arrives all the blood units are ordered based on their expiry date and placed in the unassigned inventory. The blood units needs to be periodically checked for their expiry since a blood unit arriving can be anywhere from 9 to 22 days old. Due to this high variability in the age of the blood it is ordered based on age instead of ordering based on First in First out Policy.

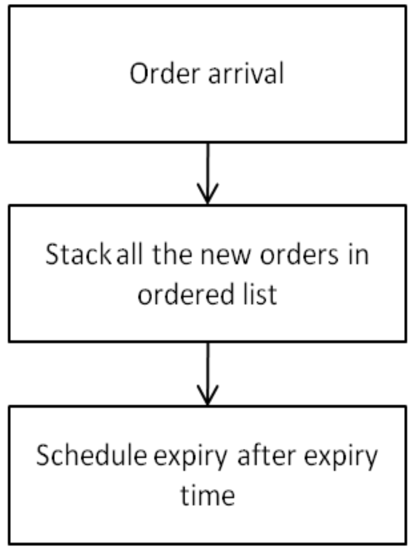

Figure4.4: Flow Chart-Order Arrival

4.2.5 Expiry Check

This is performs the process of constantly inspecting for the expiry of the blood everyday so that the expired blood is alone removed from the pool of inventory.

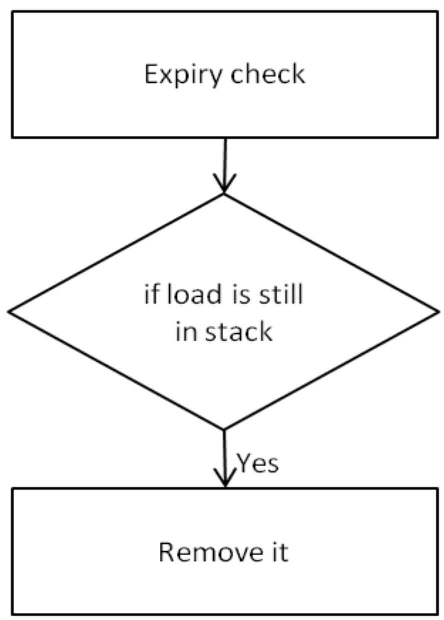

Figure 4.5: Flow Chart- Expiry check

4.3 Assumptions

- Blood enters the hospital system only from Red Cross i.e. the hospital does not accept direct donors and blood from other hospitals or blood banks.
- An assigned blood is cross-matched with one patient at a time. We are not considering multiple cross-match scenarios.
- In our model we are only accounting for wastage in terms of expired blood. We are not considering handling wastages and so on.
- There will be cross-match returns only on the scheduled demands.
- All the products follow an order up to inventory.
- The fill rate between Red Cross and hospital varies uniformly between [0.5, 0.25]
- Order fulfillment occurs once a day (information from the hospital)
- Lead time between ordering and fulfillment is 7hrs.
- Age of blood that enters the hospital usually varies uniform distribution [2, 20] days.
- Transfusion cross match ratio varies uniformly between [0.27, 0.67]
- Patient inter-arrival time follows an exponential distribution with a mean of 10
- The number of demands for each blood group is proportional to the population distribution of each blood group. For example, 35% of the population is A+ so 35% of the demands will be for A+.
- The use one blood group for the transfusion into other blood group patient is not allowed.

Chapter 5

Simulation Results

This chapter discusses the results of the simulations. The results presented contain the optimal level of safety stock needed by all the blood groups that lead to shortage and wastage to the minimum. The results also show the importance of lead time in a perishable inventory problem and the effect it can have on shortage and wastage. The following variables have a critical effect on the simulation results and must be optimized. These are variable that can be controlled by the user.

- Hold Time
- Lead time
- Safety Stock level
- Patient Inter-arrival Time

To find the optimal values for the above parameters a three factor analysis was done having constant safety stock level. By fixing the value of the Safety Stock level the other factors were changed systematically so that it minimizes shortage and wastage.

A three factor analysis was done varying Holding time, Inter-arrival time and Lead time by having a constant Safety Stock level.

Factor	Value Range
Holding Time	1 to 10 Days
Interarrival Time	8 to 14 patients per hour
Lead Time	7 to 48 hours

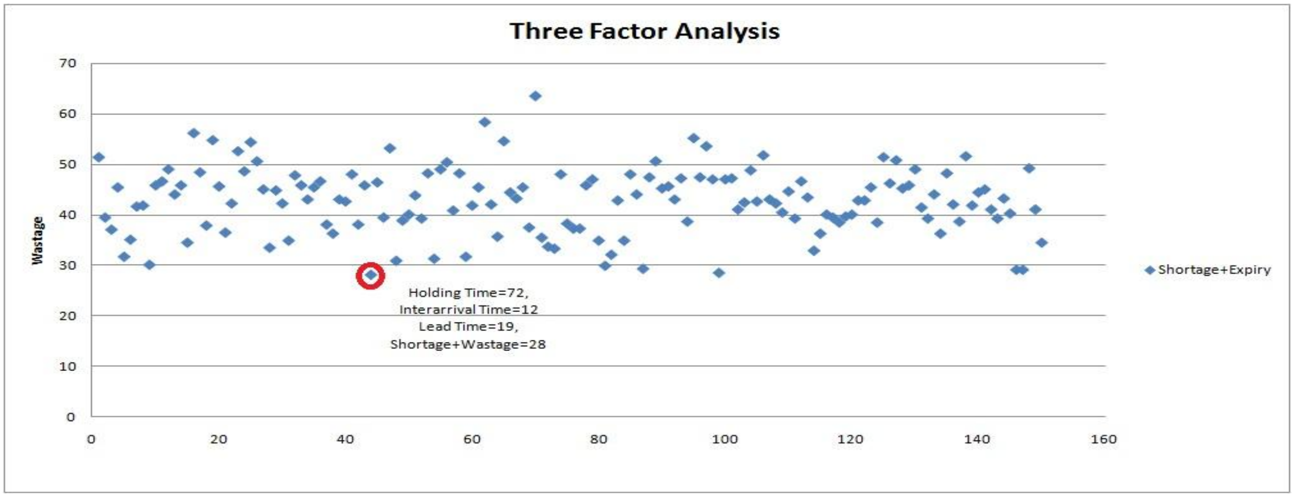

Figure 5.1 Three Factor analysis with constant Safety Stock

It was found that at Holding Time = 72 hours, Inter-arrival Time = 12 and Lead time = 19 hours the shortage and wastage was at minimum. The safety stock levels of other blood types were determined using above values.

5.1 Safety Stock level

The Safety stock levels of the various blood types were found out using the optimal values for Holding time, Inter-arrival time and Lead time. The intersection of the shortage and the wastage curve gives the optimal amount of safety stock necessary to minimize the cost.

The overall trend shows that as the safety stock level increases the amount of expiry increases and shortage decreases. This is because more is getting ordered this counters the shortage whereas leads to increase in expiry as the amount of inventory is large.

Blood Group	SSL
A+	21
A-	7
B+	10
B-	4
O+	26
O-	6
AB+	5

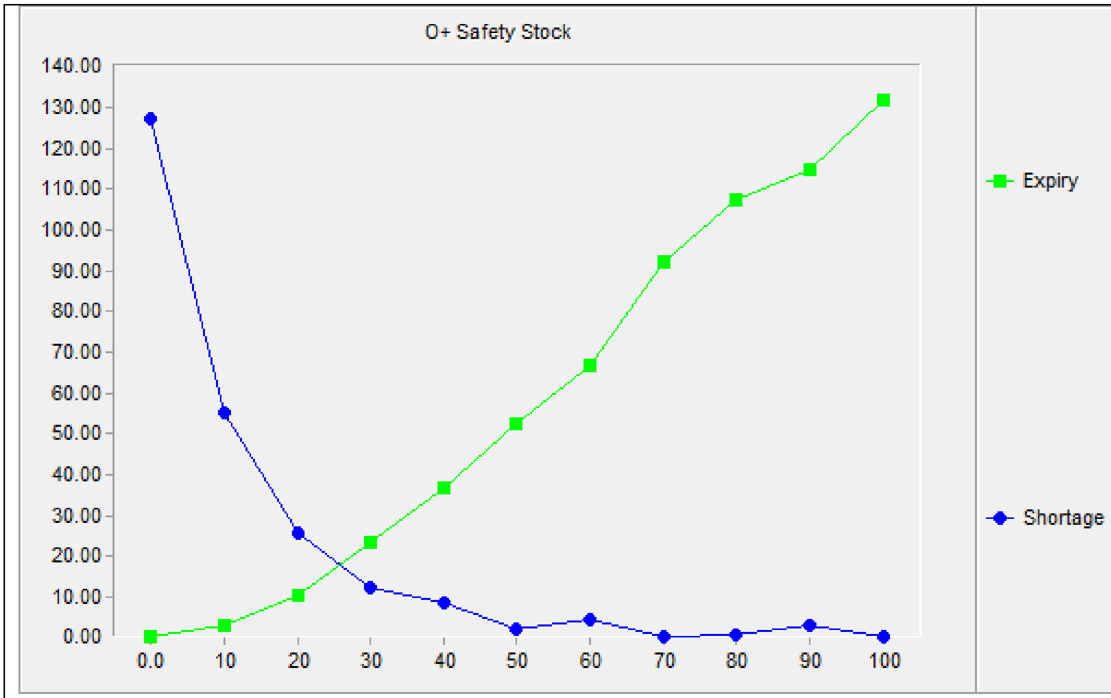

Figure 5.2 Effect of O+ Safety stock Level on Shortage and Wastage

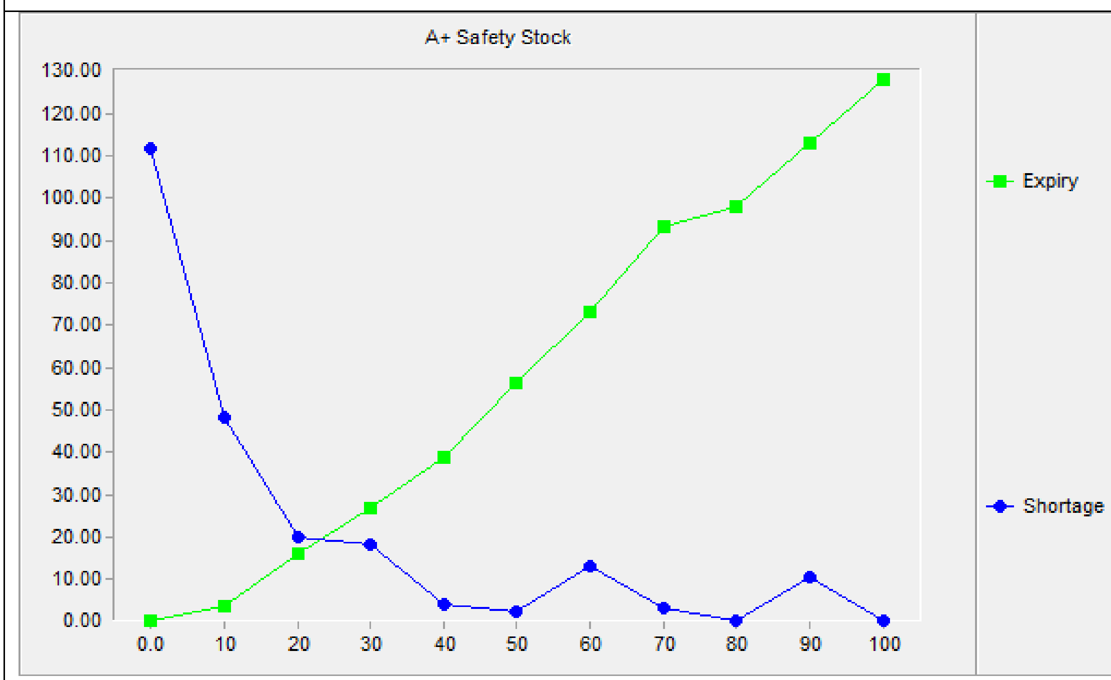

Figure 5.3 Effect of A+ Safety stock Level on Shortage and Wastage

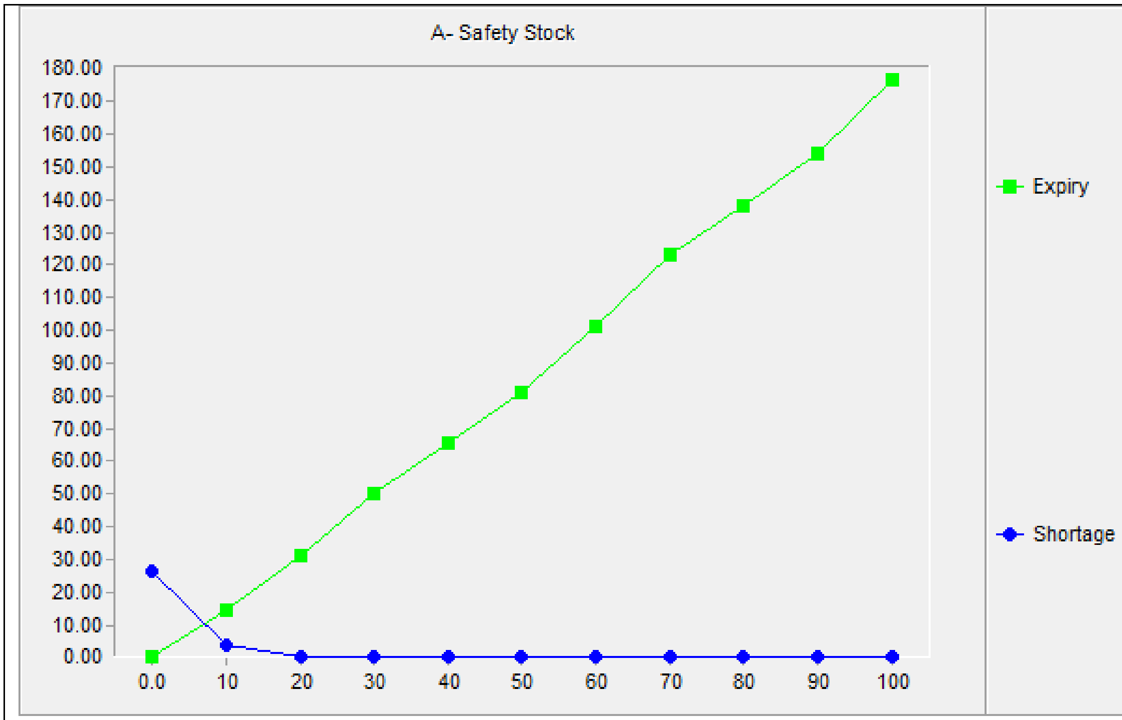

Figure 5.4 Effect of A- Safety stock Level on Shortage and Wastage

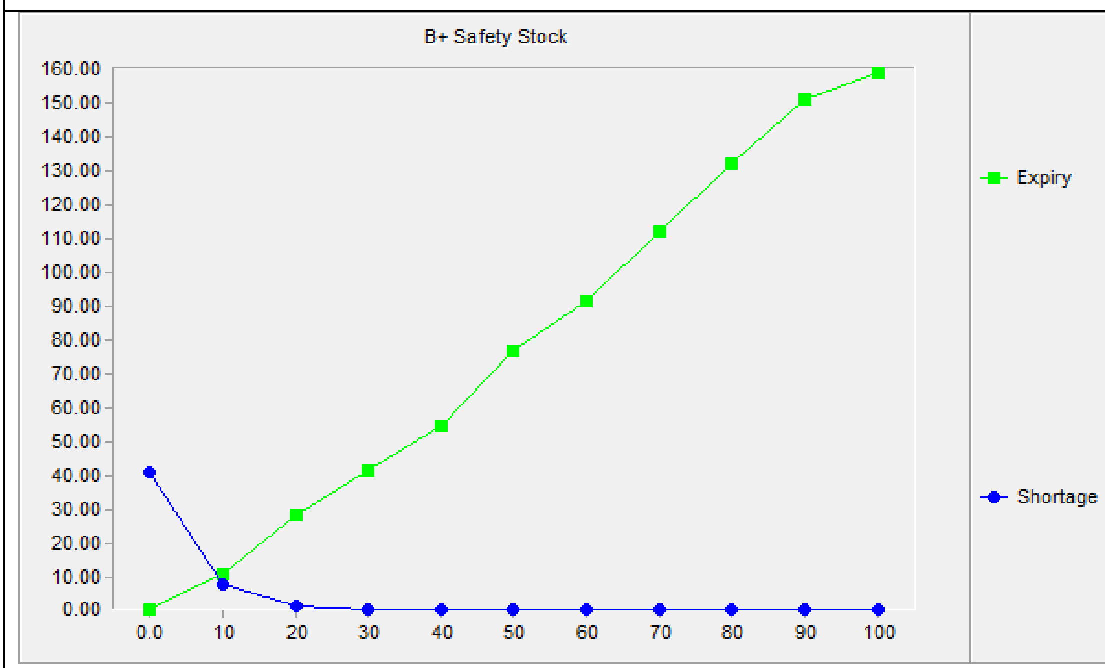

Figure 5.5 Effect of B+ Safety stock Level on Shortage and Wastage

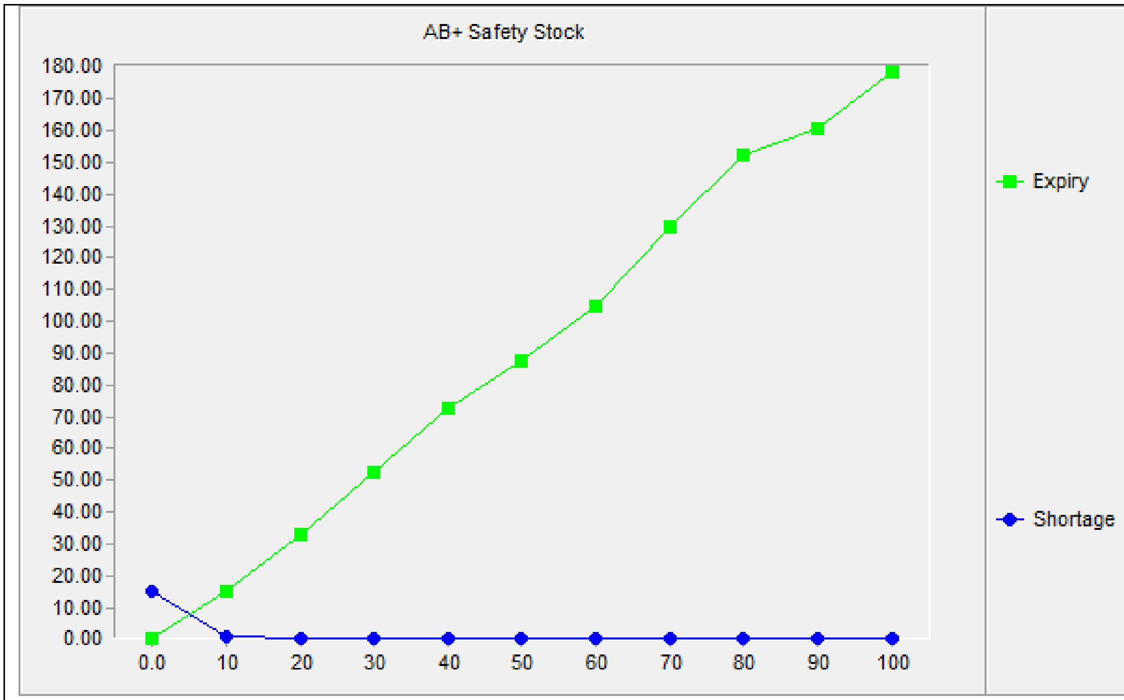

Figure 5.6 Effect of AB+ Safety stock Level on Shortage and Wastage

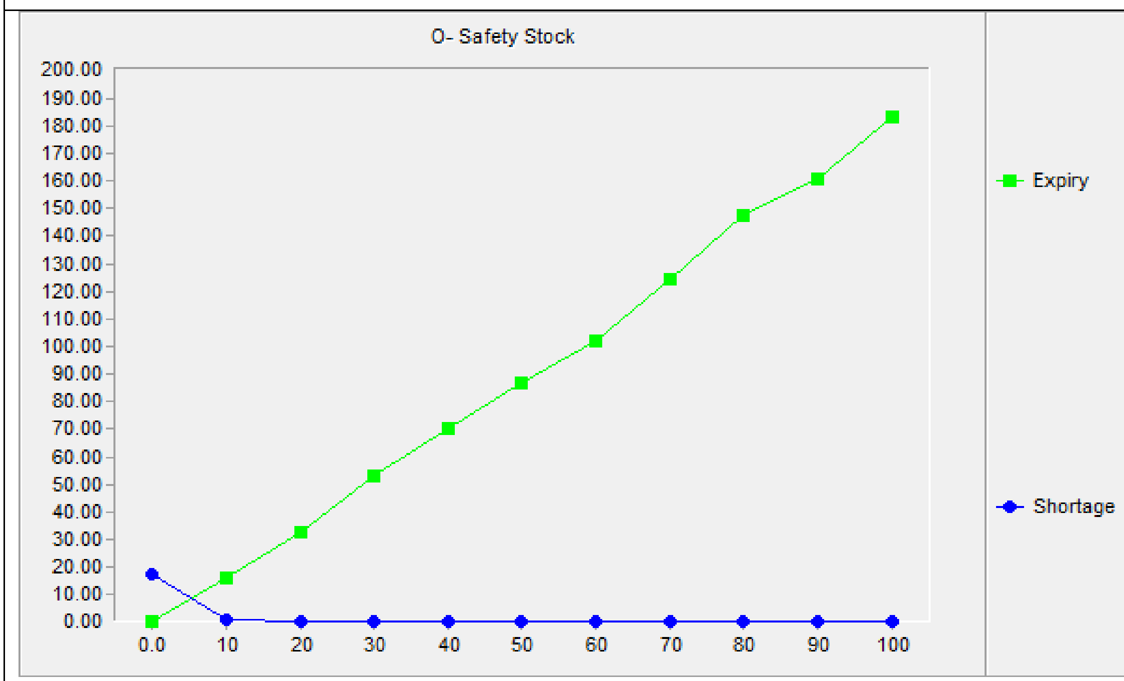

Figure 5.7 Effect of O- Safety stock Level on Shortage and Wastage

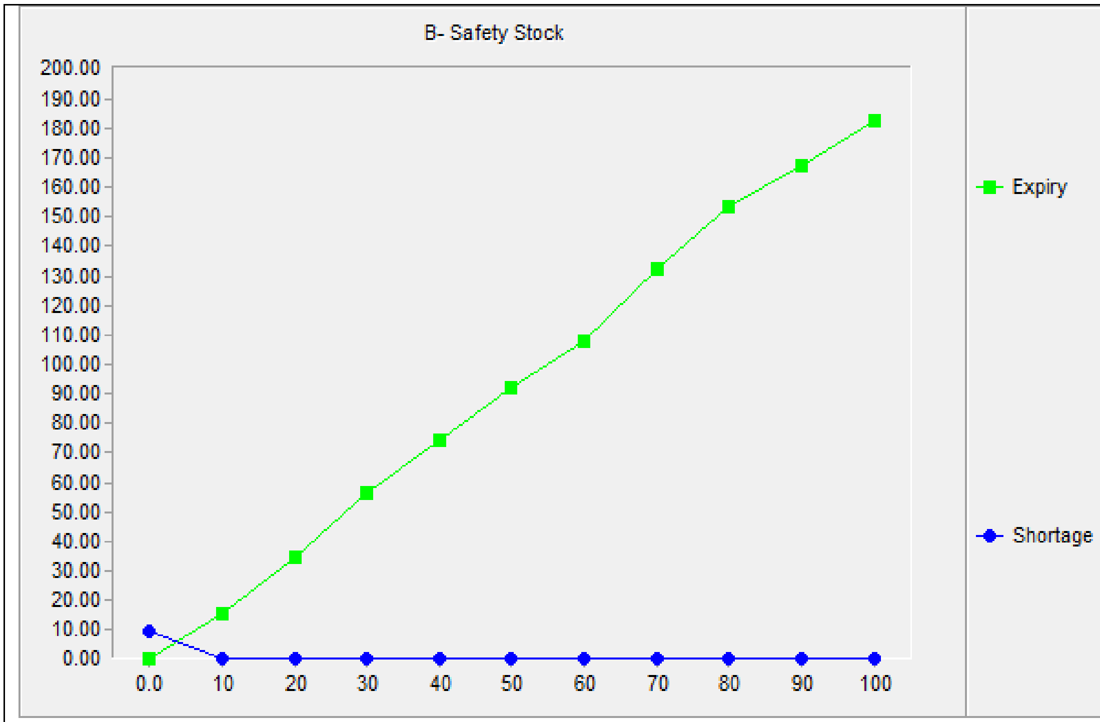

Figure 5.8 Effect of B- Safety stock Level on Shortage and Wastage

5.2 Blood Issuing Policy

The basic blood issuing policies used are

- FIFO
- LIFO
- Expiry First

To identify the system with lowest expiry and shortage a single scenario analysis was performed on FIFO (First in first out) & Expiry first model and LIFO (Last in First out) & Expiry first. The following Table 1 and Table 2 contain the important summary statistics. It is found that Expiry first model performed better in both the cases.

Analysis (FIFO Vs Expiry First) using 2-sampled t-test, the 95% CI was (15.32, 19.60). The CI doesn't contain zero thus we can conclude that the systems are statistically different. It can be seen from the table that the average expiry is lower for the second system. This is because all the products that are getting used are the ones which have earliest expiry.

Table 5.1: Summary Statistics for comparing FIFO Vs Expiry First Systems

Metric	**Parameter**	**FIFO**	**Expiry First**
Expiry	**CI Low**	**38.24**	**20.81**
	CI High	**40.04**	**23.54**
	# of Runs	**100**	**100**
Shortage	**CI Low**	**18.85**	**15.99**
	CI High	**24.98**	**20.56**
Expiry	**Average**	**39.64**	**22.18**
	Std. Dev.	**7.06**	**8.24**
Shortage	**Average**	**21.92**	**18.28**
	Std. Dev.	**15.45**	**13.77**

Table 5.2: Summary Statistics for comparing LIFO Vs Expiry First

Metric	**Parameter**	**LIFO**	**Expiry First**
Expiry	**CI Low**	**40.28**	**20.81**
	CI High	**42.86**	**23.54**
	# of Runs	**100**	**100**
Shortage	**CI Low**	**19.65**	**15.99**
	CI High	**25.59**	**20.56**
Expiry	**Average**	**41.57**	**22.18**
	Std. Dev.	**7.76**	**8.24**
Shortage	**Average**	**22.62**	**18.28**
	Std. Dev.	**17.89**	**13.77**

On further analysis using 2-sampled t-test, the 95% CI was (17.16, 21.62). The CI doesn't contain zero thus we can conclude that the systems are statistically different. It can be seen from the table that the average expiry is lower for the second system. This is because all the products that are getting used are the ones which have earliest expiry.

5.3 Future Demand

To plan for changes in the future the following parameters were changed and their effect in the safety stock level was studied.

- Demand
- Lead Time
- Inter-arrival Time

5.3.1 Demand

Table 5.3: Summary Statistics for varying demand

Metric	Parameter	M	μ+σ	μ+2σ
Demand		2.4	3.1	3.8
Expiry	Average	21.53	22.20	23.37
	Std. Dev.	7.93	6.55	8.52
	Minimum	6	12	3
	Maximum	39	34	38
	Median	31	27	31.5
	# of Runs	30	30	30
Shortage	Average	16.43	20.27	25.29
	Std. Dev.	13.57	17.6	19.47
	Minimum	0	2	1
	Maximum	55	60	65
	Median	33.5	31	29.5
	# of Runs	30	30	30

On further analysis of shortage using 2-sampled t-test between μ and $\mu+\sigma$ revealed that at 95% CI was (-11.97, 4.29). Since the confidence interval contains zero there is no appreciable difference between the systems. But a 2-sampled t-test between μ

and μ+2σ revealed that at 95% CI was (-17.54, -0.14).The CI doesn't contain Zero thus we can conclude that the systems are statistically different.

5.3.2 Inter-arrival Time

For a fixed order safety stock level as patient inter-arrival time increases this indirectly implies that the demand is decreasing, thus more blood is put on reserve. This leads to decrease in shortages and increase in expiry.

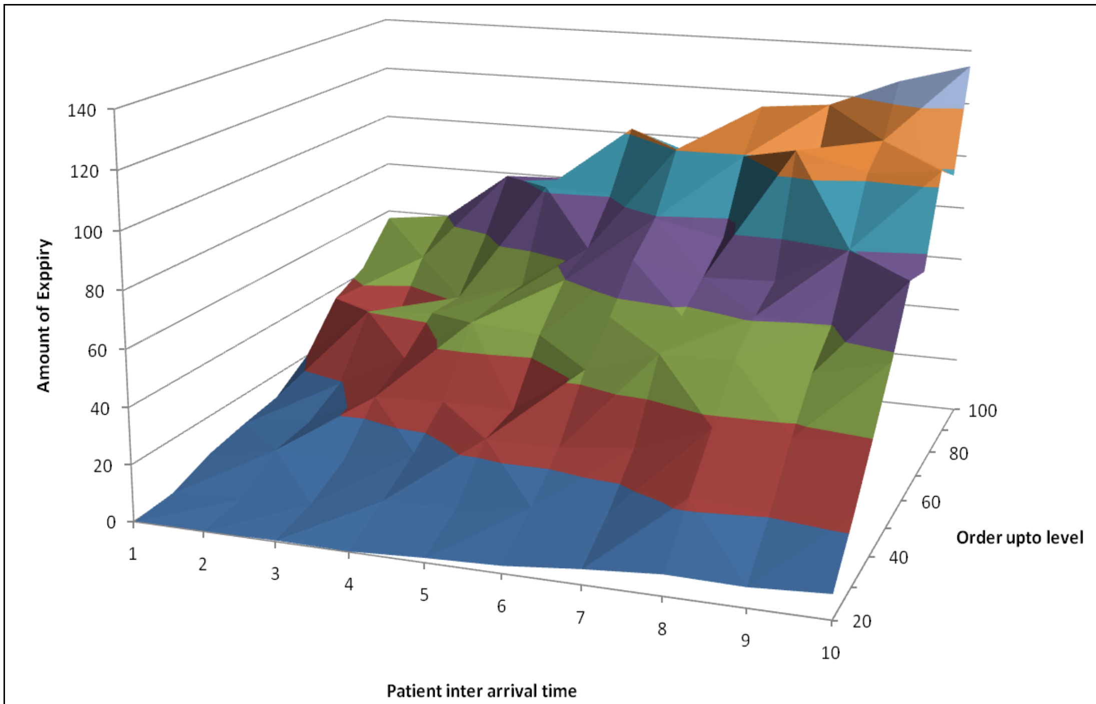

Figure 5.9 Effect of patient Inter-arrival time, Safety stock level on the amount of Expiry

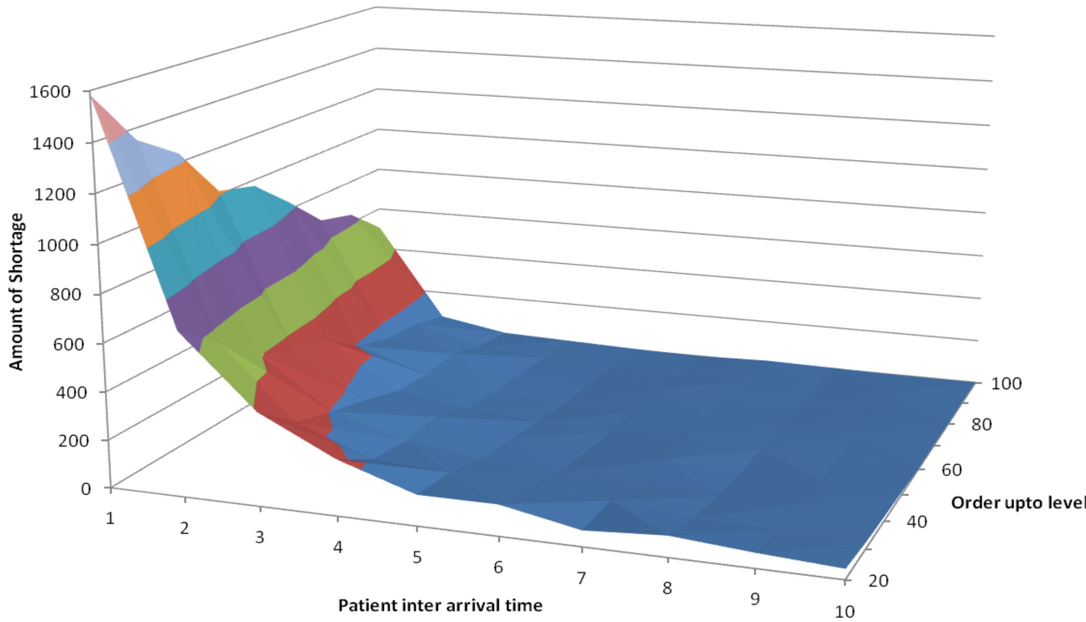

Figure5.10 Effect of patient Inter-arrival time, Safety stock level on the amount of Shortage

5.3.3 Lead Time

As the lead time increases the shortage and expiry also increases. Shortage increases because blood will be held in reserve for longer and the time before an order is realized is also increased. Expiry increases because we are using the policy of earliest expiry first, so the blood with the earliest expiry is put on hold and may not get used.

Lead time has a strong influence on the system performance. For small lead times, variations in holding time and transfusion to cross match ratio do not significantly affect expiry and shortages On the other hand, larger lead times make the inventory system vulnerable to variations in holding time and transfusion to cross-match ratio.

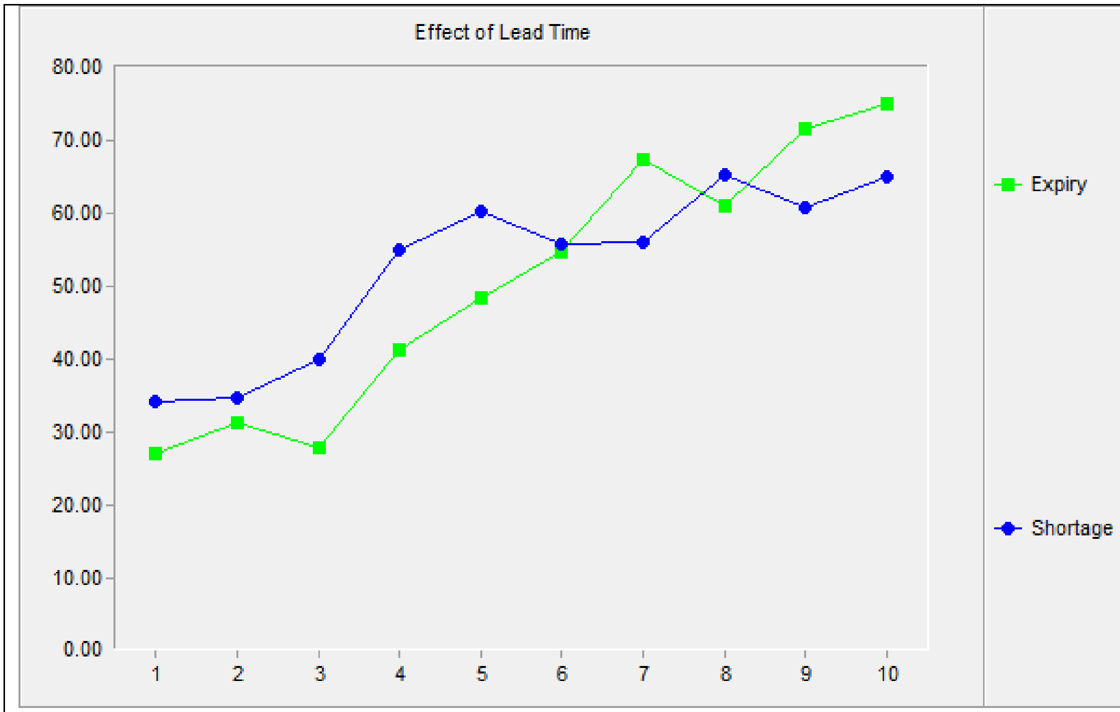

Figure 5.11 Effect of lead time on Shortage and wastage

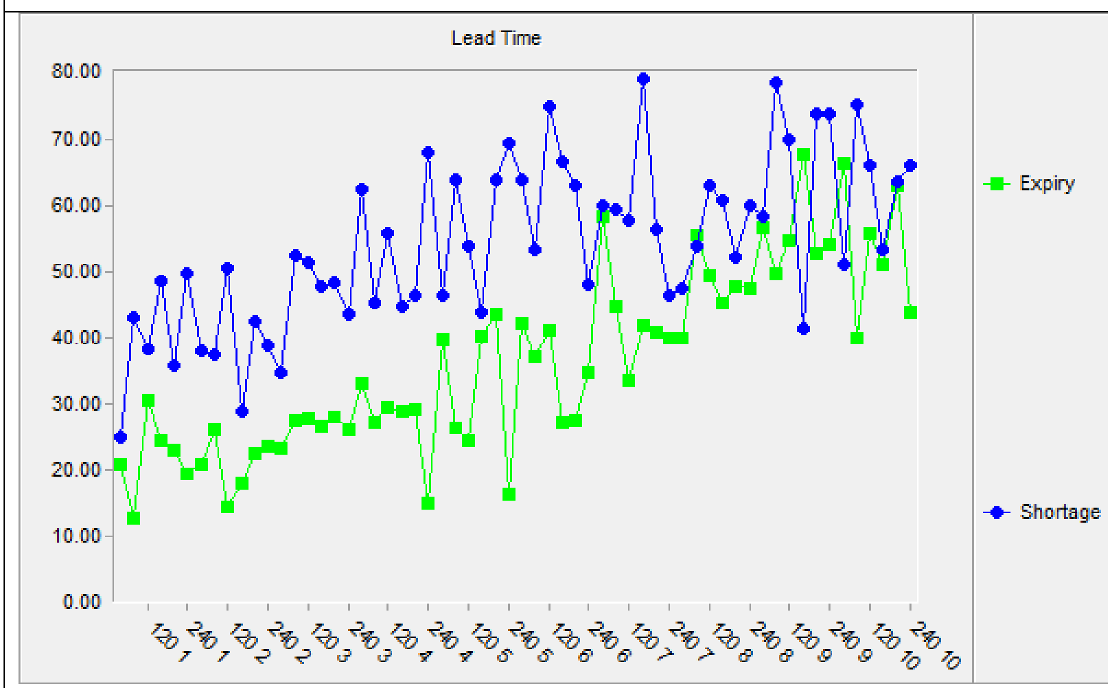

Figure 5.12 Effect of Holding time and Lead Time

5.4 Hold Time

This is referred to as cross match release period which is the amount of time the blood must be reserved before it is transfused to the patient. A two factor analysis on transfusion cross match ratio and Holding time and found that they have no effect on amount of expiry and shortage. This is because we have a small lead time. This will not be the case if the lead time was higher. As the lead time increases the average expiry and shortage also increases.

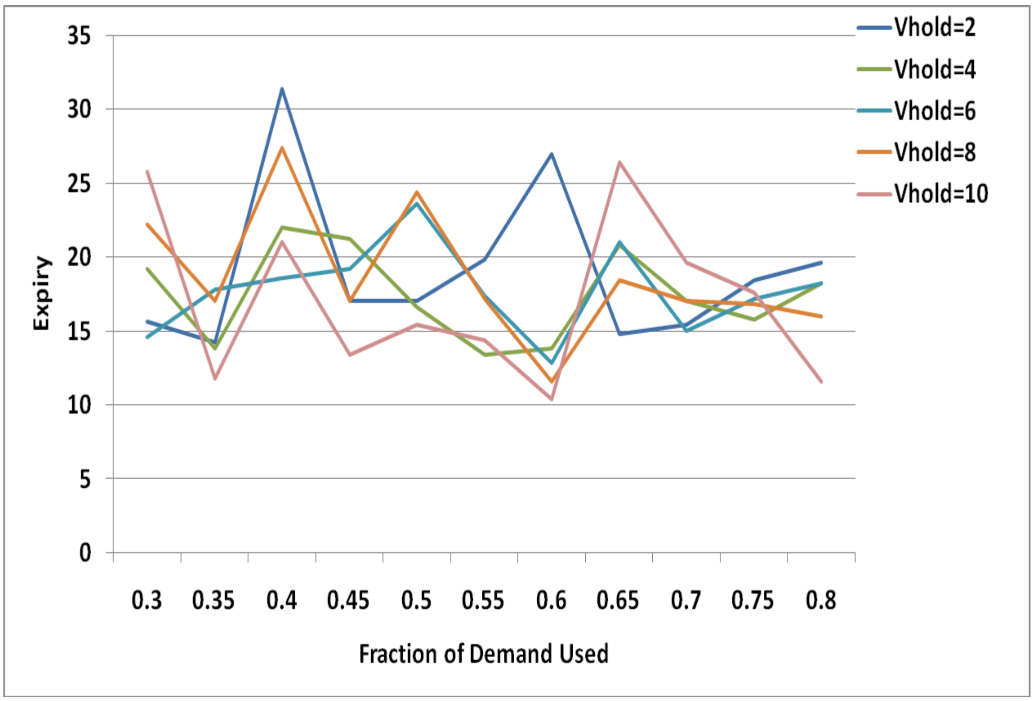

Figure 5.13 Effect of varying lead time and holding time on Expiry

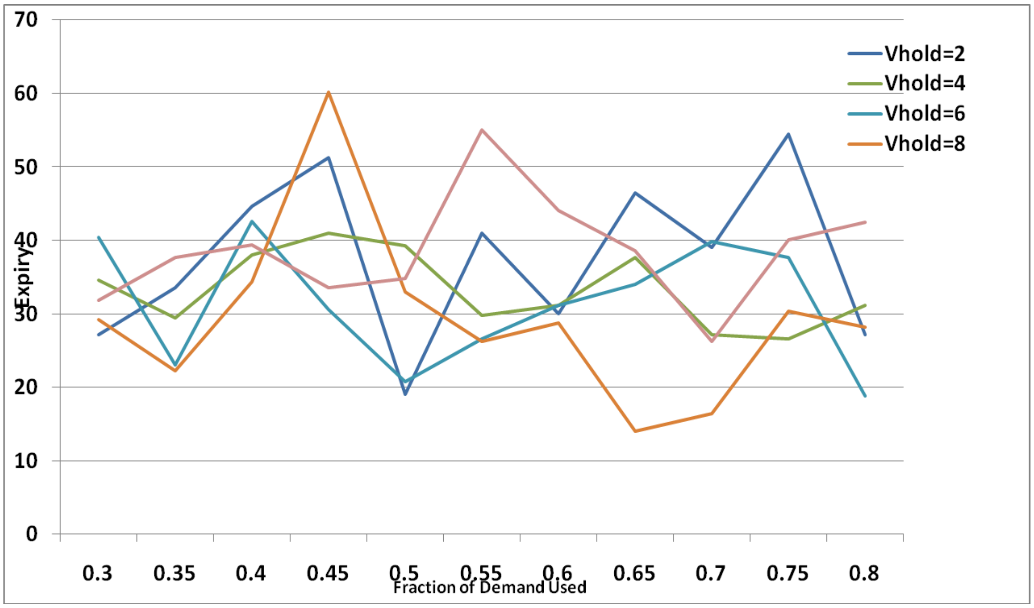

Figure 5.14 Effect of varying lead time and holding time on Shortage

Chapter 6

Conclusion

6.1 Motivation and Background

The aim of the thesis was to find the best blood issuing policies and come up with optimal amount of safety stock for all the blood types. Upon review of the literature it was found to be a complex stochastic, multi-product perishable inventory problem. Since it was difficult to be solved analytically, simulation was used to model the system and come up with results. AutoMod, discrete event system simulation software, was used to simulate the performance of the policies. The operation of the policies was coded in the software, and the products were modeled as loads in the system. The system description, parameters, simulation methodology, and assumptions used were described in detail.

Upon comparing the blood issuing policies and the effect of change in Lead time, Inter-arrival time and demand lead to the following conclusions.

- Lead Time has critical influence in system performance. The lesser the lead time the effect of other parameters in the system is significantly low. The increase in lead time makes the system more vulnerable when other parameters changes.
- The most common policy employed by hospitals is the “First In First Out”. We can see that “earliest expiry first” policy outperforms “First in First Out” policy.
- There seems to be an optimal Safety stock level at which both shortage and expiry is low. The Safety stock level seems proportional to the expired inventory and inversely proportional to demand shortages.
- When the demand increases there is a necessary to increase of safety stock level.
- In case of increase in safety stock level there needs to be further investment in storage.

6.2 Future work

The possibility of multiple cross match scenario must be investigated in depth. Double cross matching does not increase the overall probability of the use but can be used to shift some probability of use between units. In a similar the possibility of usage of one blood type for another compatible blood type must be considered.

This thesis deals only from the arrival of the blood from the blood bank, thus by modeling the system from the Blood bank perspective would improve the model further. Since the age of the incoming units and transfusion to cross match ratio were not known it was assumed from the literature. Using the actual data would maximize the accuracy of the model.

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Appendix

Code

```
/*creating 2 types of loads one is blood and the other patient*/

        begin model initialization function

        open "arc/verify_patient.txt" for writing save result as V_patient_file

        open "arc/verify_patient_detals.txt" for writing save result as V_patient_details_file

        set V_bloodtypes to 7 /*7 types of products*/

        set V_hold to 2*24 /* Default 2 days*/

        set V_leadtime to 7

        set V_ordertime to 24

        set V_lifetime_mean to 11*24 /* Default 20.5 days*/

        set V_lifetime_sd to 9*24 /* Default 4.5 days*/

        set V_patient_interarrival to 10

        set V_frac_used_mean to 0.37 /* Default 0.47*/

        set V_frac_used_sd to 0.10 /* Default 0.2*/

        set V_fill_rate_mean to 0.75

        set V_fill_rate_sd to 0.25

        set V_demand_mean to 2.9767

        set V_demand_sd to 0.4723

        set V_SSL(1) to  26 /*Stock level*/

        set V_SSL(2) to  8

        set V_SSL(3) to  7

        set V_SSL(4) to  2

        set V_SSL(5) to  27
```

```
        set V_SSL(6) to  8

        set V_SSL(7) to  4

        create 1 load of type L_bloodunit to P_bloodunit_initilize

        create 1 load of type L_patient to P_patient_arrive

        return true

end


/*assigning the other attributes for the patient load; A_ID, A_quantity_demanded and
A_quantity_demanded_used*/

begin P_patient_arrive arriving

        set V_ID to 1

        while (1=1) do

        begin

                /* Add if conditions to have customized interarrival and demand patterns for
each patient type*/

                if V_ID=1 then

                        wait for (e V_patient_interarrival)+24 hr

                else

                        wait for e V_patient_interarrival hr

                set A_bloodtype to oneof(35:1,7:2,8:3,2:4,37:5,7:6,3:7)

                set A_quantity_demanded to lognormal V_demand_mean,V_demand_sd

                set A_quantity_used to ((u V_frac_used_mean,V_frac_used_sd) *
                A_quantity_demanded)

                set A_ID to V_ID

                set A_patient_arrival to ac

                clone 1 load to P_patient
```

```
            set V_ID to V_ID+1
        end
end
/*all the used blood is sent to die whereas the unused blood is held for 5 days for a particular
patient and then sent back to the inventory*/
begin P_patient arriving
        /* The variable V_patient_number captures patinet ID. Its is used in process
P_assign_blood*/
        set V_patient_number to A_ID
        set V_curinv to OL_inventory(A_bloodtype) current
        /* The variable V_shortage captures shortage in a blood type*/
        if A_quantity_used>V_curinv then
            increment V_shortage(A_bloodtype) by  A_quantity_used-V_curinv
        /*every load that gets ordered out of OL_inventory goes to P_shortage_stat*/
        order A_quantity_used loads from OL_inventory(A_bloodtype) to P_shortage_stat
        order (A_quantity_demanded-A_quantity_used) loads from OL_inventory(A_bloodtype)
to P_assign_blood
        wait for V_hold hr
        /* The variable V_patient_number captures patinet ID. Its is used get back unused blood
from OL_holding*/
        set V_patient_number to A_ID
        order all loads satisfying A_patient_number=V_patient_number from
OL_holding(A_bloodtype) to P_unassign_blood
        set A_patient_departure to ac
        print ac as .3 "\t" A_bloodtype as 4.0 "\t" V_shortage(A_bloodtype) as .3 "\t" to
V_blood_shortage
```

```
        print A_ID as 4.0 "\t" A_quantity_demanded as .3 "\t" A_quantity_used as .3 "\t"
A_bloodtype as .3 "\t" A_patient_arrival as .3 "\t"

        A_patient_departure as .3 "\t" to V_patient_details_file

        tabulate V_shortage(A_bloodtype) in T_shortage(A_bloodtype)

        send to die

end


begin P_shortage_stat arriving

        set A_patient_number to V_patient_number

        print ac as .3 "\t" A_BloodID as 4.0 "\t" A_type as 4.0 "\t Used\t" A_patient_number as
4.0 to V_patient_file

        send to die

end


begin P_assign_blood arriving

        set A_patient_number to V_patient_number

        print ac as .3 "\t" A_BloodID as 4.0 "\t" A_type as 4.0 "\t Holds\t" A_patient_number as
4.0 to V_patient_file

        wait to be ordered on OL_holding(A_type)

end


begin P_unassign_blood arriving

        print ac as .3 "\t" A_BloodID as 4.0 "\t" A_type as 4.0 "\t Returns\t" A_patient_number
as 4.0 to V_patient_file

        set A_patient_number to 0

        wait to be ordered on OL_inventory(A_type)
```

```
end

/*assigning blood type to each blood load*/

begin P_bloodunit_initilize arriving

        set V_count2 to 1

        while V_count2<=V_bloodtypes do

        begin

                set A_type to V_count2

                set A_patient_number to 0

                clone 1 load to P_bloodunit_arrive

                set V_count2 to V_count2+1

        end

end

/*function has been used to come up with a policy to identify the number of loads that need to be
ordered (cloned in our case); wait for 24 hrs btw orders*/

begin P_bloodunit_arrive arriving

        while (1=1) do

        begin

                set V_order to (u V_fill_rate_mean,V_fill_rate_sd)* F_ordering_policy(A_type)

                clone V_order loads to P_booldunit_stock

                wait for V_ordertime hr

        end

end
```

```
/*set the expiry date for each blood load; clone one load for every blood this is used for removing expired load*/

begin P_booldunit_stock arriving

        wait for V_leadtime hr

        set A_BloodID to V_BloodID

        set V_BloodID to V_BloodID+1

        set A_order_arrival to ac

        set A_exp to ac+(u V_lifetime_mean,V_lifetime_sd hr)

        print ac as .3 "\t" A_BloodID as 4.0 "\t" A_type as 4.0 "\t Arrives\t" A_exp as .3 to V_patient_file

        clone 1 load to P_remove_expired_blood

        wait to be ordered on OL_inventory(A_type)

end


/*check for expired blood on inventory and hold*/

begin P_remove_expired_blood arriving

    wait for (A_exp-ac)

    set V_temp_ID to A_BloodID

    order all loads satisfying A_BloodID=V_temp_ID from OL_inventory(A_type) to P_expiry_stats

    order all loads satisfying A_BloodID=V_temp_ID from OL_holding(A_type) to P_expiry_stats

    print ac as .3 "\t" A_bloodtype as 4.0 "\t 1" to V_blood_shortage

    send to die

end
```

```
begin P_expiry_stats arriving

        increment V_count_expiry(A_type) by 1

        print ac as .3 "\t" A_BloodID as 4.0 "\t" A_type as 4.0 "\t Expires\t" A_exp as .3 to
V_patient_file

        tabulate V_count_expiry(A_type) in T_expiry(A_type)

        send to die

end


/*funtion for ordering policy*/

begin F_ordering_policy function

        set V_curinv to OL_inventory(Arg_type) current

        if  V_curinv<V_SSL(Arg_type) then

                set V_return to V_SSL(Arg_type)-V_curinv

        else

                set V_return to 0

        return V_return

end
```