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PLATELET INVENTORY MANAGEMENT IN BLOOD SUPPLY CHAINS

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ABSTRACT

It has been shown that a significant amount of platelets is wasted due to their short life after collection, just 5 days. Most of the previous work develop inventory policies based on a known demand pattern over a finite time horizon. Further, they assume that the entire platelet units received by the hospitals from the blood center are fresh (with all 3 days of transfusable life remaining). However, in practice, nearly 50% of the incoming platelets have one day shelf life. This research develops inventory models for the hospitals and the blood center under realistic settings (demand uncertainty, platelets with varying shelf life, finite supply at the blood center) with the objective of minimizing platelet shortage and wastage (due to outdating).

In this dissertation, single objective deterministic inventory model is first developed to determine the number of platelet units to order and time between orders at the hospital. The model is extended to multiple objective inventory models at the hospital. The deterministic models are later extended stochastic programming models under demand uncertainty for hospital inventory management. Finally, inventory management along the entire blood supply chain is studied and platelet ordering policies are developed under demand uncertainty.

Due to the computational complexity of the stochastic programming model developed for hospital inventory management, three heuristic rules are proposed for determining the platelet ordering policy at the hospital. The performance of these three ordering policies is compared against that of the traditional periodic review order-up-to policy, using real-life data obtained from a medical center. The shelf life of arriving platelets, coefficient of variation of demand and cost parameters are varied, and their impact is analyzed on the performance measures and the best rule with respect to each setting is determined. Based on the hospital setting and cost prioritization, the decision maker can decide the best performing rule.

A new variant of the genetic algorithm, called modified stochastic genetic algorithm (MSGA) is proposed for determining the order-up-to level and re-order points at the various stages of the blood supply chain consisting of a blood center, which serves several hospitals. The performance of the MSGA algorithm is tested against an existing genetic algorithm. Using actual platelet demand data, it is shown that the MSGA algorithm performs well and can be easily scaled up to solve for larger supply chain problems. The proposed MSGA methodology is generic and

can also be applied to determine ordering policies for other perishable supply chains, such as food or drug supply chains.

Keywords: Platelet wastage, stochastic integer programming, heuristic ordering policies, blood supply chain, genetic algorithm.

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Chapter 1 : Introduction

Supply chain is defined as a series of coordinated stages that are situated at various locations to ensure the procurement of raw materials, production of the semi-finished and finished goods and distribution of the products to customers. The different stages of the supply chain include supplier, manufacturer, distributor, retailer and customers who are physically distinct and geographically separated (Ravindran and Warsing, 2013). Some companies include fewer members of the supply chain and some companies include more. These entities are generally independent and operate under different constraints and objectives. An efficient supply chain will result in the delivery of the right quantity at the right time at the right place.

1.1 Supply Chain for Perishable Items

Supply chains delivering perishable products, such as blood, food, medicines, drugs and flowers, are unique with specific challenges in comparison to that of non-perishable items due to the finite product shelf life (Nagurney et al., 2011). The product's shelf life is defined by Donselaar et al., (2006) as the "lifetime of the product that is measured in days, counting from the day it is produced until the product becomes unacceptable for consumption or obsolete". Therefore perishable item supply chain will definitely result in higher wastage of products compared to that of non-perishable item supply chain. Donselaar et al., (2006) have also suggested that items which have a shelf life of 30 days or less can be categorized as perishable items. Hence, blood, food, medicines, drugs and flowers are perishable items and thereby leading to a significant wastage if not utilized within that duration (Parfitt et al., 2010).

In particular, blood supply chain deals with the delivery of different components of blood, (Red Blood Cells (RBC), White Blood Cells (WBC) and platelets suspended in liquid substance called plasma) from the donor to the hospitals and surgery centers for patient treatment as shown in Figure 1.1. Note that often the blood center and blood bank are the same.

1.2 Blood Supply Chain

Each component of blood has its own function/purpose in humans and therefore is essential to maintain appropriate inventory of these at all times.

(a) The RBC carries oxygen from the lungs to all parts of the body and is needed during surgeries and anemia of chronic disease.

(b) The WBC helps in defending the body against infections and used to prevent life threatening bleeding premature infants.

(c) Platelets are mainly used for arresting bleeding when there are any wounds and are needed during surgery to ensure coagulation of blood. In addition, platelets are used for treating cancer patients and during organ transplant.

(d) Plasma helps in the treatment of burns (Belien and Force, 2012).

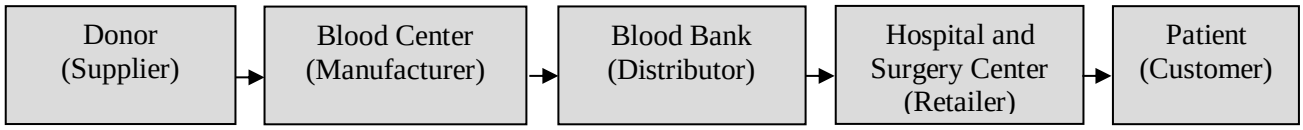


Figure 1.1: Members of the Blood Supply Chain

1.2.1 A Brief Overview of Blood Collection and Distribution Process

There are multiple suppliers for blood products in the United States. The U.S. Food and Drug Administration (FDA) has developed regulations for the blood collection and distribution process.

The American Red Cross (ARC) is the largest supplier of blood products. It has several blood collection sites across the US. ARC distributes about 50% of the blood supplies. The other 50% is collected and processed by community blood centers. Community blood centers are independent non-profits, and are typically members of America's Blood Centers (ABC). The FDA regulates all the blood centers in the US. ARC divisions at particular regions organize blood donation programs and set up blood collection sites. A regionalized blood banking system for the ARC in the USA is shown in Figure 1.2 (Nagurney et al., 2011).

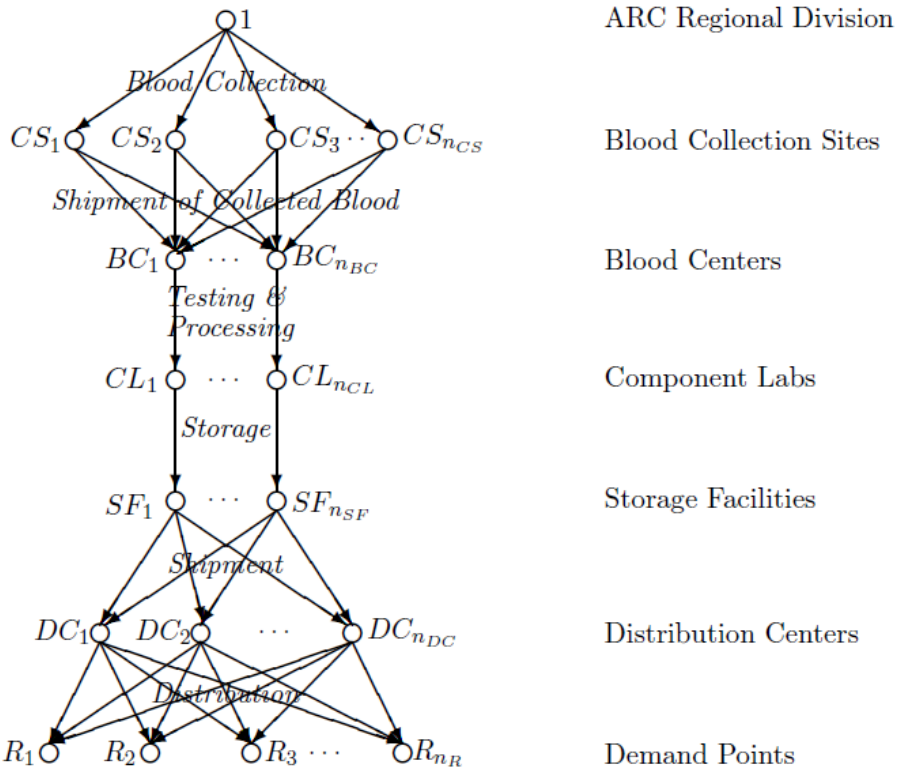


Figure 1.2: Flow of Blood along Blood Supply Chain (Nagurney et al., 2011)

The flow of blood along the supply chain takes place as follows:

- The whole blood is collected at several collection sites from various donors and is then sent to blood centers. Blood that is drawn from the donor is in whole form (Belien and Force, 2012). Every donor has to satisfy the FDA requirements. Each unit of blood that is collected from the donor is kept track (including the donor information) and these records are maintained indefinitely.
- The blood center separates the blood into three major blood components: RBC, plasma and platelets. The average unit of donated whole blood is 450 to 550 milliliters, which is used to provide one unit of RBC and one unit of plasma. Note that the plasma derived from whole blood is collected from male donors only. However, platelets drawn from five donors are pooled together to make a single unit of platelet.
- From the blood centers, the blood is sent to the component labs for testing for any infection such as HIV, Hepatitis A, Hepatitis B, Hepatitis C, West Nile Virus, etc (American Red Cross, 2013). As of 2013, ARC has 5 testing labs across the US. There are 36 blood regions that share the testing labs. The small sample that is tested at the lab is discarded irrespective of the results

of the test. From the sample testing if the blood is observed to be contaminated, the corresponding blood unit is discarded at the storage facility. The testing procedure however incurs an operational cost (Nagurney et al., 2011).

- The blood bank places orders to the blood center and thereafter blood at the storage facility is delivered to the requesting blood bank in validated, temperature controlled carriers.
- Several hospitals and surgery centers which are the demand points place orders to the blood bank for the various blood components, depending upon their needs to serve their patients. Hospitals have contract only with a single blood center and cannot procure blood products from different suppliers. For example, Mount Nittany Medical Center in State College, PA procures blood from ARC. However, Penn State Hershey Medical Center and Geisinger Medical Centers in Pennsylvania have their own collection centers and do not procure blood from any other blood centers. However, all collection centers are operated under the ARC or an ABC community blood center.

Blood centers assume that all the units of blood that are obtained by the hospitals are used by them. In other words, blood centers do not keep track of whether blood units procured by the hospitals are being utilized or not. It is the responsibility of the hospitals to have the record of the transfused and unutilized blood units.

The process of moving the blood components down the supply chain involves several costs (Ghandforoush and Sen, 2010):

- Cost of testing platelets for any infection
- Outdating cost
- Transportation cost
- Cost of separation of platelet rich plasma from RBC
- Shortage cost
- Blood components carrying cost

1.2.2 Apheresis Platelet Supply Chain

Platelets in particular, can be collected from the donor through a process called *platelet apheresis* by which blood is drawn and only platelets are extracted from the donor's blood and the remaining blood components are injected back into the donor's body. Though this method is expensive, the frequency of platelet donation is increased to once in every 2 weeks (i.e., 24 times

a year) instead of once in every 56 days, which is approximately 6 times a year (American Red Cross, 2013). From the donor site, apheresis platelets are sent to the blood center for testing and then shipped to the blood banks, and hospitals as in regular blood supply chain. A return feedback is provided from the hospital floor. For example, a feedback mentioning that there is no hole in the bag, unit procured is transfused, etc. European countries have adopted a patented production process for platelets, which utilizes a platelet additive solution instead of plasma for platelet storage, but the US FDA has not licensed this production process in America.

1.3 Forecasting Demand of Blood at BSC

Forecasting demand for blood components at the blood supply chain is very essential because advanced information can increase blood collection efforts during the lead time if more blood is required and blood collection can be limited if less units are projected (Frankurter et al., 1974). In the research paper by Boyle et al., (2008), it was said that "forecasting is an important aid in many areas of hospital management, including elective surgery scheduling, bed management, and staff resourcing". In specific, forecasting of platelet is very essential because proper forecasting can reduce shortage and outdating of platelets at the blood supply chain.

The main challenge involved in blood supply chain is the shortage of blood products due to limited donor population resulting in low service level from the blood centers and blood banks. In the paper by Frankfurter et al., (1974), the authors mentioned that during midsummer and end of year holiday season, donors do not prefer to donate and due to the short shelf life of blood, shortages occur. Also, during Easter and Christmas (which is referred to as "production breaks"), blood centers do not operate and hence supply of blood from the blood center is affected. Ordering policies of platelets for those special periods was studied in detail by Haijema et al., (2009). Therefore, adequate forecasting is required for planning future blood collection efforts to avoid outdating as well as stock-outs of blood units (Pereira, 2004).

1.4 Motivation for this Research

The study of blood collection and distribution process is very essential because

- There is a significant wastage of blood along the blood supply chain (i.e., from the time of collection of blood from the donor to the time of providing blood to the patient). It has been reported (Nagurney et al., 2011) that in 2006, "the national estimate for the number of units of whole blood and all components ***outdated*** by blood centers and hospitals was 1,276,000

out of 15,688,000 units". In other words, approximately 8% of the total units collected were wasted.

- Components of blood are used for saving human lives.

There is more wastage of blood due to high inventory levels maintained at the hospitals and at the blood banks. The reasons behind maintaining high inventory levels are as follows:

- Blood components have a very short shelf life. Moreover, blood after being collected is first being tested for any infection and only the uncontaminated blood is available for patient use. The process of testing takes about 2 days. RBC's have a shelf life of 21-42 days. Platelets have a shelf life of 5-7 days and plasma has a shelf life of a year (American Red Cross, 2013). Among these components, platelets have the least shelf life. Moreover, after being tested at the labs (culture/ bacterial testing), they have a remaining shelf life of only 3-5 days. Due to the very short shelf lives of platelets, hospitals maintain high inventory to compensate for the outdated platelets.
- The supply and demand of blood products are stochastic. Therefore, blood centers collect more blood than required to compensate for the extreme demand scenarios thereby resulting in outdating.
- Critical patients may need numerous blood transfusions prior to recovery. However, the number of units of the specific blood component needed for each treatment cannot be pre-determined. For example, platelets are mainly used for cancer patients during chemotherapy. During chemotherapy, patients ate transfused with platelets if the platelet count drops below 10,000 platelets/uL of blood. However, it is not possible to determine whether a patient will be requiring platelets during each chemotherapy treatment. Therefore, the supply of blood components must be continuously maintained depending upon the treatment type (BJC Healthcare, 1997).

It is necessary to minimize platelets wastage at hospitals for the following reasons.

- Over the past 10 years, demand for blood has increased but the supply of blood is not increasing enough to meet the demand (Landers, 2001). Moreover, increased FDA regulations reduce the number of eligible donors.
- Blood products are perishable and hence donated blood cannot be stored and used for future demand.

- Shortage of blood can even lead to the death of a person.
- Outdating of blood is also not acceptable because less than 38% of the population is eligible for donating blood and only 5% of the eligible blood donors actually donate blood (American Red Cross, 2013; LifeStream, 2009). Also, depending upon the type of blood donation, time between donations is a constraint and very frequent donations by the same person are not possible.
- Hospitals experience a surgical delay of 50 days due to shortage of blood. Sometimes even a delay of 120 days has been observed due to blood shortage. Therefore, reduction of wastage can minimize the delay in performing the surgery (Frankfurter et al., 1974).
- Cost of procurement and testing is quite high. In 2011, the average cost of purchasing one unit of RBC by hospitals from its suppliers was $210.74 (Schrijvers, 2011) and the average cost of purchasing one unit of platelet by hospitals from its suppliers was $533.90 (Toner et al., 2011).

In summary, platelets have the least shelf life and hence the highest wastage (15% to 20% of the total units collected are outdated). Demands for blood platelet are uncertain. Platelet transfusions are given to patients undergoing chemotherapy for leukemia, multiple myeloma, those with aplastic anemia, AIDS, hypersplenism, sepsis, and those in need of bone marrow transplant, radiation treatment and organ transplant. (American Association of Blood Banks, 2005; Zhou et al., 2011).

1.5 Research Plan

Consider the blood supply chain given in Figure 1.1. In most blood supply chains, blood centers interact directly with the hospitals without the need for blood banks. However, in some cases, blood banks exist and act as distributors. The following are the key decisions made in the blood supply chain, particularly with respect to platelets:

- Strategic Decisions at the Blood Centers:
    a. Number and location of blood centers
    b. Number and location of blood banks (if required)
    c. Blood center capacity levels
- Strategic Decision at the Hospitals:
    a. Determining the blood center with which each hospital has to establish a tie-up

- Tactical Decisions at the Blood Centers:
    a. Forecast of platelet demand for a given planning horizon
    b. Inventory policies for platelet management
    c. Schedule of blood drives to ensure that the platelets reach the hospitals on time to minimize outdating cost and inventory holding cost.

- Tactical Decisions at the Hospitals:
    a. Forecast of platelet demand for a given planning horizon at the hospital.
    b. Inventory policies for platelet management
    c. Inventory capacity for platelets

- Operational Decisions at the Blood Centers:
    a. Units of blood the drives must collect each day
    b. Determine the best routes for vehicles such that the total cost of transportation of platelets is reduced
    c. Determine the amount of platelets, of each shelf life, to be shipped to the hospitals each day
    d. Units of platelets to be stored each day
    e. Staffing decisions at the donor drives

- Operational Decisions at the Hospitals:
    a. Number of platelet units to order each day
    b. Units of platelet to keep in inventory each day

The models proposed in this dissertation will address the following decisions related to the design and management of blood supply chains:

- Strategic Decisions:
    a. Blood center capacity levels
    b. Inventory capacity for platelets at hospitals
- Tactical Decisions:
    a. Forecast of platelet demand for a given planning horizon at the blood supply chain

b. Inventory policies for platelet management at the blood center
c. Schedule of blood drives to ensure that the platelets reach the hospitals on time to minimize outdating cost and inventory holding cost
d. Inventory policies for platelet management at the hospitals

- Operational Decisions:
  a. Units of blood the drives must collect each day at the blood centers
  b. Quantity of platelets, of each shelf life, to be shipped to the hospitals each day
  c. Units of platelet to keep in inventory each day at the blood center
  d. Units of platelet to keep in inventory each day at the hospitals
  e. Units of platelet to order to the blood center by the hospital each day

1.6 Outline of the Proposal

The proposal is organized as follows. A review of the literature about blood supply chain and inventory management is presented in Chapter 2. The single objective mixed integer programming model for hospital inventory management is discussed in Chapter 3. In Chapter 4, three multiple objective models for hospital inventory management are developed and the results are compared. In Chapter 5, several ordering policies for hospital inventory management in proposed. In Chapter 6, ordering policies for the entire blood supply chain in discussed. The conclusions and potential future work are discussed in Chapter 7.

Chapter 2 : Literature Review

2.1 Inventory Policy for Perishable Items

Fries (1975) determined the optimal inventory policy for perishable items depending upon the shelf life of the products. Two cases were analyzed. In the first case, the shelf life of the product is considered one day (i.e., no inventory is carried from one time period to the next) with no backordering, then the inventory at each period is independent of the other and therefore, the problem becomes a "newsboy problem". In the second case, where the shelf life is more than a day and no backordering, dynamic programming was developed to determine the optimal inventory ordering policy. The results were obtained for both finite and infinite horizon problem.

Nahmias (1975a) also adopted a dynamic programming approach to develop an inventory model to reduce wastage and shortage of perishable items. In the work by Nahmias (1975b), a heuristic was proposed for determining ordering policy instead of dynamic programming approach. The author also suggested that if the shelf life of the product is greater than 1 day, then the dynamic programming problem becomes computationally difficult as well as the implementation of the policy becomes tedious. The results of heuristic approach were compared to that of the optimal policy developed by Nahmias (1975a).

Goyal and Giri (2001) provided a literature review of perishable items. The authors classified the research done in perishable items since 1990 into the following three categories: (1) Inventory models with fixed lifetime (see Schmidt and Nahmias 1985; Nandakumar and Morton, 1993; Liu and Lian, 1999; Perry, 1997), (2) Inventory models with random lifetime (see Kalpakam and Sapna, 1994; Kalpakam and Sapna, 1995; Kalpakam and Sapna, 1996; Liu and Shi, 1999), (3) Inventory models in which items decay depending upon the utility function. For fixed life time, Schmidt and Nahmias (1985) assumed fixed lead time and developed a continuous review policy. Later, Berk and Gürler (2008) developed *(s,Q)* policy assuming fixed lead time and constant life time. Kalpakam and Shanthi (2001) analyzed the scenario in which life time is exponential. Goyal and Giri (2001) also suggested that demand plays an extremely important role in developing the perishable inventory model and classified the research done in the past based on the type of demand such as deterministic demand (see Haringa, 1995; Haringa, 1996; Xu and Wang 1992; Yan and Cheng, 1998) and stochastic demand (see Dave, 1991; Kim, 1995; Kalpakam and Sapna, 1996). Deterministic demand was further classified as uniform demand, time varying demand, stock and

price dependent demand. Stochastic demand was classified as known and arbitrary probability distributions.

The research paper by Broekmeulen and van Donselaar (2009) took into account the age distribution of the inventory and developed a replenishment policy with stochastic demand and fixed lifetime. The results were compared to the base policy adopted from Tekin et al. (2001) and concluded that considering age distribution of the inventory reduced the wastage of perishable items to 8.2% for FIFO withdrawal and 11.0% for LIFO withdrawal.

A multi-item inventory model with the limited floor space availability for perishable items is discussed by Ghosh et al. (2015). The demand for each item in the paper was assumed to be stock dependent and the developed model was solved analytically to obtain the optimal solution.

2.2 Review of Literature on Forecasting

Forecasting of blood components is essential since the demand is increasing and the supply is not increasing enough to meet the demand. Forecasting of perishable items is difficult because of the limited shelf life. Forecasting techniques are seldom applied in the supermarkets to forecast perishable commodities (Donselaar et al., 2006). However, in their paper, it was also mentioned that proper forecasting techniques should be used and the approach based on individual perspective was incorrect.

In particular, forecasting demand for blood components in the blood supply chain is very essential because advanced information can increase blood collection efforts if more blood is required and blood collection can be limited, if less units are needed (Frankurter et al., 1974). In their paper, regression technique was used to forecast demand of red blood cells for two weeks considering the number of units collected and units expired. The results of the paper indicated that forecasting the short term demand for blood had a significant impact on controlling the inventory levels at the blood centers. In the paper by Pereira (2004), three forecasting techniques - autoregressive integrated moving average (ARIMA), the Holt-Winter's exponential smoothing method and neural-network based method, were applied to forecast the demand for blood at a hospital in Spain. Ten years of data were used to develop the three models. The models were validated using three years of data and the results indicated that the Holt-Winter's exponential smoothing model performed the best.

2.3 Blood Products Supply Chain

In recent years, minimizing wastage and shortage of blood products have gained a lot of attention. For example, various inventory models were developed and tested with the major focus on regional blood banks (Haijema, 2007; Haijema, 2009; van Dijk, 2009; Jabbarzadeh et al., 2014) and hospitals (Gunpinar and Centeno, 2015). The management of blood and blood products is a challenging task in blood centers and hospitals due to FDA regulations. Blood is drawn from donors and not many persons from the eligible donor population actually donate blood; in addition, the issue of infections and contaminations among donors limits the eligible donor population. The problem of supply side of blood assumes greater dimension given that hospitals need to rely on the neighborhood population, transport facilities in case of blood or blood products obtained from blood banks located elsewhere and the short response time to get blood in case of emergencies (Blake et al., 2010). The authors have suggested that minimization of the shortage and outdating cost is not necessarily the correct objective function especially for platelets ordering and inventory management.

There are different costs associated with the blood inventory system such as purchasing cost, holding cost, shortage cost, outdating cost, etc. Outdating costs are associated with the blood or blood products that have to be discarded because they have expired. Shortage costs are encountered when an alternate source of supply is to be found resulting in an increased cost of procurement; for example, an emergency supply from another hospital or a different blood bank is sought in case of shortage of on-hand blood or blood products. Since the shortage cost is rather difficult to quantify, it is a normal practice to treat the ratio of shortage cost to the outdating cost as some value, say, five (see van Dijk et al., 2009). All these aspects make the operational issues such as the collection of blood at hospitals and blood banks, blood allocation to hospitals from blood centers and blood banks, blood delivery to hospitals and determination of optimal order policy for blood products at blood banks and hospitals rather challenging and quite complex to analyze, especially given the fact that the entire blood management system need to be examined as a whole supply chain system and not just as a system of isolated sub-systems (Pierskalla, 2004; Belien and Force, 2012).

2.3.1 Taxonomy of Supply Chain Management of Blood Products

Belien and Force (2012) presented taxonomy of supply chain management of blood products in terms of the following:

i. Type of blood product (e.g. whole blood, plasma, frozen blood and blood platelets)

ii. Solution method (simulation, queuing model, mathematical programming techniques such as linear, integer and stochastic dynamic programming, heuristics and statistical analyses such as exponential smoothing for forecasting and regression analysis to determine which factors would affect outdating of blood products)

iii. Hierarchical level (individual hospital level, blood center or bank level, and supply chain level involving location, transportation logistics and order issue policies)

iv. Type of problem (inbound problems pertaining to inventory allocation to centralized blood banks and hospitals, and outbound problems in terms of delivery to hospitals)

v. Types of approach (stochastic and deterministic settings)

vi. Exact and heuristic methods; performance measures (involving service level, and costs of transportation, shortage and outdating)

vii. Implementation issues in real-life including participation and coordination of different hospitals in the blood inventory management

2.3.2 Blood Product Management: Hierarchy of Levels

It is possible that the blood products supply could be managed at different levels: at an individual hospital level; at a regional level with a blood bank serving a host of hospitals; and at a State level or inter-regional level with a set of regional blood banks or blood center. According to Prastacos (1984), operational level decision issues are related to scheduling and coordinating in terms of ordering, collections, processing and issuing; tactical issues are related to the determination of inventory levels, collection levels, issuing policies and processing policies; and strategic issues are related to design of blood bank and hospital network, location of the blood bank and hospitals, and policies related to sourcing of blood and blood products. Prastacos also observed: “since the demand and usage of blood are stochastic, a fundamental part of every hospital’s effort for improved blood inventory management is understanding the statistical pattern

of demand and usage of blood (through statistical analysis of collected data) in order to forecast these patterns better. These patterns are determined by the behavior of three random variables for each blood type: the number of daily requisitions arriving at the hospital blood bank; the size of a requisition and the actual usage (number of units) of a requisition". Once these patterns are analyzed, hospitals place orders and the ordering policy of a hospital answers the following questions: when to place an order and how much to order.

Analytical approaches make some assumptions such as the complete usage of all demanded items (i.e., both demand and usage are identical random variables) and most analytical research assume the demand to follow Poisson distribution and hence with such assumptions, closed form results are obtained. However, these assumptions limit the applicability of analytical techniques and in such cases, simulation and heuristics are used. For example, Cohen and Pierskalla (1979) assumed unit costs to shortages and outdates, and used search techniques and simulation to derive inventory levels as functions of all hospital parameters that affect shortages and outdating. An important aspect in blood inventory system is the cross matching policy. This policy is a testing procedure according to which units of blood are selected from inventory, and then allotted to patients. Note that blood products are perishable and not all units are eventually transfused. Assuming all crossmatched units are consumed, Pierskalla and Roach (1981) showed that issuing the oldest units first (FIFO) minimizes the average units short and outdated.

2.3.3 Strategic, Tactical and Operational Decisions in Blood Supply Chains

Strategic, tactical and operational decisions in blood supply chains have been discussed in the literature. The strategic decision on relocating an ARC blood collection facility in Virginia was studied by Jacobs (1996). The benefits of the proposed relocation facility and the existing facility were compared using an integer programming model and the authors concluded that it was best for the ARC not to relocate its facility. The tactical decision on scheduling the blood collection and distribution process was also studied by Jacobs (1996). A similar study was conducted by Hemmelmayr et al. (2009). The authors considered a local blood bank at Austria and proposed solutions to cost effectively organize delivery of blood products to Austrian hospitals. They also helped the blood bank to make a strategic decision of switching from a vendee-managed inventory set up to a vendor-managed inventory system by considering the potential benefits. Integer programming approach was used to evaluate the performance. Ghandforoush and Sen (2010) presented a decision support system (DSS) for blood mobile scheduling for a regional blood center

to minimize blood wastage. The model results suggested that the proposed DSS better meets the daily demand than the existing assignment method.

Brodheim and Pierskalla (1980) discuss that one of the problems faced by the regional blood bank is to allocate blood or blood products to different hospitals considering the various costs, such as transportation costs, outdate costs and shortage costs. There are *centralized systems* that help a regional blood center to allocate the resources across the hospitals with the overall objective of minimizing the costs (such as the transport costs from the center to the hospitals, emergency deliveries from the center to the hospitals and outdate costs at the hospitals), with hospitals usually not storing blood or blood products. There are also *decentralized systems*, where the problem is to determine the inventory levels for the regional center, with provisions for allocation of blood from the regional center to the hospitals and for re-allocation of excess blood from the center to the hospitals, with storage of blood being allowed in the hospitals. Sahin et al. (2007) focused on restructuring blood services to improve both their effectiveness and efficiency. The location-allocation decision problems were discussed and the impact of regionalization of blood services was studied by developing a mathematical programming model.

2.3.4 Multi-objective Blood Inventory Management

Most real-life problems deal with multiple objectives that are conflicting in nature; for example, typically conflicting goals that are considered involve keeping a certain level of inventory for a high service level, minimize outdating, shortage and collection costs. Goal programming approach is commonly used by setting goals for such objectives (Kendall and Lee, 1980; Prastacos, 1984). In the paper by Kendall and Lee (1980), goal constraints were related to blood availability, blood outdating, average age of inventory and total cost. The model was applied to American National Red Cross in the Midwest. The results indicated that the total unused blood was reduced from 14.9% to 9.2% without increasing the shortage.

2.3.5 Inventory Management of Blood Products

According to Hesse (2004), the problem with blood platelets is that they have a very short shelf life (generally 3 days) compared to other blood products, and hence the analysis of platelet inventory system is extremely complex. Jennings (1973) discussed in detail the inventory management problem at the hospital as well at the regional level. It was mentioned in the paper that the inventory control of blood was very difficult due to the stochastic nature of the demand

and supply and due to the process of "crossmatching". The author observed that for a single hospital, as the inventory level increases, the shortage and outdating increased as shown in Figure 2.1, where *S* represented the order-up-to level. For example, when *S* = 22 units, the shortage was less than 4% but the outdating was more than 12%; whereas, when *S* = 10 units, the shortage was more than 24% but the outdating was less than 8%. Therefore, it would be necessary to tradeoff between shortage and outdating.

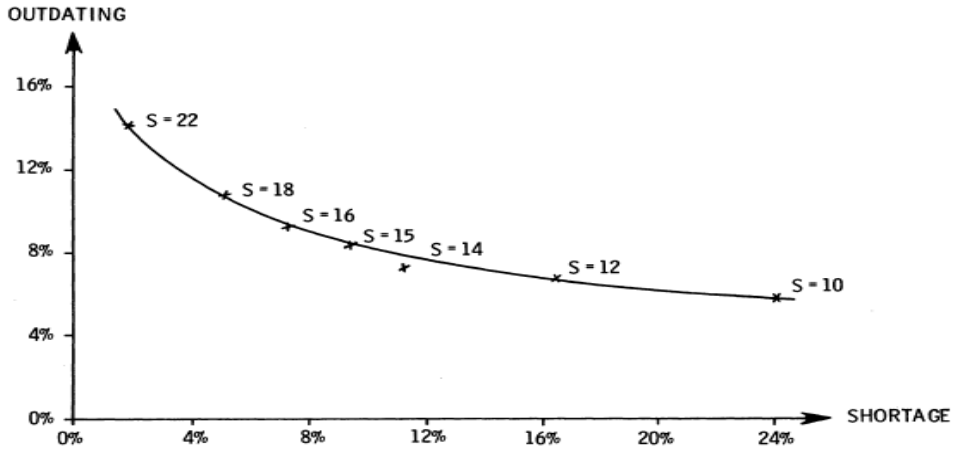


Figure 2.1: Shortage-outdating operating curve (Jennings, 1973)

Jennings (1973) also analyzed the effect of hospitals collaborating with each other and sharing RBC. He developed an inventory model investigating the potential costs and benefits of improved control of inventories of whole blood. He concluded that both shortage and outdating decreased as the number of hospitals in the multi-collaboration network increased.

As for blood platelet inventory management, techniques such as simulation, mathematical programming and dynamic programming are widely used. Most commonly considered problem is related to order policy determination and its parameters. The research on perishable inventory management has been done for more than five decades, and the early overview research articles are due to Nahmias (1982) and Prastacos (1984). Dynamic programming formulations were developed by Pierskalla and Roach (1972) and Haijema et al. (2007). Pierskalla and Roach (1972) concluded that FIFO policy is optimal for blood due to its short shelf life whereas Haijema et al. (2007) considered both FIFO and LIFO issuing policy.

In Haijema et al. (2007), it was assumed that order-up-to policies evaluated by simulation or by a Markov chain analysis had zero lead time. The authors came up with a combined Markov

dynamic programming (MDP) and simulation approach, and applied it to a real-life regional blood bank problem. A double-level order-up-to rule, called, 2D rule, was proposed, with one level corresponding to relatively new or young platelets and another related to the total inventory.

A five-step approach was proposed by van Dijk et al. (2009), where MDP was combined with computer simulation. It included the formulation of a MDP, followed by the downsizing of the problem to reduce the complexity of dynamic programming formulation. After that, a description of the process simulation and an assessment of the most frequent order-up-to levels were discussed. Order up-to rules reduced the outdating of platelet units from 15% - 20% to just 1%. While the work by van Dijk et al. (2009) used a multi-step procedure, combining dynamic programming and simulation, by selecting the order-up-to rule for each day, Blake (2009) noted that the work by van Dijk et al. (2009) ignored the age distribution of stock, and hence the work was rather restrictive. As an extension to that research, a SDP-Simulation approach was modeled, including special periods (Haijema et al., 2009). Special periods included irregular production breaks during Christmas and Easter since there was no collection of blood from the donors during Christmas, New Year and Easter. This model was applied to a Dutch Blood Bank. Then, it was observed that the average annual shortage was virtually nonexistent (reduced to .04%), and outdating was reduced from 15% - 20% to 0.11%.

A recent work by Haijema (2013) dealt with a new class of stock-level dependent order policy, called (s, S, q, Q) policy, which was basically a periodic review (s, S) policy restricted by a minimum (q) and maximum (Q). In other words, the policy followed a periodic ordering strategy per weekday with the inclusion of upper and lower level order quantities. Optimal parameter values were determined by dynamic programming and simulation. The results were compared to that of an *(s,S)* policy and it was illustrated that the total cost reduced by 7.2%.

In addition to the classical costs for inventory holding, outdating, and shortage, Civelek el al. (2015) included substitution (mismatch) costs and proposed a heuristic to minimize the expected total cost over an infinite time horizon. The problem was modelled as a Markov Decision Process (MDP), and the inventory policy was compared to other policies in the literature.

In the work by Gunpinar and Centeno (2015), stochastic and deterministic models were developed considering uncertain demand rates, demand for two types of patients, and crossmatch-

to-transfusion ratio. Their results indicated that wastage rates decreased by 87% on average, shortages and total cost were reduced by 91.43% and 20.7% respectively.

A summary of the blood inventory models discussed in the literature is given in Table 2.1.

Table 2.1: Summary of Blood Inventory Models

Article	Type of Blood Product	Solution Method	Hierarchical Level	Performance Measure	Planning Horizon
Jennings (1973)	RBC	Simulation	Blood Centers and Hospital	Shortage, Outdating	Finite
Kendall and Lee (1980)	RBC	Goal Programming	Hospital	Fresh blood availability, average age of inventory, outdating, shortage	Finite
Pierskalla and Roach (1981)	RBC	Stochastic Modeling	Hospital Blood Bank	Outdating, shortage	Finite
Hesse (2004)	Platelets	Simulation	Blood Center	$\frac{\text{Outdated units}}{\text{Order placed}}$	Infinite
Haijema et al. (2005)	Platelets	SDP	Blood Center	Shortage, outdating	Finite
Haijema et al. (2007)	Platelets	SDP	Blood Center	Shortage, outdating	Finite
Blake et al. (2010)	Platelets	Heuristics	Hospital	Shortage, outdating	Infinite
Haijema et al. (2013)	Platelets	SDP	Blood Center	Shortage, outdating, ordering	Finite
Gunpinar et al. (2015)	RBC	Stochastic Modeling	Hospitals	Shortage, outdating, purchasing	Finite
Proposed Research	Platelets	Integer Programming, Goal Programming, Stochastic Programming and Simulation	Blood Supply Chain	Shortage, wastage, purchasing, ordering, transportation	Finite and Infinite

2.4 Shortcomings of Previous Research on Blood Inventory Management

1. In the research work on inventory management of perishable items and blood in specific done thus far, reducing platelet wastage is seldom considered due to the extremely short shelf life of platelets. Most of the papers that are dealing with platelet inventory control assume the shortage cost is five times the outdating cost. However, shortage cost cannot be quantified in reality. Moreover, better inventory models can be developed if conflicting criteria such as outdating and shortage, holding cost and ordering cost are included.

2. According to Dillon et al. (2017), most research on blood inventory management assume that the demand is deterministic. However, Jennings (1973) highlighted the necessity to consider blood demand uncertainties since 50% of the total blood requested by the physicians are not transfused due to uncertainty. Therefore, in this dissertation, stochastic programming models under demand uncertainty is developed.

3. In the research work done in the platelet inventory management, it is mostly assumed that the platelets arriving at the hospital are fresh, with 3 days of shelf life. However, it is not necessarily true in real-life. Based on our interaction with the technicians and pathologist at regional medical centers, the platelets that arrive have different shelf lives. Therefore, in this paper, this assumption made in the literature is relaxed and arriving platelets will have varying shelf lives. In addition, the impact of shelf life on the wastage and shortage is also analyzed. The methods developed in this paper can act as a decision support system to any hospital management, and the most suitable ordering policy can be chosen based on the hospital size, demand variation and cost prioritization.

Therefore, this dissertation develops finite and infinite time horizon inventory models capturing the above mentioned gaps in performance measures.

Table 2.2: Performance Measures Considered in Recent Publication

Article	Performance Measures				
	Shortage	**Outdating**	**Ordering**	**Purchasing**	**Transportation Cost**
Jennings (1973)	✓	✓			
Kendall and Lee (1980)	✓	✓			
Pierskalla and Roach (1981)	✓	✓			
Hesse (2004)	✓				
Haijema et al. (2005)	✓	✓	✓	✓	✓
Haijema et al. (2007)	✓	✓	✓	✓	✓
Blake et al. (2010)	✓	✓			
Haijema et al. (2013)	✓	✓	✓	✓	✓
Gunpinar et al. (2015)	✓	✓		✓	✓
Proposed Research	✓	✓	✓	✓	✓

Chapter 3 : Single Objective Model for Hospital Inventory Management

In this chapter, a finite time horizon inventory (FTHI) model is presented to determine the optimal order quantity and time to order platelets such that wastage and shortages are reduced. A mixed-integer linear programming (MILP) model is developed and the forecasted platelet demand for the planning horizon based on the historical data is given as an input to the model. A case-study obtained from the literature (Tetteh., 2008) is presented in Section 3.2. This case study uses the daily platelet demand data for 122 days from a New York hospital.

The overview of the MILP model is given in Figure 3.1.

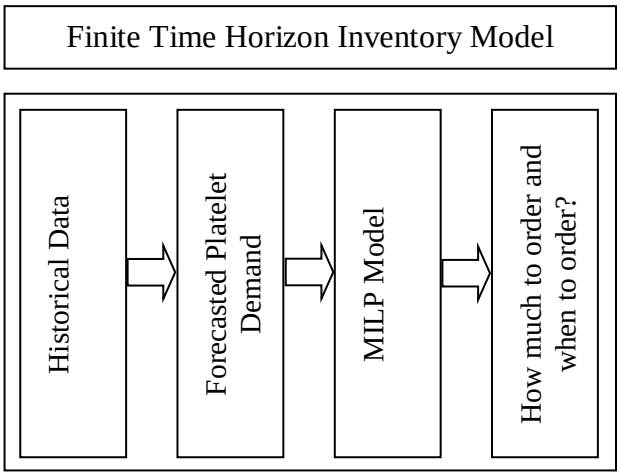


Figure 3.1: Overview of the Finite Time Horizon Inventory Model

3.1 Finite Time Horizon Inventory (FTHI) Model Description

3.1.1 Assumptions

1. Lead time for order processing is assumed to be negligible
2. All platelets that arrive at hospital from the blood center are fresh and have a remaining shelf life of 3 days
3. Model is for a single blood type
4. FIFO issuing policy is practiced at the hospital, namely, the platelets with the shortest shelf life are used first. That is, demand is first fulfilled with platelets with remaining shelf life of 1 day, followed by platelets with remaining shelf life of 2 days, followed by platelets with remaining shelf life of 3 day.

3.1.2 Model Parameters (known data)

C^F	Fixed cost of procuring platelets
C^P	Platelet purchasing cost per unit
C^H	Daily inventory cost of holding platelets per unit (based on beginning inventory)
C^E	Cost of expired platelet per unit
C^S	Cost of shortage per unit
D_t	Platelet demand at the beginning of day t
L	Constant lead time ($L \leq 2$ days)
RP	Review period in days
S^1	Initial inventory with shelf life of 1 day ($I_{1,1}$)
S^2	Initial inventory with shelf life of 2 days ($I_{1,2}$)
T	Time horizon in days (i.e., t=1, 2, 3, …, T)

3.1.3 Decision Variables (unknown):

Q_t	Quantity of platelet units ordered at the end of day t
x_t	Platelet units received from the blood center at the beginning of day t with shelf life of 3 days
D_t^1	Remaining demand for day t after using platelets with shelf life of 1 day
D_t^2	Remaining demand for day t after using platelets up to shelf life of 2 days
D_t^3	Remaining demand for day t after using platelets up to shelf life of 3 days
$I_{t,1}$	On-hand inventory at the beginning of day t with residual shelf life of 1 day
$I_{t,2}$	On-hand inventory at the beginning of day t with residual shelf life of 2 days
$I'_{t,1}$	Remaining platelet units after satisfying D_t with shelf life of 1 day
$I'_{t,2}$	Remaining platelet units after satisfying D_t^1 with shelf life of 2 days
$I'_{t,3}$	Remaining platelet units after satisfying D_t^2 with shelf life of 3 days

S_t Number of platelet units short on day t

E_t Number of units expired at the end of day t

δ_t { 1 if platelet units are ordered by hospital on day t ; 0 otherwise

3.1.4 Sequence of Events in Platelet Inventory Management

1. Hospital receives platelet units, x_t, from the blood center
2. Hospital receives platelet demand, D_t
3. If the demand at the hospital is greater than the on-hand inventory (i.e., if $D_t > (I_{t,1} + I_{t,2} + x_t)$), the demand is partially fulfilled with the available on-hand inventory and the on-hand inventory is updated to 0. The unfulfilled demand units incur shortage cost.
4. If the demand at the hospital is less than the on-hand inventory (i.e., $D_t < (I_{t,1} + I_{t,2} + x_t)$), then there are 3 possible cases:
    - Case (i): If $D_t < I_{t,1}$, then the unutilized platelet units with remaining shelf life of 1 day $(I_{t,1} - D_t)$ are thrown away at the end of the day and incur outdating cost. The remaining platelets (after discarding the outdated units) are carried over to the next day and the on-hand inventory is updated.
    - Case (ii): If $I_{t,1} \leq D_t < I_{t,1} + I_{t,2}$, then there are no unutilized platelet units with remaining shelf life of 1 day and hence no outdating cost is incurred. The remaining platelets are carried over to the next day and the on-hand inventory is updated.
    - Case (iii): If $I_{t,1} + I_{t,2} \leq D_t < I_{t,1} + I_{t,2} + x_t$, then there are no unutilized platelet units with remaining shelf life of 1 day and 2 days, and hence no outdating cost is incurred. The remaining platelets are carried over to the next day and the on-hand inventory is updated.
5. Hospital determines platelet order quantity (Q_t) at the end of day t

3.1.5 Formulation of Finite Time Horizon Inventory Model

Model Objective

Equation (3.1) represents the objective function, which is to minimize the total cost comprising of fixed cost of procurement, variable purchasing cost, holding cost, shortage cost and outdating cost.

$$\text{Minimize TC} = \sum_{t=1}^{T}[C^F * \delta_t + C^P * Q_t + C^H * (I_{t,1} + I_{t,2}) + C^S * S_t + C^E * E_t] \quad (3.1)$$

Model Constraints:

(1) Platelet Units Ordered

Equation (3.2) ensures that δ_t takes the value 1 if platelet units are ordered from the blood center by the hospital on day t and 0 otherwise. Platelets must be ordered only during the review periods and not during the other days which is taken care by Equation (3.3).

$$Q_t \leq M\delta_t \quad \text{for } t = 1, 1+RP, 1+2RP, +\ldots \quad (3.2)$$

$$Q_t = 0 \quad \text{for all other } t \quad (3.3)$$

Equations (3.2) and (3.3) guarantee that Q_t is defined only for those time period t when platelets can be ordered. For example, if the review period RP = 2 days, then platelets can only be ordered on day 1, 3, 5, 7,…

(2) Platelet Units Received

Equations (3.4) and (3.5) are used to calculate the total units received by hospital at the beginning of day t (x_t), which must be equal to the order quantity placed before the lead time (Q_{t-L}).

$$x_t = Q_{t-L} \quad \forall t > L \quad (3.4)$$

$$x_t = 0 \text{ or known constants} \quad \forall t \leq L \quad (3.5)$$

(3) Demand Constraints

If the demand, D_t, is greater than platelet units with shelf life of 1 day, $I_{t,1}$, then the left-over demand upon consumption of $I_{t,1}$ is D_t^1 and is given by $D_t^1 = D_t - I_{t,1}$. Also, $I'_{t,1}$= 0. On the other hand if the demand, D_t, is less than platelet units with shelf life of 1 day, $I_{t,1}$, then the left-over demand, D_t^1 is 0 and the remaining platelet units after satisfying the demand is given by $I'_{t,1}$= $I_{t,1} - D_t$. Equation (3.6) is used to calculate D_t^1 and $I'_{t,1}$. Note that both D_t^1 and $I'_{t,1}$ cannot be positive simultaneously.

$$D_t - I_{t,1} = D_t^1 - I'_{t,1} \quad \forall t \quad (3.6)$$

If the left-over demand, D_t^1, is positive, then it is completely or partially fulfilled by platelet units with shelf life of 2 days, $I_{t,2}$. If D_t^1 is greater than $I_{t,2}$, then the left-over demand, D_t^2, is given by $D_t^2 = D_t^1 - I_{t,2}$. If D_t^1 is less than $I_{t,2}$, then the left-over demand, D_t^2, is 0 and the remaining platelet units after satisfying D_t^1 is given by $I'_{t,2} = I_{t,2} - D_t^1$. Equation (3.7) is used to calculate D_t^2 and $I'_{t,2}$. Note that both D_t^2 and $I'_{t,2}$ cannot be positive simultaneously.

$$D_t^1 - I_{t,2} = D_t^2 - I'_{t,2} \qquad \forall t \qquad (3.7)$$

If D_t^2 is positive, then it is completely or partially fulfilled by platelet units with shelf life of 3 days, x_t. If D_t^2 is greater than x_t, then the left-over demand, D_t^3, is given by $D_t^3 = D_t^2 - x_t$. D_t^3 is the platelet shortage at end of day t. If D_t^2 is less than x_t, then no shortage is incurred and remaining platelet units after satisfying D_t^2 is given by $I'_{t,3} = x_t - D_t^2$. Equation (3.8) is used to calculate D_t^3 and $I'_{t,3}$. Note that both D_t^3 and $I'_{t,3}$ cannot be positive simultaneously.

$$D_t^2 - x_t = D_t^3 - I'_{t,3} \qquad \forall t \qquad (3.8)$$

(4) Inventory Updates

At the end of the day t, the inventory is updated for the next day using Equations (3.9) and (3.10).

$$I_{t+1,1} = I'_{t,2} \qquad \forall t \qquad (3.9)$$

$$I_{t+1,2} = I'_{t,3} \qquad \forall t \qquad (3.10)$$

(5) Expired Platelets

Unutilized platelet units with remaining shelf life of 1 day, $I'_{t,1}$, are discarded at the end of the day and given using Equation (3.11).

$$E_t = I'_{t,1} \qquad \forall t \qquad (3.11)$$

(6) Platelet Shortages

The unfulfilled demand units, D_t^3, is considered as shortage in day t and is calculated using Equation (3.12).

$$S_t = D_t^3 \qquad \forall t \qquad (3.12)$$

(7) Initial Inventory of Platelets

Equations (3.13) and (3.14) gives the initial conditions at time t = 1.

$$I_{1,1} = S^1 \qquad (3.13)$$

$$I_{1,2} = S^2 \qquad (3.14)$$

(8) Non-negativity

Constraints (3.15 – 3.16) force non-negativity and binary restrictions in the model.

$$D_t^1, D_t^2, D_t^3, E_t, I'_{t,1}, I'_{t,2}, I'_{t,3}, I_{t,1}, I_{t,2}, Q_t, S_t, x_t \geq 0 \qquad \forall t = 1,2,3,\dots,T \qquad (3.15)$$

$$\delta_t \in (0,1) \qquad \forall t = 1,2,3,\dots,T \qquad (3.16)$$

Figure 3.2 illustrates the possible outcomes (Eqns 3.6 – 3.12) between platelet demand and availability at time t.

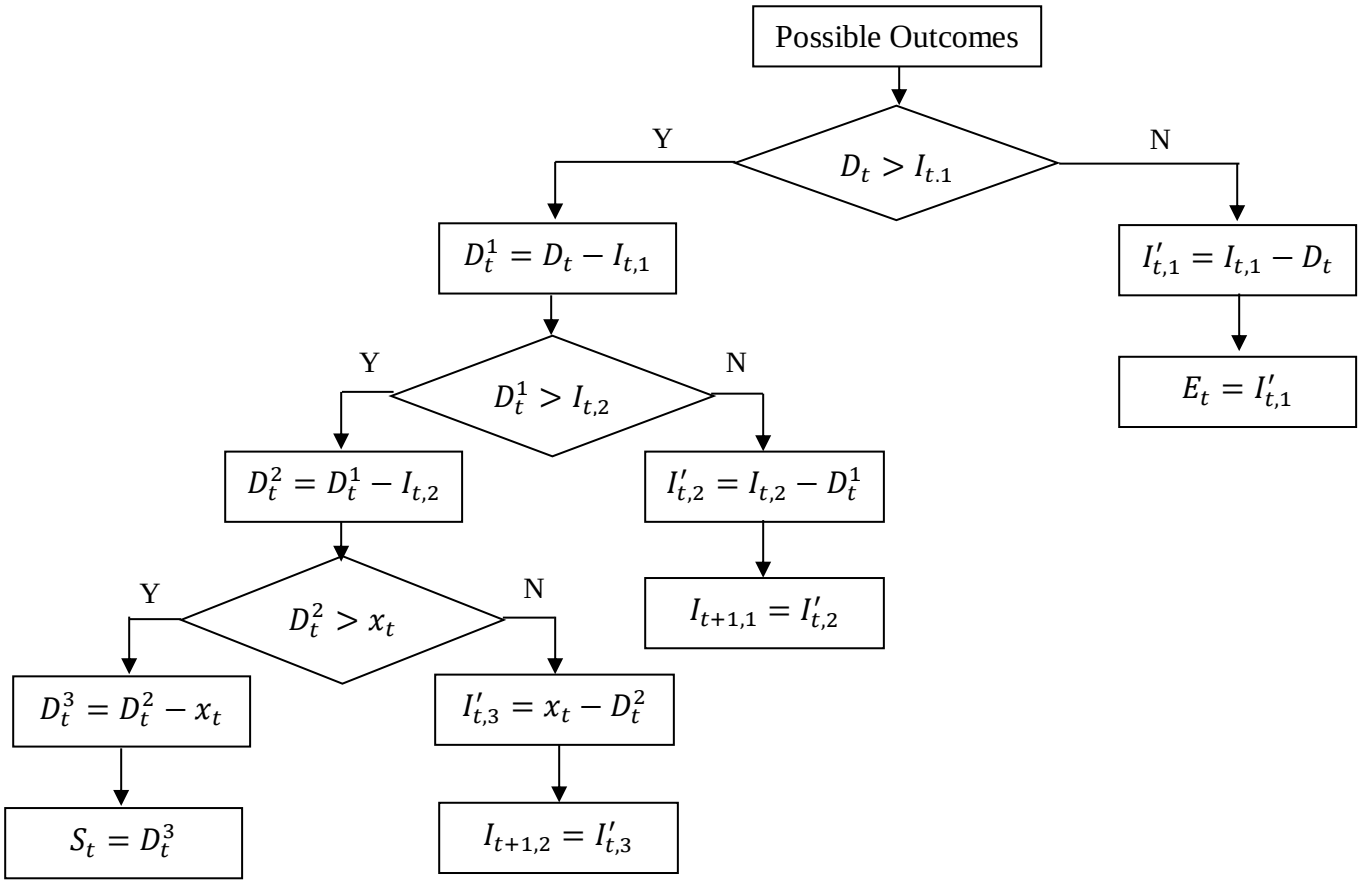


Figure 3.2: Flowchart of the finite time horizon model

3.1.6 Finite Time Horizon Model - Illustrative Example

For a given t, let the platelets inventory be as follows.

$I_{t,1} = 16$

$I_{t,2} = 9$

$x_t = 20$

Thus, the on-hand inventory on day t is 16 + 9 + 20 = 45.

Case 1: $0 < D_t \leq I_{t,1}$

Let $D_t = 15$

From Equation (3.6),

$15 - 16 = D_t^1 - I'_{t,1}$

Therefore, $I'_{t,1} = 1$ and $D_t^1 = 0$

From Equation (3.7),

$0 - 9 = D_t^2 - I'_{t,2}$

Therefore, $I'_{t,2} = 9$ and $D_t^2 = 0$

From Equation (3.8),

$0 - 20 = D_t^3 - I'_{t,3}$

Therefore, $I'_{t,3} = 20$ and $D_t^3 = 0$

Total expired units is $E_t = 1$ (Eq. 3.11)

Total units shortage is $S_t = 0$ (Eq. 3.12)

Case 2: $I_{t,1} < D_t \leq I_{t,1} + I_{t,2}$

Let D_t = 20, then, $D_t^1 = 4$, $D_t^2 = 0$, $D_t^3 = 0$, $I'_{t,1} = 0$, $I'_{t,2} = 5$, $I'_{t,3} = 20$, $E_t = 0$ and $S_t = 0$

Case 3: $I_{t,1}+I_{t,2} < D_t \leq I_{t,1}+I_{t,2} + x_t$

Let D_t = 35, then, $D_t^1 = 19$, $D_t^2 = 10$, $D_t^3 = 0$, $I'_{t,1} = 0$, $I'_{t,2} = 0$, $I'_{t,3} = 10$, $E_t = 0$ and $S_t = 0$

Case 4: $D_t > I_{t,1}+I_{t,2} + x_t$ (i.e., $D_t >$ on-hand inventory)

Let D_t = 55, then, $D_t^1 = 39$, $D_t^2 = 30$, $D_t^3 = 10$, $I'_{t,1} = 0$, $I'_{t,2} = 0$, $I'_{t,3} = 0$, $E_t = 0$ and $S_t = 10$

3.1.7 Finite Time Horizon Model Summary

Minimize TC = $\sum_{t=1}^{T}[C^F * \delta_t + C^P * Q_t + C^H * (I_{t,1} + I_{t,2}) + C^S * S_t + C^E * E_t]$

$Q_t \leq M\delta_t$	for t =1, 1+RP, 1+2RP, +...
Q_t = 0	for all other t
$x_t = Q_{t-L}$	$\forall t > L$
$x_t = 0$ or known constants	$\forall t \leq L$
$D_t - I_{t,1} = D_t^1 - I'_{t,1}$	$\forall t$
$D_t^1 - I_{t,2} = D_t^2 - I'_{t,2}$	$\forall t$
$D_t^2 - x_t = D_t^3 - I'_{t,3}$	$\forall t$
$I_{t+1,1} = I'_{t,2}$	$\forall t$

$$I_{t+1,2} = I'_{t,3} \qquad \forall t$$

$$E_t = I'_{t,1} \qquad \forall t$$

$$S_t = D_t^3 \qquad \forall t$$

$$I_{1,1} = S^1$$

$$I_{1,2} = S^2$$

$$D_t^1, D_t^2, D_t^3, E_t, I'_{t,1}, I'_{t,2}, I'_{t,3}, I_{t,1}, I_{t,2}, Q_t, S_t, x_t \geq 0 \qquad \forall t$$

$$\delta_t \in (0,1) \qquad \forall t$$

The optimization model is a mixed integer linear programming model. An optimal solution will provide the best ordering policy to minimize cost over the planning horizon.

3.2 Case Study-1

The platelet demand data is obtained from Tetteh (2008) in which the daily demand data of platelets at a hospital in New York for 122 days are available. Demand data indicate that there exist seasonality and hence seasonality is incorporated while forecasting the demand.

3.2.1 Forecasting Platelet Demand

Forecasting demand for blood components in the blood supply chain is very essential because advanced information can increase blood collection efforts if more blood is required and blood collection can be limited if less units are needed (Frankurter et al., 1974). Therefore, adequately forecasting the demand for platelet can reduce outdating as well as stock-outs of blood units.

From the time series demand data, it is observed that there exist daily variations in the demand pattern. Hence seasonality is incorporated in the constant level forecasting method by calculating the seasonality indices for each day of the week.

3.2.1.1 Steps in Forecasting Platelet Demand

Step 1: Calculation of the Seasonality Index

$$\text{Seasonality index for day } i = \frac{\text{average demand during day } i}{\text{overall average of demand for all days}}$$

For example: day 1 average = 193.6923 and overall average = 184.8352

$$\text{Seasonality index for day } 1 = \frac{193.6923}{184.8352} = 1.047919$$

Step 2: Computation of Deseasonalized Demand Data

Deseasonlaized demand is obtained by dividing the actual demand data by the respective seasonality index.

For example: actual demand on day 1 is 174 units and seasonality index is 1.047919

$$\text{Deseasonalized demand for day 1} = \frac{174}{1.047919} = 166.0433451 \approx 166 \text{ units}$$

Step 3: Forecasting Demand using Exponential Smoothing Method

Exponential smoothing method is the most popular forecasting method in practice and it is basically a weighted averaging method with weights decreasing exponentially on older demands. The forecast for period $(n + 1)$ is given by

$$F_{n+1} = \alpha D_n + (1 - \alpha) F_n$$

where D_n is the actual demand for period n

F_n is the forecasted demand for period n

α is called the smoothing constant

α is generally chosen between 0.1 and 0.4. We varied α from 0.1 to 0.4 in increments of 0.1 to determine the forecast for the planning horizon. Then the models was validated using the three techniques mentioned in Section 3.3.1.2 and the best value of α that reduces the errors will be used to forecast the future demand.

Initial condition: F_1 is assumed to be equal to D_1

For example, Let D_n = 166 units, F_n=173 units and α = 0.1, then

$$F_{n+1} = 0.1 \cdot 166 + (0.9) \cdot 173 \approx 172 \text{ units}$$

Step 4: Converting the Deseasonalized Forecast to Actual Forecast

The actual forecast is computed by multiplying the deseasonalized forecast by the respective seasonality index.

$$\text{Actual forecast for day 1} = 172 \cdot 1.047919 \approx 180 \text{ units}$$

Appendix contains the seasonality indices and the forecasted demand data.

3.2.1.2 Selection and Validation of the Forecasting Method (Ravindran and Warsing, 2013):

Three different measures of forecast errors, MAD, MSE and BIAS, are used for determining the smoothing constant (α) and validating the method.

1. Mean Absolute Deviation (MAD)

$$\text{MAD} = \frac{1}{\text{n}}\sum_{t=1}^{n} |e_t|$$

2. Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{\text{n}}\sum_{t=1}^{n} e_t^2$$

3. BIAS

$$\text{BIAS} = \sum_{t=1}^{n} e_t$$

These forecast errors are used to obtain the best value of parameter α. If a specific α value yields the best result for all the three measures, then the corresponding value of α is used to forecast the platelet demand. Otherwise, an average of the two best α values will be used for forecasting.

Among the 122 days of platelet demand data that were obtained from the literature, 92 days are used to forecast and the remaining 30 days are used for validation. The results of the forecasting errors (i.e., the values of MAD, MSE and BIAS) are shown in Table 3.1.

Table 3.1: Results of forecasting errors for varying value of α

	BIAS	MAD	MSE
α = 0.1	-233.84	22.16	790.75
α = 0.2	-139.06	22.42	829.98
α = 0.3	-99.07	22.85	882.58
α = 0.4	-77.45	23.62	942.56

3.2.1.3 Selection of the Best Method for Forecasting Demand

From Table 3.1, the exponential smoothing method for α = 0.1 yields the least MAD and MSE. For α = 0.4, the least BIAS is achieved. Therefore, the average of the forecasted values of α = 0.1 and α = 0.4 is used as the platelet demand for the next 30 days. The forecasted demand for the next 30 days is shown in Table 3.2.

Table 3.2: Forecasted demand for 30 days

	Week 1	Week 2	Week 3	Week 4	Week 5
Day 1	198	198	198	198	198
Day 2	216	216	216	216	216
Day 3	202	202	202	202	
Day 4	187	187	187	187	
Day 5	186	186	186	186	
Day 6	169	169	169	169	
Day 7	161	161	161	161	

Using the forecasted platelet demand, finite time horizon model is developed to determine how much to order and when to order the platelets.

3.2.2 Performance Measures Used in the Inventory Model

To illustrate the performance of the proposed finite time horizon inventory model, four performance measures are used: Wastage As a Percentage of Procurement (WAPP), Holding As a Percentage of Procurement (HAPP), Shortage As a Percentage of Demand (SAPD), and Total Cost (TC).

- Wastage As a Percentage of Procurement (WAPP) = $\frac{\text{Units outdated}}{\text{Units procured}}$ x 100
- Holding As a Percentage of Procurement (HAPP) = $\frac{\text{Units in inventory}}{\text{Units procured}}$ x 100
- Shortage As a Percentage of Demand (SAPD) = $\frac{\text{Shortage Units}}{\text{Total demand}}$ x 100
- Total Cost (TC) = fixed cost of procurement + variable purchasing cost + holding cost + shortage cost + expiration cost

3.2.2.1 Numerical Example to Show Performance Measures Calculation in Finite Time Horizon Model

For the purpose of illustration, the following are the values of the known and unknown data that are considered for the base model.

- Time horizon (T): 30 days
- Lead time (L): 0 day
- Review period (RP): 1 day

In this example, the following cost ratios are considered*.

Fixed Cost of Procuring Platelets	Platelet Purchasing Cost	Holding Cost	Cost of Expired Platelets	Shortage Cost
1	1	1	1	2

*These are the initial relative cost values assumed for the base model. Note that the relative costs are all equal, except for the shortage cost which is assumed to be twice as much as the other costs. Impacts of varying these values will be discussed in Section 3.2.3 under Sensitivity Analysis.

Assumption

It is assumed that the orders for new platelets are placed at the end of the day. Hence, the initial inventory is set to 198 units to avoid shortage during day 1 (note that the demand for day 1 is 198 units).

For the above data set, the MILP model had the following features:

- Total number of decision variables: 390 (out of which 30 are binary variables)
- Total number of constraints: 392
- The mathematical model discussed in Section 3.1.5 is programmed using C++ and solved using IBM CPLEX®12.4.0.0 optimizer.
- Solution time is approximately 23 seconds

Optimal Solution

In this example, shortage cost is twice the holding cost and all other cost components are given equal importance. In order to reduce wastage and inventory cost, no units are held in inventory. At the end of each day, platelet units are ordered depending upon the next day's demand. Therefore, there exist no shortage and outdating cost. Except for the cost incurred for holding the initial inventory (i.e., 198 units), no other holding cost is incurred in the model. For this example, the optimal solution is given below:

- Total number of units expired ($\sum_{t=1}^{30} E_t$): 0
- Total number of units shortage ($\sum_{t=1}^{30} S_t$): 0
- Total number of units in inventory ($\sum_{t=1}^{30}(I_{t,1} + I_{t,2})$): 198
- Total number of units purchased ($\sum_{t=1}^{30} Q_t$): 5492
- Total demand ($\sum_{t=1}^{30} D_t$): 5690

- Total number of times shipments were made from the blood center to hospital ($\sum_{t=1}^{30} \delta_t$): 29

Then,

- Wastage As a Percentage of Procurement (WAPP) = $\frac{0}{5492}$ x 100 = 0%
- Holding As a Percentage of Procurement (HAPP) = $\frac{198}{5492}$ x 100 = 3.605%
- Shortage As a Percentage of Demand (SAPD) = $\frac{0}{5690}$ x 100 = 0%
- Total Cost (TC) = $\sum_{t=1}^{30}\left[C^F * \delta_t + C^P * Q_t + C^H * (I_{t,1} + I_{t,2}) + C^S * S_t + C^E * E_t\right]$

  = 1*30 + 1*5492 + 1*198 + 2*0 + 1*0 = $ 5720

3.2.3 Sensitivity Analysis of the Finite Time Horizon Policy

The different cost scenarios that are considered for the sensitivity analysis are given in Table 3.3. Cost scenario 1 is the base model discussed in Section 3.2.2. The cost ratios are varied and the changes in the performance measures are analyzed.

Table 3.3: Cost Scenarios

Cost scenario	Fixed Cost	Variable Cost	Holding Cost	Expiration Cost	Shortage Cost
1	1	1	1	1	2
2	1	1	1	1	5
3	4	1	1	1	5

In cost scenario 1, shortage cost is two times the holding cost and the ratio of each of the other cost component to the holding cost is 1. In cost scenario 2, shortage cost is five times the holding cost and all the other cost components are same as in cost scenario 1. Therefore, it is expected that under scenario 2, the total units shortage will be less compared to cost scenario 1. In cost scenario 3, shortage is five times the holding cost and also fixed cost is set four times the holding cost. It is expected that the total units shortage will be less and also frequency of placing orders will be less compared to cost scenario 1.

For each cost scenario, the lead time and review period are varied and the changes in WAPP, HAPP, SAPD and TC are analyzed. The summary of the possible combinations of lead time and review period is given in Table 3.4. Because of the 3-day shelf life of platelets, lead time of 3 days is not considered.

Table 3.4: Combinations of lead time and review period (in days)

Lead time (L)	0	1	2
Review Period (RP)	1,2	1,2	2

3.2.3.1 Effect of Varying Lead Time and Review Period on WAPP

Recall that WAPP is defined as follows:

$$\text{Wastage As a Percentage of Procurement (WAPP)} = \frac{\text{Units outdated}}{\text{Units procured}} \text{ x } 100$$

It is observed that WAPP is 0 for all different combinations of lead time and review period for all the cost scenarios. In other words, varying cost parameters has no impact on WAPP. This is true because, when the review period is 1 day, platelets can be frequently ordered. This results in reduced number of units being held in inventory. When the review period is 2 days and lead time is 0 or 1 day, platelets held in inventory are exactly equal to the demand during the lead time plus review period. Hence, there is no wastage. However, when the review period is 2 days and lead time is 2 days, it is not possible to reduce shortage during the lead time plus review period (L+RP = 4 days) because of the very short shelf life of new platelets (1 day). Therefore, demand during the lead time plus review period cannot be satisfied, resulting in no wastage.

3.2.3.2 Effect of Varying Lead Time and Review Period on HAPP

Recall that HAPP is defined as follows:

$$\text{Holding As a Percentage of Procurement (HAPP)} = \frac{\text{Units in inventory}}{\text{Units procured}} \text{ x } 100$$

Table 3.5: Sensitivity Analysis - Effect of lead time and review period on HAPP

	RP=1, L=0	RP=1, L=1	RP=2, L=0	RP=2, L=1	RP=2, L=2
Cost scenario 1	3.61%	3.61%	29.81%	7.51%	7.51%
Cost scenario 2	3.61%	3.61%	51.64%	61.94%	7.51%
Cost scenario 3	3.61%	3.61%	51.64%	61.94%	7.51%

Table 3.5 illustrates the changes in HAPP values when the lead time and review period are varied for different cost scenarios. When the review period is 1 day and lead time is 0 and 1 day, it is observed that HAPP is the same for all the three cost scenarios due to frequent orders. There exist only initial inventory carrying cost and hence reduced HAPP. However, when the review

period is 2 days and lead time is 0 day, 1 day and 2 days, HAPP varies across the cost scenarios as shown in Figure 3.3.

It is observed that, when the review period is 2 days and lead time is 0 or 1 day, HAPP is greater for cost scenarios 2 and 3. For cost scenarios 2 and 3, shortage is five times the holding cost. As the lead time increases, in order to avoid shortage of platelets during the lead time plus review period, there are more platelet units held in inventory, thereby leading to an increase in inventory. For cost scenario 1, when the review period is 2 days, in order to satisfy the demand during lead time plus review period, there should be excess units held in inventory. But in cost scenario 1, shortage cost is only two times the holding cost; hence, a tradeoff is made between shortage and holding platelets for two days (since RP is two days). When the review period is 2 days and lead time is 2 days, HAPP remains the same across all three cost scenarios for the following reasons. When the lead time is 2 days, the platelets that are arriving at the hospital have a remaining shelf life of 1 day only. Therefore, platelets arriving at the hospital on day *t* can only satisfy the demand till the end of day *t*; hence, shortage of platelets cannot be avoided during the lead time plus review period. Even though cost scenarios 2 and 3 give more priority to reduce shortage, it is not possible to reduce shortage during the lead time plus review period (L+RP = 4 days) because of the very short shelf life of the new platelets of just 1 day.

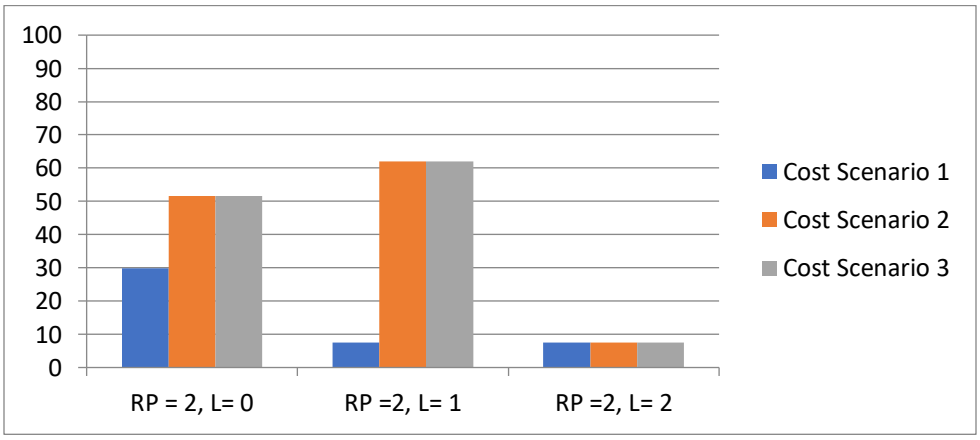


Figure 3.3: HAPP when review period is 2 days, with varying lead times

3.2.3.3 Effect of Varying Lead Time and Review Period on SAPD

Recall that SAPD is defined as follows:

$$\text{Shortage As a Percentage of Demand (SAPD)} = \frac{\text{Shortage Units}}{\text{Total demand}} \text{ x } 100$$

Table 3.6: Sensitivity Analysis - Effect of lead time and review period on SAPD

	RP=1, L=0	RP=1, L=1	RP=2, L=0	RP=2, L=1	RP=2, L=2
Cost scenario 1	0.00%	0.00%	30.02%	50.16%	50.16%
Cost scenario 2	0.00%	0.00%	0.00%	0.00%	50.16%
Cost scenario 3	0.00%	0.00%	0.00%	0.00%	50.16%

Table 3.6 shows the changes in the SAPD values when the lead time and review period are varied for different cost scenarios. When the review period is 1 day and lead time is 0 and 1 day, it is observed that SAPD is 0 for all the three cost scenarios, because orders can be placed frequently, thereby reducing shortage cost. However, when the review period is 2 days and lead time is 0 day, 1 day and 2 days, SAPD varies across the cost scenarios as shown in Figure 3.4.

It is observed that when the review period is 2 days and lead time is 0 or 1 day, SAPD is 0 for cost scenarios 2 and 3, because in those scenarios, shortage cost is five times the holding cost and hence SAPD is 0. However, SAPD is not 0 for cost scenario 1, when the review period is 2 days. In order to satisfy the demand during lead time plus review period, there should be excess units held in inventory incurring holding cost. But in cost scenario 1, since shortage cost is only two times the holding cost, a tradeoff is made between shortage and holding platelets for two days (since RP is two days). When the review period is 2 days and lead time is 2 days, SAPD remains the same across the three cost scenarios because when lead time is 2 days, the platelets that are arriving at the hospital have a remaining shelf life of 1 day only. Therefore, it is not possible to reduce shortage during the lead time plus review period (L+RP = 4 days) because of the very short shelf life of new platelets of 1 day.

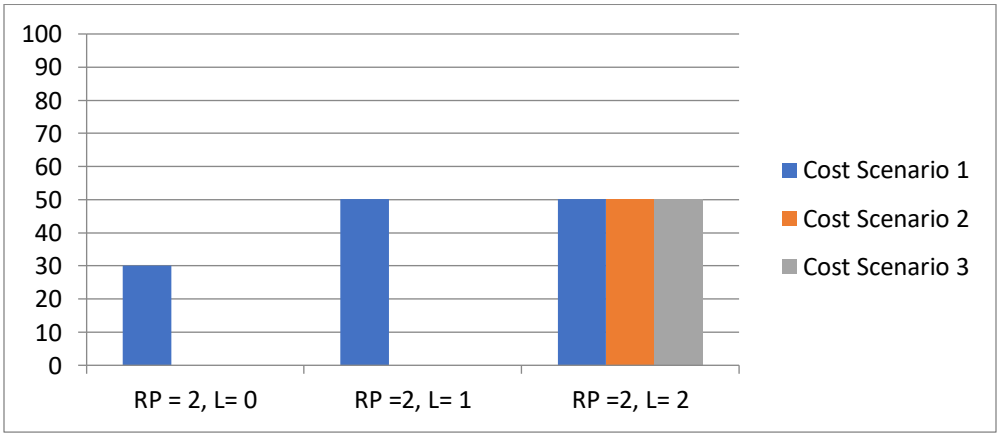


Figure 3.4: SAPD when review period is 2 days, with varying lead times

3.2.3.4 Effect of Varying Lead Time and Review Period on Total Cost (TC)

Assuming that the holding cost is $1/unit, the total cost is given as follows.

Total Cost (TC) = fixed cost of procurement + variable purchasing cost + holding cost + shortage cost + expiration cost

Table 3.7: Sensitivity Analysis - Effect of lead time and review period on Total Cost

	RP=1, L=0	RP=1, L=1	RP=2, L=0	RP=2, L=1	RP=2, L=2
Cost scenario 1	$ 191	$ 191	$ 278	$ 285	$ 285
Cost scenario 2	$ 191	$ 191	$ 278	$ 287	$ 571
Cost scenario 3	$ 194	$ 195	$ 280	$ 287	$ 572

Table 3.7 shows the changes in total cost when the lead time and review period are varied for different cost scenarios. When the review period is 1 day and lead time is 0 or 1 day, the total cost is higher for cost scenario 3. In cost scenario 3, fixed cost of procurement is higher compared to cost scenarios 1 and 2. Therefore, even though the same number of units are purchased as in the previous two cases, cost scenario 3 incurs higher fixed cost and hence the total cost increases. It is observed that when the review period is 2 days and lead time is 0 or 1 day, the total cost is almost the same for all the three cost scenarios as shown in Table 3.7 and Figure 3.5. However, when review period is 2 days and lead time is 2 days, the total cost is significantly less for cost scenario 1, compared to cost scenarios 2 or 3, because in the latter scenarios, shortage cost is five times the inventory holding cost. When L+RP = 4 days and the shelf life of platelets arriving at hospital is only 1 day, shortages are occurring, resulting in more shortage cost and higher total cost.

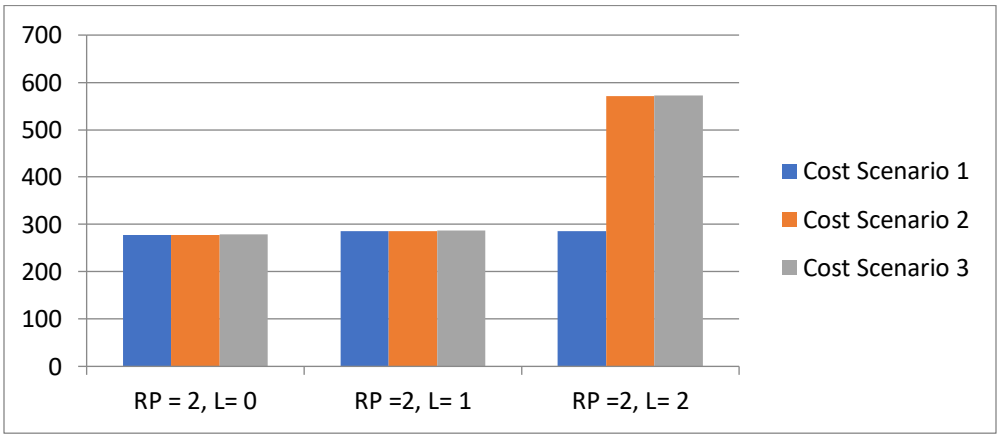


Figure 3.5: Total Cost when review period is 2 days, with varying lead times

3.2.4. Use of Rolling Horizon Approach

This model can be used to assist the hospital management decide on the units purchased based on their operational settings. Even though more effort is required in the implementation of the FTHI model and the forecasts have to be updated periodically, the model will result in less wastage and shortage.

In practice, the same order policy may not be used for all the 30 days of the planning horizon. Instead a rolling horizon approach may be followed to implement the optimal solution. For example, even though the MILP model gives an optimal order policy for 30 days, only the first week of the optimal solution is implemented. At the end of the first week, the MILP model is rerun for the next 30 days, after updating inventory and demand forecast. The new optimal policy will be used for the second week and the process is repeated weekly. Since long term forecasts may not be as good as short term forecasts, a rolling horizon policy helps to update forecasts weekly and determine the best solution based on the revised forecasts.

Chapter 4 : Multiple Objective Models for Hospital Inventory Management

In the single objective model discussed in Chapter 3, units shortage and outdated were assigned cost values and the objective of the model was to minimize the total cost. However, costs such as shortage and outdating cannot be quantified in reality. Therefore, in this chapter, a multiple criteria mathematical programming (MCMP) model is developed for hospital inventory management and is discussed in Section 4.1. The model is solved using 3 MCMP techniques; preemptive goal programming, non-preemptive goal programming and weighted objective methods and these techniques are discussed in Sections 4.2 and 4.3. The forecasted platelet demand from case study-1 in Chapter 3 is used to illustrate the multiple objective models and the results are compared and presented in Section 4.4.

4.1. Multiple Criteria Mathematical Programming (MCMP) Model

Recall that the following notations were used in Chapter 3 for the single objective finite time horizon inventory model.

Model Parameters (known data)

C^F	Fixed cost of procuring platelets
C^P	Platelet purchasing cost per unit
C^H	Daily inventory cost of holding platelets per unit (based on beginning inventory)
D_t	Platelet demand at the beginning of day *t*
L	Constant lead time in days
RP	Review period in days
S^1	Initial inventory with shelf life of 1 day ($I_{1,1}$)
S^2	Initial inventory with shelf life of 2 days ($I_{1,2}$)
T	Planning horizon in days (i.e., t=1, 2, 3, …, T)

Decision Variables (unknown):

Q_t	Quantity of platelet units ordered at the end of day t
x_t	Platelet units received from the blood center at the beginning of day t with shelf life of 3 days
D_t^1	Remaining demand for day t after using platelets with shelf life of 1 day
D_t^2	Remaining demand for day t after using platelets up to shelf life of 2 days
D_t^3	Remaining demand for day t after using platelets up to shelf life of 3 days

$I_{t,1}$ On-hand inventory at the beginning of day t with residual shelf life of 1 day

$I_{t,2}$ On-hand inventory at the beginning of day t with residual shelf life of 2 days

$I'_{t,1}$ Remaining platelet units after satisfying D_t with shelf life of 1 day

$I'_{t,2}$ Remaining platelet units after satisfying D_t^1 with shelf life of 2 days

$I'_{t,3}$ Remaining platelet units after satisfying D_t^2 with shelf life of 3 days

S_t Number of platelet units short on day t

E_t Number of units expired at the end of day t

δ_t { 1 if platelet units are ordered by hospital on day t ; 0 otherwise

4.1.1. Objective Function

The single objective model, in Chapter 3, minimized the total cost comprising of fixed cost of procurement, variable purchasing cost, holding cost, shortage cost and outdating cost (see Equation 3.1). Hence, the objective function included the following decision variables:

- Number of times platelets have been shipped to the hospital from the blood center
- Units purchased
- Units held in inventory
- Units shortage
- Units outdated

For the multiple criteria mathematical programming model, the following three objectives are considered.

Objective 1: Minimize procurement and holding cost (PHC)

$$\text{Minimize } Z_1 = \sum_{t=1}^{T} PHC_t \qquad \forall t \qquad (4.1)$$

where procurement and holding cost on day t (PHC_t) is the sum of the fixed procurement cost, platelet purchasing cost and inventory holding cost of platelet units on day t and is given by Equation 4.2.

$$PHC_t = C^F * \delta_t + C^P * x_t + C^H * \left(I_{t,1} + I_{t,2}\right) \qquad \forall t \qquad (4.2)$$

Objective 2: Minimize shortage of platelets

$$\text{Minimize } Z_2 = \sum_{t=1}^{T} S_t \qquad \forall t \qquad (4.3)$$

Objective 3: Minimize expiration of platelets

Minimize $Z_3 = \sum_{t=1}^{T} E_t$ $\forall t$ (4.4)

It can be observed that when the shortage decreases, the total units purchased increases and hence the PHC increases. Similarly, an increase in shortage leads to decrease in purchasing platelets and hence decrease in the PHC. Moreover, if more platelets are purchased, then more units are held in inventory leading to more platelet wastage. Therefore, it is evident that the three criteria are conflicting in nature.

4.1.2. Model Constraints

The model constraints are the same as discussed in Chapter 3 and are reproduced below.

(1) Platelet Units Ordered

$Q_t \leq M\delta_t$ for t =1, 1+*RP*, 1+2*RP*, +... (4.5)

$Q_t = 0$ for all other t (4.6)

(2) Platelet Units Received

$x_t = Q_{t-L}$ $\forall t > L$ (4.7)

$x_t = 0$ or known constants $\forall t \leq L$ (4.8)

(3) Demand Constraints

$D_t - I_{t,1} = D_t^1 - I'_{t,1}$ $\forall t$ (4.9)

$D_t^1 - I_{t,2} = D_t^2 - I'_{t,2}$ $\forall t$ (4.10)

$D_t^2 - x_t = D_t^3 - I'_{t,3}$ $\forall t$ (4.11)

(4) Inventory Updates

$I_{t+1,1} = I'_{t,2}$ $\forall t$ (4.12)

$I_{t+1,2} = I'_{t,3}$ $\forall t$ (4.13)

(5) Expired Platelets

$E_t = I'_{t,1}$ $\forall t$ (4.14)

(6) Platelet Shortages

$S_t = D_t^3$ $\forall t$ (4.15)

(7) Demand Fulfillment Rate

Equation 4.16 ensures that at least 90% of the daily demand is fulfilled. In other words, total units shortage at the end of each day must not exceed 10% of the demand during that day.

$S_t \leq \frac{(1-FR)}{100} * D_t$ $\forall t$ (4.16)

Where FR is the hospital-specified demand fulfillment rate.

(8) Initial Inventory of Platelets

$$I_{1,1} = S^1 \quad (4.17)$$

$$I_{1,2} = S^2 \quad (4.18)$$

(9) Non-negativity

$$D_t^1, D_t^2, D_t^3, E_t, I_{t,1}^{'}, I_{t,2}^{'}, I_{t,3}^{'}, I_{t,1}, I_{t,2}, Q_t, S_t, x_t, TC_t \geq 0 \quad \forall t \quad (4.19)$$

$$\delta_t \in (0,1) \quad \forall t \quad (4.20)$$

4.2. Goal Programming Model

Goal programming (GP) is a technique used to solve multiple criteria mathematical programming (MCMP) models. In goal programming, the objective functions in the MCMP model are set as goals. Each goal has a pre-specified preference and target value proposed by the decision maker (DM). These target values can be satisfied with acceptable deviations and the objective function in the GP model is to minimize these deviations from the target values. Therefore, GP approach attempts to obtain a solution that is as close as possible to the targets based on the DM's preferences.

There are three goals considered in the MCMP model developed for hospital inventory management and are as follows.

- Goal 1 (G1): Cost not to exceed $\$b_1$ for objective 1, given in Equations 4.1 and 4.2.
- Goal 2 (G2): Shortage of platelets not to exceed b_2 units for objective 2, given in Equation 4.3
- Goal 3 (G3): Outdating of platelets not to exceed b_3 units for objective 3, given in Equation 4.4

The three goal constraints are given below.

Goal Constraint -1 (G1)

$$\sum_{t=1}^{T} PHC_t - d_1^+ + d_1^- = b_1 \quad \forall t \quad (4.21)$$

Goal Constraint -2 (G2)

$$\sum_{t=1}^{T} S_t - d_2^+ + d_2^- = b_2 \quad \forall t \quad (4.22)$$

Goal Constraint -3 (G3)

$$\sum_{t=1}^{T} E_t - d_3^+ + d_3^- = b_3 \quad \forall t \quad (4.23)$$

where d_i^+ and d_i^- are the positive and negative deviational variables from target value for goal i.

Equations (4.21) – (4.23) represent the goal constraints (also known as soft constraints) in the GP model.

Since the goals are not to exceed the targets, the deviational variables, d_1^+, d_2^+ and d_3^+ have to be minimized in the GP model. The targets, b_1, b_2 and b_3 have to be specified by the hospital and are given as inputs to the GP model. Note that the targets may or may not be achievable depending on their values specified.

In this chapter, two types of goal programming formulations are discussed to solve the hospital inventory management problem. They are based on how the preferences on achieving the goals are specified.

- Preemptive Goal Programming (PGP)
- Non-Preemptive Goal Programming (NPGP)

4.2.1. Preemptive Goal Programming (PGP) Model

In PGP, the ordinal preference of achievement of goals is specified by the decision maker. Therefore, the high priority goals are achieved first followed by the fulfillment of low priority goals (Masud and Ravindran, 2008). The priorities for the objectives can be obtained using ranking methods such as Borda count, rating method or pair-wise comparison methods such as the Analytic Hierarchy Process (AHP).

PGP Model Objective

Minimize Z = $P_1 d_1^+ + P_2 d_2^+ + P_3 d_3^+$ (4.24)

P_1, P_2 and P_3 are the priorities assigned to goals 1, 2 and 3 respectively. In this case, cost is assigned priority 1, followed by shortage of platelets and outdating. It is to be noted that $P_p >> P_{p+1}$. In other words, the goal which is given the p^{th} priority (P_p) is achieved first, followed by the fulfillment of the goal which is given the $(p+1)^{\text{th}}$ priority (i.e., P_{p+1}).

PGP Model Constraints

The constraints of the PGP model include the hard constraints, 4.5 through 4.20, the three goal constraints, 4.21 – 4.23, and the non-negativity constraints on the deviational variables, given by Equation 4.25.

$d_i^+, d_i^- \geq 0 \qquad i = 1,2,3$ (4.25)

Equation (4.24) represents the objective function of the goal programming model, which is to minimize the goal deviations from their target values.

For the illustration, it is assumed that the decision maker at the hospital ranks minimizing cost as Priority 1, shortage as Priority 2 and units outdated as Priority 3.

4.2.2. Non-Preemptive Goal Programming (NPGP) Model

In the non-preemptive goal programming, numerical weights are assigned to the goals and the values of the weights indicate the relative importance of the goals. The objective is to minimize the weighted sum of deviations from the target values. Unlike the preemptive goal programming model, equal weights can be assigned to each objective ensuring equal importance to all criteria or different weights can be assigned in the order of the importance of the goals.

Criteria Weights (Ravindran and Warsing, 2013):

The first step in the NPGP method is to obtain criteria weights. There are three methods discussed in the literature (Ravindran and Masud, 2008) to obtain the relative weights of each goal:

- Ranking Method (Borda Count)
- Rating Method
- Analytic Hierarchy Process (AHP)

Ranking Method (Borda Count):

This method obtains the rank order of the criteria, and the weights are computed based on these ranks. If there are *p* criteria under consideration, then the decision maker assigns rank 1 for the most important criteria and rank *p* for the least important criteria. The criterion which is assigned the first rank gets *p* points, second rank gets (*p*-1) points and so on. Finally, the criterion which is assigned the last rank gets 1 point. Each criterion weight is obtained by diving the criterion's point by the sum of all the points (for further details, refer to Chapter 6, Ravindran and Warsing, 2013).

Rating Method:

In the rating method, the decision maker (DM) rates each criterion on a certain scale, say, 1-10, and the weights are obtained by normalizing the rating.

If there are *p* criteria and r_j is the rating assigned for criteria *j*, then the weight, w_j, is given by:

$$w_j = \frac{r_j}{\sum_{j=1}^{p} r_j}$$

Analytic Hierarchy Process:

Analytic Hierarchy Process (AHP) is a pair-wise comparison method developed by Saaty (1980). Two criteria are compared by the DM at a time indicating his preference and the strength of preference on a scale of 1 to 9. They are then used to compute the relative weights using Eigen-value theory.

It is to be noted that these method can produce different sets of weights and the optimal solution for each set of weight can be determined. Based on the different solutions, the decision maker can select the best compromise solution.

NPGP Model Objective:

Equation (4.26) represents the objective function, which is to minimize the weighted sum of the goal deviations.

Minimize Z = $w_1 d_1^+ + w_2 d_2^+ + w_3 d_3^+$ (4.26)

It is to be noted that scaling of the objectives is necessary because the goals have different units and magnitude. Otherwise, a goal with large magnitude, will dominate the optimal solution irrespective of the weight assigned to it. There are several scaling methods available and are discussed in detail in Chapter 6 of Ravindran and Warsing (2013). Denoting the scaling factors as v_1, v_2 and v_3, the scaled objective function is given in Equation 4.27.

Minimize Z = $\frac{w_1 * d_1^+}{v_1} + \frac{w_2 * d_2^+}{v_2} + \frac{w_3 * d_3^+}{v_3}$ (4.27)

where w_i is the weight assigned to goal i.

Subject to the constraints:

Equations (4.5) – (4.23) and (4.25).

4.3. Weighted Objective Model (WOM)

In the weighted objective method, relative weights are assigned to each objective based on its importance. The objective function is to minimize the weighted sum of the objectives. This approach also requires that the objectives are scaled properly.

WOM Objective:

Equation (4.28) gives the scaled weighted objective function.

Minimize Z= $\frac{w_1 * TOTPHC}{v_1} + \frac{w_2 * SHORT}{v_2} + \frac{w_3 * EXP}{v_3}$ (4.28)

Subject to the constraints:

Equations (4.5) – (4.20)

where $TOTPHC = \sum_{t=1}^{T} PHC_t = \sum_{t=1}^{T}(C^F * \delta_t + C^P * x_t + C^H * (I_{t,1} + I_{t,2}))$

$SHORT = \sum_{t=1}^{T} S_t$

$EXP = \sum_{t=1}^{T} E_t$

4.4. Case Study – 1

In this section, the demand data from case study-1, discussed in Chapter 3, is used to compare the results of the three different multiple criteria models. Recall that case study-1 consists of daily demand data from a hospital in New York for 122 days. The demand fulfillment rate is set at 90% (i.e., FR=90%) for all the three MCMP models. Also, the models are run for 30 days, with zero lead time and one day review period (i.e., T= 30, L = 0 and RP=1).

The forecasted demand for 30 days presented in Section 3.2.1 is given in Table 4.1.

Table 4.1: Forecasted demand for 30 days

	Week 1	Week 2	Week 3	Week 4	Week 5
Day 1	198	198	198	198	198
Day 2	216	216	216	216	216
Day 3	202	202	202	202	
Day 4	187	187	187	187	
Day 5	186	186	186	186	
Day 6	169	169	169	169	
Day 7	161	161	161	161	

4.4.1. Input Parameters

Cost Settings

Table 4.2 gives the cost data used for the case study. These costs are estimates obtained from a regional medical center in Pennsylvania. The fixed cost represents the fixed transportation cost.

Table 4.2: Cost Setting

Cost	**Fixed Cost of Procurement**	**Variable Purchasing Cost**	**Holding Cost**
Value	\$650/shipment	\$650/unit	\$1.45/unit/day

Target Values

In order to compute the target values for the GP models, the Ideal Solution for each objective (minimize cost, minimize units shortage and minimize platelet wastage) is first calculated. The Ideal Solution is obtained by minimizing each objective independently, ignoring the other objectives, subject to the constraints. However, this solution cannot be achieved and is infeasible because of the conflicting nature of the three objectives. For example, the Ideal Solution for cost is obtained by minimizing cost (Z_1) ignoring the objectives of shortage (Z_2) and wastage (Z_3). Similarly, the ideal solution of Z_2 is obtained by minimizing Z_2 ignoring the objectives of Z_1 and Z_3. From the Ideal Solutions, realistic bounds on the three objectives can be obtained. The results of solving the model with three objectives independently are given in Table 4.3. The upper bound and the lower bound values for the three criteria are also given in Table 4.3 for 90% demand fulfillment.

Table 4.3: Ideal Solutions and Bounds on the Objectives

	Minimizing Cost	Minimize Shortage	Minimize Outdating	Lower Bound	Upper Bound
Cost	$3,224,276	$3,584,835	$3,552,262	$3,224,276	$3,584,835
Units Shortage	522	0	50	0	522
Units Outdated	0	0	0	0	0

Table 4.4: Ideal Values and Target Values

	Ideal Value	Target Value
Cost	$3,224,276	$3,385,489
Units Shortage	0 units	260 units
Units Outdated	0 units	0 units

Based on the upper and the lower bounds of the three objectives given in Table 4.3, the target values are selected. The target value for each goal is set by the decision maker based on the ideal values. The target value of the cost is assumed to be at 105% of the ideal value, which is $3,385,489 (i.e., b_1=$3,385,489). The target value for shortage is set at 5% of the total demand, which is approximately 260 units (i.e., $b_2 = 260$ units). Since the lower and the upper bound of expiration is 0, the target value for expiration is set at 0 units (i.e., $b_3 = 0$ units). The ideal and the target values are given in Table 4.4. The target values used here are for illustrative purposes only. A hospital administrator can use different target values, including the ideal values as targets.

4.4.2. Solution for the MCMP Model by Preemptive Goal Programming (PGP)

For the case study-1 data discussed in Section 4.4.1, the PGP model had the following features:

- Total number of decision variables: 426 (out of which 30 are binary variables)
- Total number of constraints: 455
- The mathematical model discussed in Section 4.2.1 is programmed using C++ and solved using IBM CPLEX®12.4.0.0 optimizer.
- Solution time is approximately 25 seconds

Table 4.5: Results of Preemptive Goal Programming Model

	Ideal Value	Target Value	Achieved Objective Value	Goal Achievement	Priority
Cost ($)	$3,224,276	$3,385,489	$3,385,455	Achieved	P_1
Units Shortage	0 units	260 units	305 units	Not Achieved (14.75%)	P_2
Units Outdated	0 units	0 units	0 units	Achieved	P_3

Table 4.5 shows the value of the objectives obtained from the preemptive goal programming model. Table 4.5 represents the scenario where cost has the highest priority, followed by shortage and outdating. This scenario is considered as the base scenario. The results indicate that the cost and units expired are less than the target value (goals achieved). However, the total units shortage is greater than the target by 14.75% (goal not achieved). Effects of changing the goal priorities are discussed in Section 4.4.6 under Sensitivity Analysis.

4.4.3. Solution for the MCMP Model by Non-Preemptive Goal Programming

An initial set of weights used in the non-preemptive goal programming model are given in Table 4.6. A sensitivity analysis will be performed in Section 4.4.6 by varying the selected weights.

Table 4.6: Weights given to the Goals in Non-Preemptive Goal Programming (NPGP)

	Cost (G_1)	Shortage (G_2)	Wastage (G_3)
Weight (w_i)	0.5	0.3	0.2

The weights reflect the relative importance given in the preemptive GP model. For instance, cost is given the highest weight of 0.5, followed by shortage at 0.3 and wastage at 0.2.

For scaling the objectives, v_1 is set at 10000, v_2 and v_3 are set at 1. This ensures that all three goals are scaled to be of comparable magnitudes.

For the case study-1 data discussed in Section 4.4.1, the NPGP model had the following features:

- Total number of decision variables: 426 (out of which 30 are binary variables)
- Total number of constraints: 455
- The mathematical model discussed in Section 4.2.2 is programmed using C++ and solved using IBM CPLEX®12.4.0.0 optimizer.
- Solution time is approximately 25 seconds

Table 4.7: Results of Non-Preemptive Goal Programming Model

	Ideal Value	Target Value	Achieved Objective Value	Goal Achievement	Weights
Cost ($)	$3,224,276	$3,385,489	$3,413,389	Nearly Achieved (0.82%)	0.5
Units Shortage	0 units	260 units	260 units	Achieved	0.3
Units Outdated	0 units	0 units	0 units	Achieved	0.2

For the given weights, Table 4.7 shows the value of the objectives obtained from the non-preemptive goal programming model. From Table 4.7, it can be observed that the total units shortage is 260 units making the deviational variable associated with the shortage objective to be 0 (goal achieved). The units expired is also equal to the target value (goals achieved). The cost is slightly higher (0.82%) than the target cost (goal nearly achieved). Even though more weight is given to the cost, the target assigned for cost is not achievable because the NPGP model only tries to minimize the sum of the weighted deviations from the target values.

4.4.4. Solution by the Weighted Objective Model (WOM)

The weights and the scaling factors used in the weighted objective model are the same as those used for NPGP model.

For the case study-1 data discussed in Section 4.4.1, the WOM model had the following features:

- Total number of decision variables: 423 (out of which 30 are binary variables)
- Total number of constraints: 455

- The mathematical model discussed in Section 4.2.3 is programmed using C++ and solved using IBM CPLEX®12.4.0.0 optimizer.
- Solution time is approximately 23 seconds

Table 4.8: Results of the Weighted Objective Model

	Ideal Value	Achieved Objective Value	Deviation from the Ideal	Weights
Cost ($)	$3,224,276	$3,584,835	10.06%	0.5
Units Shortage	0 units	0 units	0%	0.3
Units Outdated	0 units	0 units	0%	0.2

For the given weights, Table 4.8 shows the value of the objectives obtained using the weighted objective model (WOM). The model results in no shortage and no outdating of platelets. Recall that the ideal value represents the minimum value for all the criteria. Therefore, minimizing directly the weighted sum of the criteria in WOM is equivalent of minimizing deviations from the ideal value. In NPGP, the deviations from the target values are minimized and in WOM, the deviations from the ideal values are minimized. Therefore, the WOM is similar to the NPGP technique with the targets set as ideal values.

4.4.5. Comparison of Results from the Three Multiple Objective Models

Table 4.9 gives a comparison of the objective values achieved by the three different approaches to solving the multiple criteria mathematical programming problem. It can be observed that for this particular case study, the units expired is always 0 across all the methods. Hence, it is evident that only the cost and the shortage objectives are conflicting in nature. Since, there are only two conflicting criteria, a two dimensional graph is drawn to graphically compare the solutions (see Figure 4.1). Note that the three optimal solutions are non-dominated solutions. For example, comparing PGP and NPGP solutions, a decrease in shortage of 45 units (305 – 260) is obtained at a cost increase of $27,934 ($3,413,389-$3,385,455). Similarly, zero shortage can be achieved at an additional cost of $171,446 ($3,584,835-$3,413,389).

Table 4.9: Comparison of Results from the Multiple Objective Models

	PGP	NPGP	WOM
Cost ($)	$3,385,455	$3,413,389	$3,584,835
Units Shortage	305 units	260 units	0 units
Units Outdated	0 units	0 units	0 units

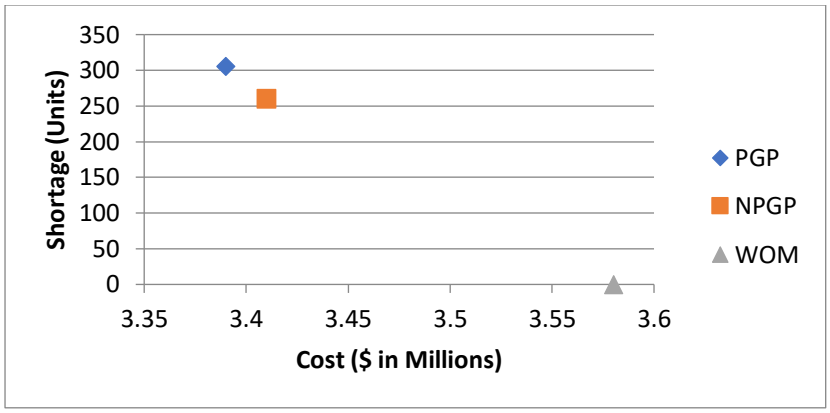


Figure 4.1: Cost and Shortage Values for the Three Different Approaches

From Figure 4.1, the decision maker can analyze and obtain the tradeoff among the three solutions. If there are more than two conflicting objectives, the value path approach of Schilling et al., (1983) can be used. In the value path approach, the solutions are displayed using parallel scales and it helps the decision maker to identify whether an optimal solution dominates another. It is also used to determine the tradeoff among the solutions.

4.4.6. Sensitivity Analysis

In this section, the effect of changing the goal priorities in the PGP model and the weights in the NPGP model and WOM are discussed.

4.4.6.1. Effect of Changing Goal Priorities in the PGP Model

The different priority scenarios considered for the sensitivity analysis are given in Table 4.10. The priority setting used in Section 4.4.2 is considered the base scenario, where cost is given the highest priority, followed by shortage and outdating. In alternate scenario-1 (A-1), cost goal is given in priority 1, followed by outdating and shortage. Therefore, it is expected that the cost under A-1 will be same as that of the base scenario. In alternate scenario-2 (A-2), shortage goal is given priority 1, followed by cost and outdating. Therefore, it is expected that the cost will be more under A-2 compared to that of the base scenario. In alternate scenario-3 (A-3), outdating goal is given priority 1, followed by cost and shortage. In alternate scenario-4 (A-4), shortage goal is given priority 1, followed by outdating and cost. Therefore, it is expected that the cost will be more and shortage will be less under A-4 compared to those of the base scenario. In alternate scenario-5 (A-5), outdating goal is given priority 1, followed by the shortage and cost. Therefore, it is expected that the cost will be the highest in this scenario.

Table 4.10: Alternate Scenarios Considered for the PGP Model

Scenario	Priorities		
	G_1	G_2	G_3
Base	P_1	P_2	P_3
A-1	P_1	P_3	P_2
A-2	P_2	P_1	P_3
A-3	P_2	P_3	P_1
A-4	P_3	P_1	P_2
A-5	P_3	P_2	P_1

Table 4.11 gives the results for the PGP model under the different scenarios. The results are identical for scenarios A-2, A-4 and A-5. In all the three scenarios, shortage is given more priority than cost. The total units shortage is therefore, exactly equal to the target shortage making the corresponding shortage deviational variable in the objective function to be zero (goal achieved). The units expired is also equal to the target value (goal achieved). Since the shortage objective is achieved, the cost is greater than the target cost by 0.82% (goal nearly achieved).

When shortage is equal to the target shortage, the corresponding deviational variable in the objective function is equal to 0. Further decrease in shortage cannot decrease the shortage deviational variable but will result in increase in the cost thereby increasing the cost deviational variable. Therefore, when priority is given to minimize shortage, the shortage is made exactly equal to the target shortage in the PGP model.

The results are identical for the base scenario, A-1 and A-3. In these three scenarios, cost objective is given more priority than shortage. Therefore, as in the base scenario, the cost and units expired are less than the target value (goals achieved). The total units shortage is greater than the target shortage by 14.75% (goal not achieved).

From all the six scenarios considered, it is evident that the priority for expiration objective has no impact on the results. This is because the maximum number of units that can be purchased within the target cost will result in 305 units shortage.

Table 4.11: Effect of Alternate Scenarios on the Objectives under PGP

Objective	Ideal Value	Target Value	Achieved Objective Value	Goal Achievement	Priority
Base Scenario 1					
Cost ($)	$3,224,276	$3,385,489	$3,385,455	Achieved	P_1
Units Shortage	0 units	260 units	305 units	Not Achieved (14.75%)	P_2
Units Outdated	0 units	0 units	0 units	Achieved	P_3
Alternate Scenario 1 (A-1)					
Cost ($)	$3,224,276	$3,385,489	$3,385,455	Achieved	P_1
Units Shortage	0 units	260 units	305 units	Not Achieved (14.75%)	P_3
Units Outdated	0 units	0 units	0 units	Achieved	P_2
Alternate Scenario 2 (A-2)					
Cost ($)	$3,224,276	$3,385,489	$3,413,389	Not Achieved (0.82%)	P_2
Units Shortage	0 units	260 units	260 units	Achieved	P_1
Units Outdated	0 units	0 units	0 units	Achieved	P_3
Alternate Scenario 3 (A-3)					
Cost ($)	$3,224,276	$3,385,489	$3,385,455	Achieved	P_2
Units Shortage	0 units	260 units	305 units	Not Achieved (14.75%)	P_3
Units Outdated	0 units	0 units	0 units	Achieved	P_1
Alternate Scenario 4 (A-4)					
Cost ($)	$3,224,276	$3,385,489	$3,413,389	Nearly Achieved (0.82%)	P_3
Units Shortage	0 units	260 units	260 units	Achieved	P_1
Units Outdated	0 units	0 units	0 units	Achieved	P_2
Alternate Scenario 5 (A-5)					
Cost ($)	$3,224,276	$3,385,489	$3,413,389	Nearly Achieved (0.82%)	P_3
Units Shortage	0 units	260 units	260 units	Achieved	P_2
Units Outdated	0 units	0 units	0 units	Achieved	P_1

4.4.6.2. Effect of Changing Goal Priorities in NPGP Model and WOM

Effect of Changing Weights in the NPGP Model:

Table 4.12 gives the different set of weights assigned to the NPGP model and they reflect the priorities given in the preemptive GP model.

Table 4.12: Alternate Scenarios Considered for the NPGP Model

Scenario	Priorities		
	G_1	G_2	G_3
Base	0.5	0.3	0.2
A-1	0.8	0.1	0.1
A-2	0.4	0.5	0.1
A-3	0.4	0.1	0.5
A-4	0.1	0.45	0.45
A-5	0.3	0.3	0.3

The results obtained for all the alternate scenarios are same as those of the base scenario. In other words, the change in weights has no impact on the NPGP model results for this particular case study. This can happen in the NPGP model because only the relative weights are specified; hence, it is not necessary that the optimal solutions have to change.

Effect of Changing Weights in the WOM:

In the weighted objective method, the weights discussed in Table 4.12 are used and results for all the alternate scenarios are same as those of the base scenario. As in the NPGP model, the change in weights has no impact on the WOM results for this particular case study.

4.5 Comparison of the MCMP Model by the Three Solution Techniques

In the preemptive goal programming (PGP) model, first-priority goals are achieved first followed by the second, third priority goals and so on. As a result, there are infinite tradeoffs made between the criteria under different priorities. The PGP model is solved in a sequential procedure and hence, the scaling of the objectives is not necessary.

On the other hand, in the non-preemptive goal programming (NPGP) and weighted objective method (WOM), only relative weights are assigned to all the objectives. The weights can be equal indicating that all the criteria are equally important or different when certain criteria are given more importance. The weights represent the DM's utility for each criterion and the objective is to minimize the weighted sum of deviations from the target values. Hence, a linear utility

function is assumed in the NPGP. Another drawback of both the NPGP and the WOM is that the scaling of the objectives is required to avoid any biasness in the magnitudes or units used to measure the 3 objectives.

Chapter 5 : Platelet Ordering Policies at Hospitals using Stochastic Programming

In this chapter, two mixed integer stochastic programming models under demand uncertainty are developed. In the first stochastic programming model, an optimal platelet order policy for the finite time horizon is determined under stochastic demand. The second stochastic programming model uses an (s, S) periodic review policy to determine the platelet order quantity each day. Due to the computational complexity of the mathematical models, four heuristic rules are proposed for determining the platelet ordering policy at the hospital. The performance of these order policies is compared against the stochastic programming models, using real data obtained from a regional medical center. The shelf life of arriving platelets, coefficient of variation of demand and cost parameters are then varied, and their impacts are analyzed on the performance measures and the best order policy is identified for each hospital setting. Based on the hospital setting and cost prioritization, the decision maker can decide the best platelet order policy.

5.1 Stochastic Inventory Models under Demand Uncertainty

In this section, two finite time horizon stochastic programming models under demand uncertainty are developed in this section. Scenario approach is used to solve the two stochastic programming models by generating multiple scenarios for the platelet demand. Each scenario represents a demand pattern. Demand patterns can be generated from the hospital's historical demand data or from a distribution based on the decision maker's knowledge. In the first stochastic programming model (referred to as SP1), the number of units to procure through regular shipments remain the same and number of units to procure under emergency shipments (i.e., during a shortage) varies. The second stochastic programming model (referred to as SP2) uses the periodic review policy, known as the (s, S) policy, to determine the order quantity each day. The constraints in both models take into consideration the different demand scenarios and the objective function is to minimize the expected total cost across all the scenarios. In both models, it is assumed that the hospital follows a FIFO policy for platelet use (i.e., the platelets with the shortest shelf life are used first, i.e., demand is first fulfilled with platelets with shelf life of 1 day, followed by platelets with shelf life of 2 days, followed by platelets with shelf life of 3 days). We will begin with the development of the first stochastic programming model (SP1), which is a finite time horizon model under stochastic demand.

5.1.1. Stochastic Programming Model-1 (SP1)

5.1.1.1 Model Notations

Model Parameters (known data)

i	Index for shelf life of platelets (i=1,2,3)
ω	Index for scenarios (platelet demand patterns)
t	Index for day
Ω	Total number of scenarios (i.e., ω=1, 2, 3, …, Ω)
T	Time horizon in days (i.e., t=1, 2, 3, …, T)
c^f	Fixed cost of procuring platelets ($/shipment)
c^p	Platelet purchasing cost ($/unit)
c^h	Inventory holding cost of platelets ($/unit/day)
c^{ex}	Cost of expired/outdated platelet ($/unit)
c^{sh}	Shortage cost ($/unit) (Note: This is the additional cost of procuring one unit of platelet through emergency shipment)
d_t^ω	Platelet demand for day t under scenario ω (units)
L	Procurement lead time (days)
RP	Review period (days)
in^i	Initial inventory with shelf life of i days for day 1
γ_i	Percentage of arriving platelets with shelf life of i days (Note: $\sum_{i=1}^{3} \gamma_i = 1$)
p^ω	Probability of occurrence of scenario ω

Decision Variables (unknown)

Q_t	Quantity of platelet units ordered at the end of day t (same across all the demand scenarios)
TC	Expected total cost incurred for the hospital across the finite time horizon
$X_{t,i}$	Platelet units received from the blood center at the beginning of day t with a shelf life of i days (note: maximum remaining shelf life of the arriving platelets is 3 days)
X_t	Total platelet units received from the blood center at the beginning of day t (i.e., $X_t = \sum_{i=1}^{3} X_{t,i}$)

$D_{t,i}^{\omega}$ Remaining demand on day t, after using platelets with shelf life of i days under scenario ω

$I_{t,i}^{\omega}$ On-hand inventory at the beginning of day t with shelf life of i days under scenario ω ($i = 1,2$). Note: Since platelets have a maximum shelf life of 3 days, on-hand inventory at the beginning of day t (carried over from day $t-1$) can have a maximum of 2 days shelf life.

$IPR_{t,1}^{\omega}$ Leftover platelets after satisfying d_t^s with shelf life of 1 day under scenario ω

$IPR_{t,i}^{\omega}$ Leftover platelets after satisfying $D_{t,i-1}^{s}$ with shelf life of i days under scenario ω ($i = 2,3$)

SH_t^{ω} Number of platelet units shortage at the end of day t under scenario ω (these are procured through emergency shipment by the hospital from the blood center)

E_t^{ω} Number of platelet units outdated (expired) at the end of day t under scenario ω

δ_t { 1 if platelet units are ordered by the hospital on day t ; 0 otherwise

The stochastic programming model discussed in this section is an extension of the single objective integer programming model with deterministic demands, discussed in Chapter 3.

5.1.1.2. Sequence of Daily Events at the Hospital

6. Hospital receives platelet units, X_t, from the blood center.
7. Based on the scenario ω, hospital receives platelet demand, d_t^{ω}, on day t
8. If the demand at the hospital is greater than the on-hand inventory, then demand is partially fulfilled with the available on-hand inventory and the on-hand inventory is updated to 0. The unfulfilled demand units incur the corresponding shortage cost.
9. If the demand at the hospital is less than the on-hand inventory, then the unutilized platelet units with remaining shelf life of 1 day are thrown away at the end of the day and incur an outdating cost. The remaining platelets (after discarding the outdated units) are carried over to the next day and the on-hand inventory is updated.

10. Hospital determines platelet order quantity (Q_t) at the end of day t. The units ordered at the end of each day t is will be received by the hospital on the day after the lead time, l (i.e., on day $t + l$, hence $X_{t+l} = Q_t$).

5.1.1.3. Formulation of the SP1 Model

Equation (5.1) represents the objective function, which is to minimize the expected cost across all scenarios. The total cost comprises of fixed cost of procurement, variable purchasing cost, holding cost, shortage cost, and outdating cost.

Minimize TC $= \sum_{t=1}^{T}[c^f * \delta_t + c^p * Q_t + \sum_{\omega=1}^{\Omega}[p^\omega * \{c^h * (I_{t,1}^\omega + I_{t,2}^\omega) + c^{sh} * SH_t^\omega + c^{ex} * E_t^\omega\}]]$ (5.1)

(Note: The number of units ordered through regular shipments, Q_t, remain the same across all scenarios. However, emergency shipments vary by scenario).

Model Constraints:

(1) Platelet Units Ordered

Equation (5.2) ensures that δ_t becomes 1 even if a single platelet unit is ordered from the blood center on day t and 0 otherwise. Equation (5.3) ensures that orders for platelet units can take place only during the days corresponding to multiples of the review period, RP.

$Q_t \leq M\delta_t$ for $t = RP, 2\ RP, 3\ RP$ … (5.2)

$Q_t = 0$ for all other t (5.3)

(Note: M is a large positive number)

(2) Platelet Units Received

Equations (5.4) and (5.5) are used to calculate the total units received by the hospital at the beginning of day t (i.e., X_t), which corresponds to the order quantity placed on the day before the lead time (Q_{t-L}). X_t comprises of platelets with different shelf life. The total units arriving with a remaining shelf life of i days is given by Equation (5.6).

$X_t = Q_{t-L}$ $\forall t > L$ (5.4)

$X_t = 0$ or known constants $\forall t \leq L$ (5.5)

$X_{t,i} = \gamma_i * X_t$ $\forall t$ and $i = 1,2,3$ (5.6)

(Note: γ_i is the percentage of platelets received with a shelf life of i days and $\sum_{i=1}^{3} \gamma_i = 1$)

(3) Demand Constraints

Consider day t under scenario s with a platelet demand of d_t^ω:

- If d_t^ω is greater than the platelet units with shelf life of 1 day (i.e., $I_{t,1}^\omega + X_{t,1}$), then the leftover demand is $D_{t,1}^\omega$, and is given by $D_{t,1}^\omega = d_t^\omega - I_{t,1}^\omega - X_{t,1}$. Also, $IPR_{t,1}^\omega = 0$. On the other hand if the demand, d_t^ω, is less than platelet units with shelf life of 1 day, then the leftover demand, $D_{t,1}^\omega$, is 0 and the remaining platelet units after satisfying the demand is given by $IPR_{t,1}^\omega = I_{t,1}^\omega + X_{t,1} - d_t^\omega$. Equation (5.7) is used to calculate $D_{t,1}^\omega$ and $IPR_{t,1}^\omega$. Note that both $D_{t,1}^\omega$ and $IPR_{t,1}^\omega$ cannot be positive simultaneously.

$$d_t^\omega - I_{t,1}^\omega - X_{t,1} = D_{t,1}^\omega - IPR_{t,1}^\omega \qquad \forall t, \omega \qquad (5.7)$$

- If the leftover demand, $D_{t,1}^\omega$, is positive, then it is first fulfilled by platelet units with a shelf life of 2 days (i.e., $I_{t,2}^\omega + X_{t,2}$). If $D_{t,1}^\omega$ is greater than $I_{t,2}^\omega$, then the leftover demand, $D_{t,2}^\omega$, is given by $D_{t,2}^\omega = D_{t,1}^\omega - I_{t,2}^\omega - X_{t,2}$. If $D_{t,1}^\omega$ is less than $I_{t,2}^\omega$, then the leftover demand, $D_{t,2}^\omega$, is 0 and the remaining platelet units after satisfying $D_{t,1}^\omega$ is given by $IPR_{t,2}^\omega = I_{t,2}^\omega + X_{t,2} - D_{t,1}^\omega$. Equation (5.8) is used to calculate $D_{t,2}^\omega$ and $IPR_{t,2}^\omega$. Note that both $D_{t,2}^\omega$ and $IPR_{t,2}^\omega$ cannot be positive simultaneously.

$$D_{t,1}^\omega - I_{t,2}^\omega - X_{t,2} = D_{t,2}^\omega - IPR_{t,2}^\omega \qquad \forall t, \omega \qquad (5.8)$$

- If $D_{t,2}^\omega$ is positive, then it is fulfilled by platelet units with a shelf life of 3 days, $X_{t,3}$. If $D_{t,2}^\omega$ is greater than $X_{t,3}$, then the leftover demand, $D_{t,3}^\omega$, is given by $D_{t,3}^\omega = D_{t,2}^\omega - X_{t,3}$, and $D_{t,3}^\omega$ is the platelet shortage at the end of day t. The shortage units are obtained through emergency procurement. If $D_{t,2}^\omega$ is less than or equal to $X_{t,3}$, then no shortage is incurred, and leftover platelet units after satisfying $D_{t,2}^\omega$ is given by $IPR_{t,3}^\omega = X_{t,3} - D_{t,2}^\omega$. Equation (5.9) is used to calculate $D_{t,3}^\omega$ and $IPR_{t,3}^\omega$. Note that both $D_{t,3}^\omega$ and $IPR_{t,3}^\omega$ cannot be positive simultaneously.

$$D_{t,2}^\omega - X_{t,3} = D_{t,3}^\omega - IPR_{t,3}^\omega \qquad \forall t, \omega \qquad (5.9)$$

(4) Expired/Outdated Platelets

The unutilized platelet units with the remaining shelf life of 1 day in scenario ω, $I_{t,1}^\omega$, are discarded at the end of the day t and is given by Equation (5.10).

$$E_t^\omega = IPR_{t,1}^\omega \qquad \forall t, \omega \qquad (5.10)$$

(5) Inventory Updates

At the end of the day t, the inventory is updated for the next day using Equations (5.11) and (5.12). Note that the ending inventory varies depending on the scenario, ω.

$$I_{t+1,1}^{\omega} = IPR_{t,2}^{\omega} \qquad \forall t, \omega \qquad (5.11)$$

$$I_{t+1,2}^{\omega} = IPR_{t,3}^{\omega} \qquad \forall t, \omega \qquad (5.12)$$

Note: By Equation (5.10), $IPR_{t,1}^{\omega}$ is discarded due to outdating.

(6) Platelet Shortages

The units of unfulfilled demand in scenario ω, $D_{t,3}^{\omega}$, is considered as the shortage in day t, as given by Equation (5.13) and it is calculated using Equation (5.9).

$$SH_t^{\omega} = D_{t,3}^{\omega} \qquad \forall t, \omega \qquad (5.13)$$

(7) Initial Inventory of Platelets

Equation (5.14) gives the initial conditions at time t = 1 for each scenario, ω.

$$I_{1,i}^{\omega} = in^i \qquad \forall \omega \text{ and } i = 1,2,3 \qquad (5.14)$$

(8) Non-negativity

Constraints (5.15-5.17) represent non-negativity and binary restrictions in the model.

$$X_t, X_{t,1}, X_{t,2}, X_{t,3}, Q_t \geq 0 \qquad \forall t \qquad (5.15)$$

$$D_{t,1}^{\omega}, D_{t,2}^{\omega}, D_{t,3}^{\omega}, SH_t^{\omega}, y_t^{\omega}, E_t^{\omega}, IPR_{t,1}^{\omega}, IPR_{t,2}^{\omega}, IPR_{t,3}^{\omega}, I_{t,1}^{\omega}, I_{t,2}^{\omega} \geq 0 \qquad \forall t, \omega \qquad (5.16)$$

$$\delta_t \in (0,1) \qquad \forall t \qquad (5.17)$$

5.1.2. Stochastic Programming Mathematical Model-2 (SP2)

The ordering policy obtained under SP1 is more cumbersome to follow since the hospital staff has to follow an optimal order policy which would be different each day. However, the hospital might be interested in following a simple ordering policy without compromising the quality of the solution. Hence, in this section, a (s, S) periodic review policy is also developed for the finite time horizon. Under this policy, at the end of each review period (RP), the inventory position is reviewed. The inventory position is the sum of the actual on-hand inventory and the past orders that are in transit. If the inventory position is below the reorder point s, then an order is placed to bring the inventory to level S. If the inventory position is greater than or equal to the reorder point s, then no platelets are ordered at that time.

5.1.2.1. Sequence of Daily Events at the Hospital under the (s,S) Policy

1. Hospital receives platelet units, X_t^ω, from the blood center on day t under scenario ω.
2. Hospital receives platelet demand, d_t^ω, on day t.
3. If the demand at the hospital is greater than the on-hand inventory, then demand is partially fulfilled and unfulfilled demand units incur the corresponding shortage cost. If the demand at the hospital is less than the on-hand inventory, then the unutilized platelet units with remaining shelf life of 1 day are thrown away and the remaining platelets are carried over to the next day.
4. At the end of day t under scenario ω ($t = RP,\ 2\,RP,\ 3\,RP$ ...), hospital determines the inventory position (IP_t^ω) and if IP_t^ω is less than re-order point s, then platelets are ordered to raise the inventory level up-to S (i.e., $Q_t^\omega = S - IP_t^\omega$). On the other hand, if IP_t^ω is greater than s, then no order is placed (i.e., $Q_t^\omega = 0$). The units ordered at the end of each day t is will be received by the hospital on the day after the lead time, L (i.e., on day $t + L$, hence $X_{t+L}^\omega = Q_t^\omega$).

Note: Both the re-order point (s) and the order up-to-level (S) at the hospital are the same across the planning horizon and for all scenarios, which makes the (s,S) policy easier to implement by a hospital administrator.

5.1.2.2. Notations Used in the SP2 Model

Model parameters (known data) that are used in the SP1 model are applicable to SP2 model also. However, the decision variables have to be modified as follows:

Decision Variables (unknown)

Q_t^ω Quantity of platelet units ordered at the end of day t under scenario ω by the hospital

$X_{t,i}^\omega$ Platelet units received by the hospital from the blood center at the beginning of day t with a shelf life of i days in scenario s (note: maximum remaining shelf life of the arriving platelets is 3 days)

X_t^ω Total platelet units received by the hospital from the blood center at the beginning of day t in scenario ω (i.e., $X_t^\omega = \sum_{i=1}^{3} X_{t,i}^\omega \quad \forall\omega$)

$D_{t,i}^\omega$ Remaining demand on day t, after using platelets with shelf life of i days under scenario ω

IP_t^ω Inventory position at the end of day t in scenario ω

s Re-order point (same across all the scenarios)

S Order-up-to level (same across all the scenarios)

$$\Delta_t^\omega \begin{cases} 1 \text{ if } IP_t^\omega \le s & t = RP,\ 2\ RP,\ 3\ RP\ \ldots \\ 0 \text{ otherwise} \end{cases}$$

The other decision variables $I_{t,i}^{\omega}, IPR_{t,i}^{\omega}, D_{t,i}^{\omega}, SH_t^{\omega}$ and E_t^{ω} used in Model SP1 are used in Model SP2 also.

5.1.2.3. Formulation of the Stochastic Programming Mathematical Model using (s, S) Policy

Equation (5.18) represents the objective function, which is to minimize the expected cost across all scenarios at the hospital. The total cost comprises of fixed cost of procurement, variable purchasing cost, holding cost, shortage cost, and outdating cost.

Minimize $TC = \sum_{t=1}^{T}[\sum_{\omega=1}^{\Omega}\left[p^{\omega} * \{c^{f} * \Delta_t^{\omega} + c^{p} * Q_t^{\omega} + c^{h} * \left(I_{t,1}^{\omega} + I_{t,2}^{\omega}\right) + c^{sh} * SH_t^{\omega} + c^{ex} * E_t^{\omega}\}\right]]$ (5.18)

Model Constraints:

Equations 5.10 to 5.14 used in Model SP1 are applicable to Model SP2 also. The constraints used in Model SP1 that need to be modified for Model SP2, namely, Equations 5.4 through 5.9, are described below:

Platelet Units Ordered and Received

Equations (5.19) – (5.24) are similar to Equations (5.4) – (5.9) used in model SP1, with the difference that the total units ordered and procured from the blood center is dependent on the scenario, ω, even though the optimal values of s and S are the same across all the scenarios. Under the SP1 model, the total units ordered remains the same across all the scenarios.

$$X_t^{\omega} = Q_{t-L}^{\omega} \qquad \forall \omega, t > L \qquad (5.19)$$

$$X_t^{\omega} = 0 \text{ or known constants} \qquad \forall \omega, t \le L \qquad (5.20)$$

$$X_{t,i}^{\omega} = \gamma_i * X_t^{\omega} \qquad \forall i, t, \omega \qquad (5.21)$$

Demand-Inventory Balance

$$d_t^{\omega} - I_{t,1}^{\omega} - X_{t,i}^{\omega} = D_{t,1}^{\omega} - IPR_{t,1}^{\omega} \qquad \forall t, \omega \qquad (5.22)$$

$$D_{t,1}^{\omega} - I_{t,2}^{\omega} - X_{t,2}^{\omega} = D_{t,2}^{\omega} - IPR_{t,2}^{\omega} \qquad \forall t, \omega \qquad (5.23)$$

$$D_{t,2}^{\omega} - X_{t,3}^{\omega} = D_{t,3}^{\omega} - IPR_{t,3}^{\omega} \qquad \forall t, \omega \qquad (5.24)$$

Inventory Position and Order Quantity

Equations (5.25) is used to calculate the inventory position at the end of each day for each scenario, IP_t^ω. Under the (s, S) policy, if the inventory position $IP_t^\omega \geq s$, then no order is placed; otherwise, we order an amount $Q_t^\omega = S - IP_t^\omega$. These are enforced in the model by Equations (5.26) through (5.30). If $\Delta_t^\omega = 0$, then $IP_t^\omega \geq s$ according to Equation (5.26) and Equation (5.27) is inactive. On the other hand, if $\Delta_t^\omega = 1$, then Equation (5.26) is inactive and $IP_t^\omega \leq s$ according to Equation (5.27). If $\Delta_t^\omega = 1$, then from Equations (5.28) and (5.29), $Q_t^\omega = S - IP_t^\omega$ and Equation (5.30) is inactive. On the other hand, if $\Delta_t^\omega = 0$, then Equations (5.28) and (5.29) are inactive and Equation (5.30) forces Q_t^ω to take the value 0. The order up-to level (S) must be greater than the reorder point (s) at the hospital and is ensured by Equation (5.31).

$$IP_t^\omega = IPR_{t,2}^\omega + IPR_{t,3}^\omega + \sum_{lt=1}^{L-1} Q_{t-lt}^\omega \qquad \forall t, \omega \qquad (5.25)$$

$$IP_t^\omega \geq s - M\Delta_t^\omega \qquad \forall t, \omega \qquad (5.26)$$

$$IP_t^\omega \leq s + M(1 - \Delta_t^\omega) \qquad \forall t, \omega \qquad (5.27)$$

$$Q_t^\omega \leq (S - IP_t^\omega) + M(1 - \Delta_t^\omega) \qquad \forall t, \omega \qquad (5.28)$$

$$Q_t^\omega \geq (S - IP_t^\omega) - M(1 - \Delta_t^\omega) \qquad \forall t, \omega \qquad (5.29)$$

$$Q_t^\omega \leq M(\Delta_t^\omega) \qquad \forall t, \omega \qquad (5.30)$$

$$S > s \qquad (5.31)$$

Non-negativity Constraint

Constraints (5.32) – (5.34) represent non-negativity and binary restrictions in the model.

$$X_t^\omega, X_{t,1}^\omega, X_{t,2}^\omega, X_{t,3}^\omega, Q_t^\omega, D_{t,1}^\omega, D_{t,2}^\omega, D_{t,3}^\omega, SH_t^\omega, E_t^\omega, IPR_{t,1}^\omega, IPR_{t,2}^\omega, IPR_{t,3}^\omega, I_{t,1}^\omega, I_{t,2}^\omega, IP_t^\omega \geq 0 \qquad \forall t, \omega \qquad (5.32)$$

$$s, S \geq 0 \qquad (5.33)$$

$$\delta_t^\omega, \Delta_t^\omega \in (0,1) \qquad \forall t, \omega \qquad (5.34)$$

5.1.3. Computational Complexity of the stochastic programming models

The stochastic programming models discussed in Sections 5.1.1 and 5.1.2 are coded using Microsoft Visual C++ 6.0 Professional and solved using IBM CPLEX®12.4.0.0 optimizer on a computer with 8GB RAM, Intel i5 2.50 GHz processor. The computational complexity of the stochastic programming models increases quickly as the number of platelet demand scenarios and the time horizon increase. For example, assuming t=30 days, review period of 1 day and lead time of 1 day, the maximum number of scenarios for which SP1 and SP2 models can run for the specified computer system are 35 and 42 respectively.

For 35 scenarios and 30-day planning horizon, the problem size is the following:

Complexity measures	SP1	SP2
Total number of decision variables	12750, of which 1050 are binary variables	22682, of which 2520 are binary
Total number of constraints	7455	20203
Solution time	60 minutes	60 minutes

5.2 Heuristic Rules for Ordering Quantities

As discussed in Section 5.1.3, the complexity of the stochastic programming models increases as the number of scenarios and time horizon increase. Moreover, the usage of stochastic programming models not only requires users to have a good knowledge of optimization models, but also skills to solve them. Therefore, four heuristic policies are developed for determining the platelet ordering policy without solving the stochastic programming models. The performance of these policies is compared against the optimal policies obtained by solving the stochastic programming models by CPLEX solver. The computation time of the heuristics will be minimal and the policies will also be easy to implement at the hospitals.

5.2.1. Order-up-to-Level Policy

This rule is based on the traditional periodic review, order-up-to level policy, under stochastic demand. In the order-up-to level policy, the inventory position is checked at the end of every review period (RP) and an order is placed to bring the level to S, i.e., the inventory position is raised to a constant value, S, by placing an order, $Q_t = S - IP_t$ where IP_t is the inventory position at the end of day t, where $t = RP, 2RP, 3RP$ etc (Ravindran and Warsing, 2013).

Assuming that the daily demand follows a normal distribution with mean μ_D and standard deviation σ_D,

- Mean demand during lead time plus review period = $\mu_{DLTR} = (L + RP)\mu_D$
- Standard deviation of the demand during lead time plus review period = $\sigma_{DLTR} = \sigma_D\sqrt{L + RP}$
- $S = \mu_{DLTR} + z_{SL}\sigma_{DLTR}$ (5.35)
- Safety stock, $SS = z_{SL}\sigma_{DLTR}$

where $z_{SL} = \phi^{-1}(SL)$, where SL is the service level (the expected in-stock probability of meeting platelet demand in each replenishment cycle), ϕ is the standard normal cumulative distribution function, and L and RP are the lead time and review period respectively.

5.2.2. Modified Order-up-to-Level Policy

In this rule, order-up-to-level policy is used considering the coefficient of demand variation (CV). CV is the ratio of the standard deviation to the mean of the demand during the lead time and the review period as given in Equation (5.36). The value of order-up-to level (S') is calculated as a multiple of the mean demand during lead time and review period (μ_{DLTR}) as given in Equation (5.37).

$$CV = \frac{\sigma_{DLTR}}{\mu_{DLTR}} \tag{5.36}$$

$$S' = c * \mu_{DLTR} \tag{5.37}$$

where c is a positive value and is a function of the CV.

In the base stock policy, if we set $\sigma_{DLTR} = \frac{(c-1)\mu_{DLTR}}{z_{SL}}$, then from Equation (5.35), we get

$S = \mu_{DLTR} + z_{SL}\frac{(c-1)\mu_{DLTR}}{z_{SL}} = c * \mu_{DLTR}$

Therefore, the base stock policy becomes the modified base stock policy under this special case and there is no need to specify a service level criterion. If CV is low (i.e., less than 10%), then c takes the value 1 and when CV is high, then c is varied and the value of c that yields the least total operating cost is chosen.

5.2.3. Weighted Mean-Variance Policy

This rule is based on weighted moving average technique. The ordering policy is developed considering the weighted average of the platelet demand over several periods. The most recent demand is given the highest weight and the weights gradually decrease for older platelet demands. If the last n weeks of demand are considered for determining the order policy and t is the current day, then the weighted mean of the most recent demands, denoted by μ_t, is computed using Equation (5.38).

$$\mu_t = \left(\frac{u_n}{7}\right) * (d_{t-1} + d_{t-2} + \cdots + d_{t-7}) + \left(\frac{u_{n-1}}{7}\right) * (d_{t-8} + d_{t-9} + \cdots + d_{t-14}) + \cdots + \left(\frac{u_1}{7}\right) * \left(d_{(n-1)*7+1} + d_{(n-1)*7+2} + \cdots + d_{n*7}\right) \tag{5.38}$$

$$u_n \geq u_{n-1} \geq \cdots \geq u_1$$

$$u_1 + u_2 + \cdots + u_n = 1$$

In Equation (5.38), d_t is the platelet demand on day t, u_1 is the weights assigned to the oldest moving average, and u_n is the weight assigned to the most recent moving average. The number of weeks for the moving average and their weights must be chosen by the decision maker

(DM). If the DM observes a trend in the demand data, then more weight can be given to the most recent demand. On the contrary, if the demand is stable, then $u_1 \cong u_2 \cong \cdots \cong u_{n-1} \cong u_n$.

If L and RP are the lead time and review periods respectively and IP_t is the inventory position at the end of day t considering the outdated platelets units, then the units ordered to the blood center by the hospital at the end of day t is given by Equation (5.39).

$$Q_t = (L + RP)\mu_t + k\sqrt{L + RP}\sigma_t - IP_t \tag{5.39}$$

where k is a positive integer and σ_t^2 is the weighted variance of the past n weeks' demand, which is calculated using Equation (5.40).

$$\sigma_t^2 = [\left(\frac{u_n}{7}\right) * (d_{t-1}^2 + d_{t-2}^2 + \cdots + d_{t-7}^2) + \left(\frac{u_{n-1}}{7}\right) * (d_{t-8}^2 + d_{t-9}^2 + \cdots + d_{t-14}^2) + \cdots + \left(\frac{u_1}{7}\right) * \left(d_{(n-1)*7+1}^2 + d_{(n-1)*7+2}^2 + \cdots + d_{n*7}^2\right)] - \mu_t^2 \tag{5.40}$$

5.2.4. Last Value Policy

This policy is based on the concept of last value method for forecasting. Under this ordering policy, the total units ordered at the end of day t will be equal to the sum of the demand during day t and the prior demands during lead time plus review period. Therefore, the total units ordered by the hospital at the end of day t is given by Equation (5.41).

$$Q_t = \sum_{i=t-(LT+RP)}^{t} d_i \tag{5.41}$$

For example, if LT = RP = 1, then $Q_t = d_t + d_{t-1} + d_{t-2}$

The main advantage of the weighted mean-variance and last value policies is that they take into consideration increases in platelet demand over time. It has been reported that there has been an increase of nearly 4% of blood demand each year (Borkent-Raven et al., 2010). Therefore, it is expected that developing ordering policies considering the trend in demand will result in less shortage.

5.3. Results and Analysis

The stochastic programming models are coded using C++ and solved using IBM CPLEX®12.4.0.0 optimizer on a computer with 8GB RAM, Intel i5 2.50 GHz processor. The four heuristic ordering policies are coded in Microsoft *Visual C++ 6.0* Professional. To illustrate the performance of the proposed stochastic programming and heuristic models, five performance measures are considered; Units Held in Inventory, Units Shortage, Units Outdated, and Expected Total Cost. The ordering policies, obtained by the two stochastic programming models and the four heuristic rules, are compared for the same demand patterns using real data for platelet demand.

5.3.1. Input Data

In this section, the data used for illustrating the stochastic programming and heuristic models are discussed.

Demand Distribution

The daily platelet demand data reported by Tetteh (2008) for a New York hospital for 122 days is fitted to a probability distribution and for each day, platelet demand is generated from that distribution. The parameters of the daily demand follow a normal distribution with mean 200 and standard deviation 32.

Shelf life of Arriving Platelets

Based on our interaction with the pathologist and technicians at a Regional Medical Center (RMC) in Pennsylvania, USA, we found that hospitals receive platelets with varying shelf life. Hence, we collected data for 72 days of incoming platelet at the RMC and obtained the distribution of the shelf life of arriving platelets as given in Table 5.1.

Table 5.1: Distribution of Shelf Life of Arriving Platelets

Shelf life (i)	Probability that an arriving platelet has a shelf life of i days
1	0.3
2	0.2
3	0.5

(Note: Platelet with shelf life of 3 days are fresh and the youngest)

In most medical centers, the inventory position is reviewed at the end of each day and orders are placed to the blood center in the evening daily and received at the beginning of the next day. Therefore, the lead time (L) is assumed to be 1 day and the review period (RP) is also 1 day. However, the decision maker can vary the lead time and review period in the models depending upon the hospital's ordering practice. When RP = 1, the order-up-to-level policy is known as the base stock policy in the literature. Hence, we will refer to Policies 1 and 2 as Base Stock and Modified Base Stock Policies respectively in this section.

Cost Settings

Most of the cost parameters (fixed cost and variable purchasing cost) are obtained from the RMC at Pennsylvania, USA. The inventory holding cost (IHC) is calculated based on the cost of storing platelets in the agitator and the electricity cost. However, IHC must include the working capital tied up in inventory because, platelets are very expensive. Therefore, in this Chapter, IHC is taken as 20% of the purchasing cost. The shortage is considered five times the variable

purchasing cost and outdating costs is taken as the purchasing cost based on the ratios given in the literature (Hill, 2011; Haijema, 2013). Table 5.2 summarizes the cost data used for the analysis.

Table 5.2: Cost Parameters

Cost Parameter	Value	Units
Fixed Cost of Procurement (FCP)	225	$/shipment
Inventory Holding Cost (IHC)	130	$/unit/day
Variable Purchasing Cost (VPC)	650	$/unit
Shortage Cost (SC)	3250	$/unit
Outdating Cost (OC)	650	$/unit

Heuristic Input Parameters

The input parameters for each heuristic ordering policy are varied and the parameter values that result in the least expected total cost for the base setting is given in Table 5.3. Also, it is to be noted that the platelet demand data under consideration is observed to be stable and the variation of weights did not significantly impact the performance measures. Therefore, in the weighted mean-variance method, equal weights are chosen.

Table 5.3: Heuristic Input Parameters

Parameter	Policy	Value
Service Level (SL)	Base stock policy	99%
c	Modified base stock policy	18.75
n	Weighted mean-variance policy	4
$u_1 = u_2 = \cdots = u_{n-1} = u_n$	Weighted mean-variance policy	$\frac{1}{4}$
k	Weighted mean-variance policy	3
Lead Time (L)	All policies	1 day
Review Period (RP)	All policies	1 day

5.3.2. Comparison of the Stochastic Programming Models and Heuristic Methods

As discussed in Section 5.1.3, the stochastic programming models were able to run efficiently upto 35 scenarios for a time horizon of 30 days. For the same 35 demand scenarios, the expected units ordered under the stochastic programming models (SP1 and SP2) and the four heuristic policies (base stock (BS), modified base stock (MBS), weighted mean-variance (WMV) and last value method (LVM)) for each day are obtained, and the results are compared in Table 5.4. Each demand scenario is considered to be equally likely in the stochastic programming

models. For the heuristic methods, each order policy is simulated for 30 days using the same demand scenarios. The expected values of the performance measures are computed assuming again that each demand scenario is equally likely. However, the probability of occurrence of each demand scenario can be varied based on the decision maker's preference and the expected performance measures can be computed accordingly.

Table 5.4: Comparison of Ordering Policies across Stochastic Programming and Heuristic Models (time horizon T=30 days and demand scenarios ω=35)

Policy	Days									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
SP1	202	230	230	240	210	220	230	180	200	220
SP2	203	226	250	215	200	200	198	209	203	210
BS	201	226	200	203	202	206	203	208	203	209
MBS	201	229	200	204	202	206	203	208	203	209
WMV	204	218	199	197	207	204	194	199	204	195
LVM	201	202	199	202	201	204	202	207	201	208
	11	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
SP1	210	200	220	180	210	200	210	240	200	180
SP2	200	205	199	203	199	208	197	203	204	204
BS	204	205	198	200	203	208	199	200	195	203
MBS	204	205	198	200	203	208	199	200	195	203
WMV	205	206	202	201	200	213	205	205	201	198
LVM	202	204	197	198	201	206	198	198	194	201
	21	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
SP1	230	190	220	220	200	210	200	200	220	-
SP2	195	214	199	204	209	201	199	211	189	-
BS	201	199	197	211	211	202	199	209	194	-
MBS	201	199	197	211	211	202	199	209	194	-
WMV	189	200	198	202	198	195	200	205	208	-
LVM	199	198	196	210	210	201	198	208	192	-

From Table 5.4, it can be seen that the platelets are ordered daily, and their values are around the mean demand of 200 units. The units ordered under SP1 is more than those of SP2 for nearly 70% of the days, because the units purchased under SP1 remains the same across all the scenarios and the solver tries to order units such that the shortages across all the scenarios are minimized. However, for all the other methods, the units purchased vary by scenario. It can also be observed that the average units ordered per scenario is almost the same for the base stock and modified base stock policies. Since the finite time horizon period is only for 30 days, no units are ordered at the end of 30^{th} day to avoid purchasing cost.

The average values of the performance measures, using the stochastic programming models (SP1 and SP2) and the four heuristic approaches, are given in Table 5.5, including the total "cost-gaps" from the optimal policies of SP1 and SP2. If $PM_{m,t}^{\omega}$ is the value of the performance measure m, on day t, under scenario ω, then the average performance measure, APM_m, is computed using Equation (5.42).

Average value of the performance measure m, $APM_m = \sum_{\omega=1}^{\Omega} \sum_{t=1}^{T} \frac{PM_{m,t}^{\omega}}{\Omega * T}, \forall m$ (5.42)

Table 5.5: Average Values of Performance Measures for Stochastic Programming and Heuristic Policies (Ω=35, T=30)

Policy	**Average Performance Measures**						
	Units Shortage	Units Outdated	Inventory Units	Units Purchased	Total Cost ($)	Gap from SP1	Gap from SP2
SP1	0	9	48	205	$141,969	-	6.22%
SP2	1	2	68	185	$133,656	-5.86%	-
BS	8	3	316	201	$174,204	22.71%	30.34%
MBS	1	1	316	203	$174,089	22.62%	30.25%
WMV	0	1	292	198	$167,572	18.03%	25.38%
LVM	1	2	316	202	$173,950	22.53%	30.15%

Table 5.5 gives the comparison of the performance measures using SP1, SP2 and the four heuristic policies. It can be observed that the units purchased is more under SP1 resulting in more outdating. Shortage is more under SP2 because fewer units are purchased. The total expected cost of SP2 is less than that of SP1 by more than 6%. In other words, (s, S) policy gives the lowest expected total cost! After evaluating the four heuristics, we found that for small sized problems, weighted mean-variance policy performs the best overall. In the weighted mean-variance policy, the units outdated and the shortage are the least; in fact, even lower than those obtained using the stochastic programming models. This can be explained by the fact that the objectives of the stochastic programming models are to minimize the expected total cost. Hence, it is not necessary that each performance measure obtained must be the least.

5.3.3. Comparison of Heuristic Ordering Policies for Larger Problems

To further study the effectiveness of the four heuristic rules, they are simulated for larger problems with 100 demand scenarios and a time horizon of 500 days. The average values of the daily performance measures of each ordering policy is presented in Table 5.6. From Table 5.6, it

can be seen that no single policy is superior across all performance measures. For example, units held in inventory, units purchased and total cost using last value policy are less compared to those of the base stock policy; however, units shortage and units outdated are more compared to the base stock policy. It is to be noted that the weighted mean-variance policy performs the best for the expected total cost measure for both small and large-sized problems. Also, modified base stock rule performs the best for units shortage measure. Hence, the decision maker (DM) has to look at the tradeoff among the measures and choose the rule that works best for the hospital. For example, if the hospital's highest priority is to minimize the total operating cost, then weighted mean-variance policy should be used. On the other hand, last value policy works best if minimizing inventory is given the highest priority.

Table 5.6: Average Values of Performance Measures for Larger Problems (Ω=100, T=500)

Policy	**Average Performance Measures**				
	Units Shortage	Units Outdated	Inventory Units	Units Purchased	Total Cost ($)
Base Stock (BS)	0.11	0.07	273	207	$170,561
Modified Base Stock (MBS)	0.04	0.09	299	201	$169,913
Weighted Mean-Variance (WMV)	0.07	0.10	290	201	$168,568
Last Value Method (LVM)	1.42	0.13	252	202	$168,718

5.4. Sensitivity Analysis

Sensitivity analysis is performed to evaluate the effectiveness of the heuristic rules due to changes in the input data. Coefficient of variation of demand, the shelf life of arriving platelets and cost settings are varied from those used in the base setting (Tables 5.1, 5.2 and 5.3 in Section 5.3.1).

5.4.1. Change in Coefficient of Variation (CV) of Demand

Figure 5.1 shows the change in units purchased when the coefficient of variation increases. The units purchased increases significantly under the base stock and weighted mean-variance policy, because, the variation in the demand is captured to a greater extent, while determining the order policy. The change in the units purchased, as CV increases, is insignificant for modified base stock and last value policies. The impact of CV on units held in inventory is given in Figure 5.2. Due to the increase in the number of units purchased with the increase in CV, the units in inventory increase significantly for base-stock and weighted mean-variance policies. It can also be observed

that the performance of weighted mean-variance policy decreases with the increase in CV. When the CV is less than 30%, the average units held in inventory is least under last value policy and becomes the second best performer when CV is greater than 30%.

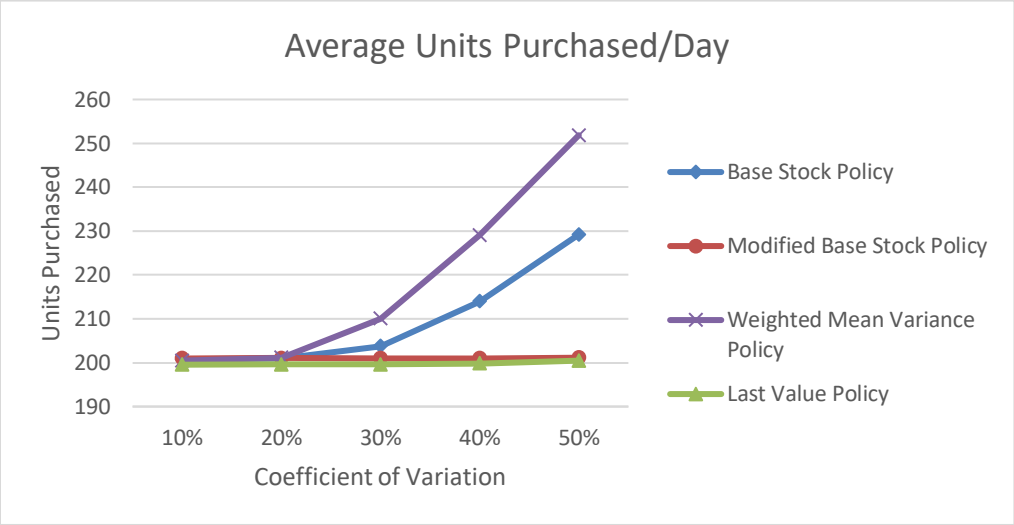


Figure 5.1: Impact of CV on Platelets Purchased

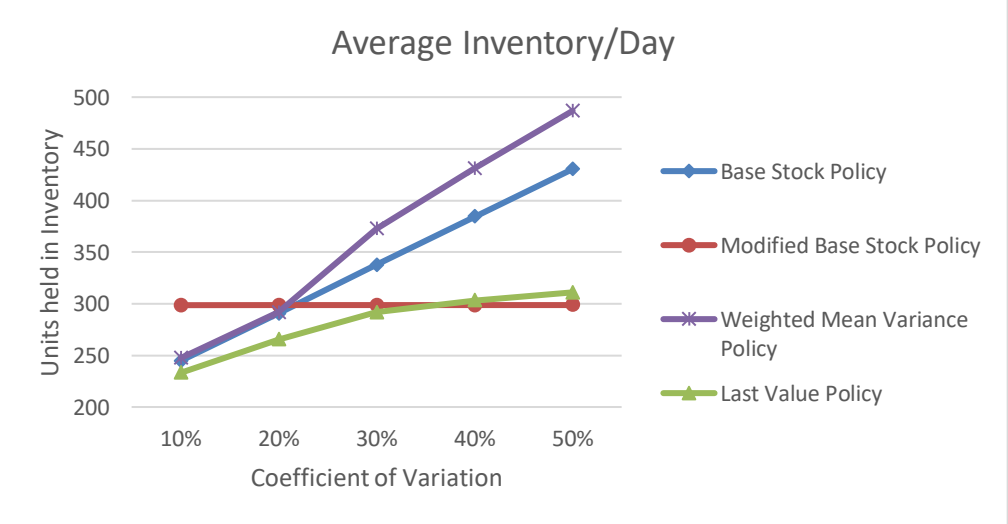


Figure 5.2: Impact of CV on Platelets Held in Inventory

Figure 5.3 shows the units outdated for various rules, as a function of CV. The units outdated increases for all the rules as CV increases. As CV increases, the variation in the platelet demand increases and due to the short shelf life of platelets, more units are outdated. Due to the significant increase in the units purchased under the base stock and weighted mean-variance policies, the average number of units outdated is more for these rules compared to the other policies. The units shortage for all the rules due to change in CV are given in Figure 5.4. The units

shortage is less for base stock and weighted mean-variance policies, and the increase in units shortage with the increase in CV is also very insignificant. This happens because the excess units purchased under these rules compensates for the units outdated and still achieve a high service level. All the other rules incur more shortages as CV increases.

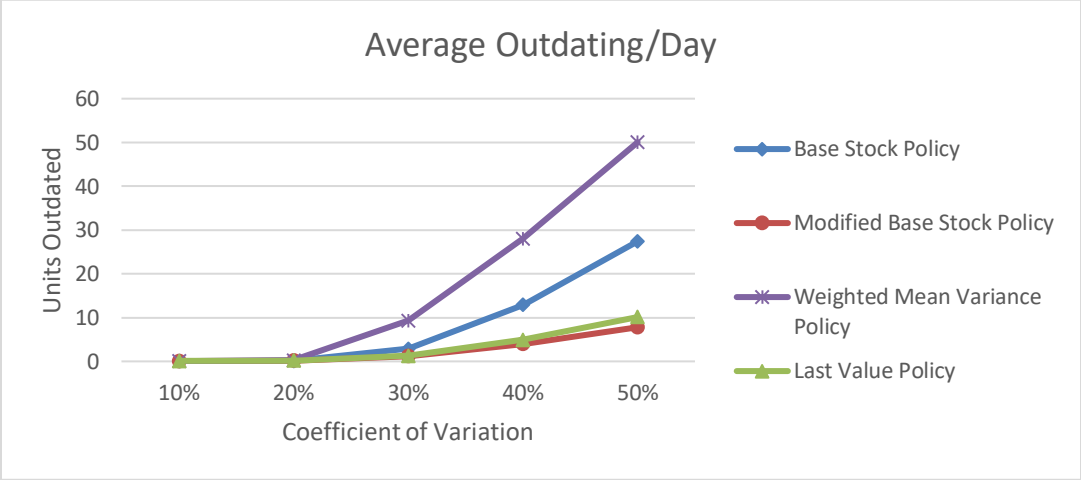


Figure 5.3: Impact of CV on Platelets Outdated

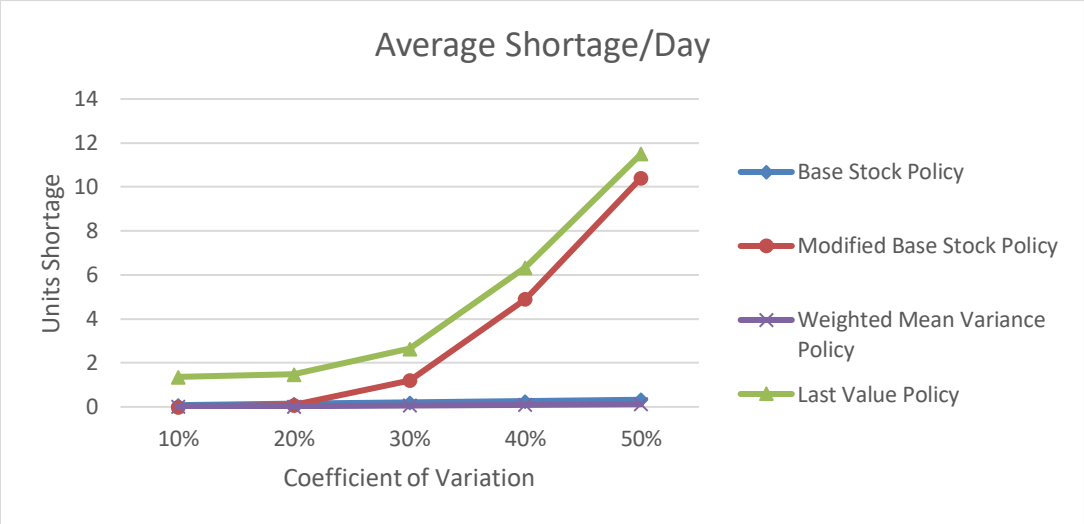


Figure 5.4: Impact of CV on Platelets Shortage

Based on the expected daily cost shown in Figure 5.5, it is evident that the total cost increases as the CV increases for all cost settings, due to the increase in shortage and outdating. Last value policy performs the second best across all CV change. When CV is 10% and 20%, weighted mean-variance policy performs the best for cost performance measure and when CV is 30%, 40% and 50%, modified base stock policy performs the best. In other words, if hospital's

demand pattern indicates a low variation in demand, then the hospital may use weighted mean-variance policy and when the variation is high, the modified base stock policy performs the best.

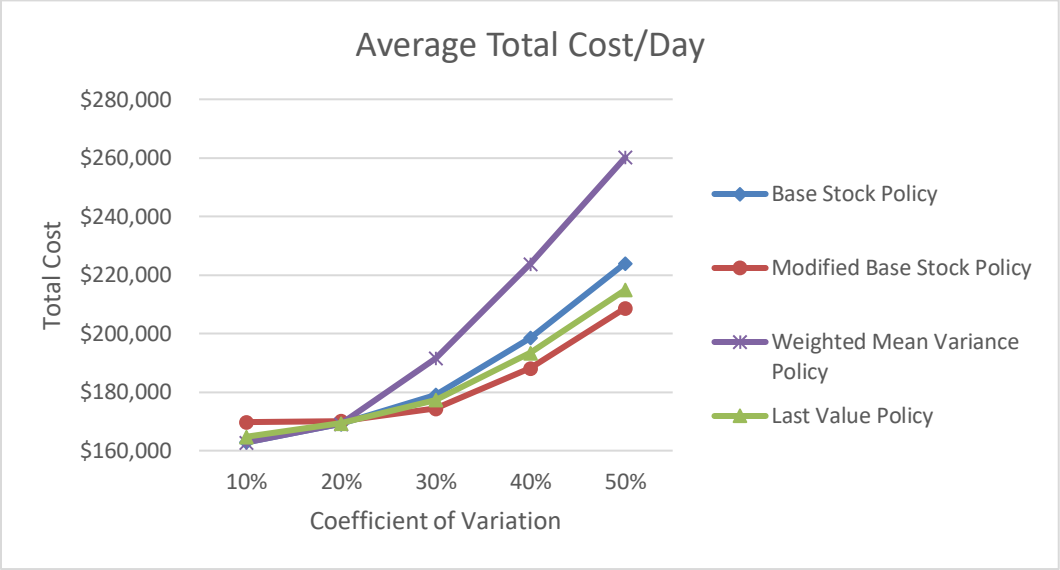


Figure 5.5: Impact of CV on the Expected Total Cost

5.4.2. Changes in the Shelf life of Arriving Platelets

Seven-shelf life settings, given in Table 5.7, are used to evaluate the heuristic rules. SL1 is the base setting given in Table 5.1. In shelf life settings 1 and 2 (SL1 and SL2), 50% of the incoming platelets are fresh and hence, less outdating is expected. In shelf life settings 2 and 3 (SL2 and SL3), more than 80% of the arriving platelets have a remaining life of 2 or 3 days. In shelf life settings 5 and 6 (SL5 and SL6), 50% of the arriving platelets have a remaining life of 1 day only and hence, more outdating is expected in these two scenarios. Shelf life setting 7 (SL7) indicates that all the platelets received are fresh. We shall discuss the impact of the shelf life settings on the performance measures.

Table 5.7: Shelf Life Settings

Shelf life setting	Probability of platelets arriving with a shelf life of 1 day	Probability of platelets arriving with a shelf life of 2 days	Probability of platelets arriving platelets with a shelf life of 3 days
SL1 (Base)	0.3	0.2	0.5
SL2	0.2	0.3	0.5
SL3	0.2	0.5	0.3
SL4	0.3	0.5	0.2
SL5	0.5	0.2	0.3
SL6	0.5	0.3	0.2
SL7	0	0	1

The average daily units purchased for the various shelf life settings is almost the same across all the shelf life settings. This is because, when calculating the order quantity at the end of each day, only the inventory position, mean and the standard deviation of the demand, are considered and they do not take into account the probability of shelf life of incoming platelets. Figure 5.6 shows the units held in inventory for the various shelf life settings. For all the rules, the units held in inventory is the highest for SL7 compared to other settings. This is because, in SL7, all units arriving at the hospital are fresh and hence platelet outdating is less and more units are held in inventory. The total units held in inventory under SL3 is greater than SL4 because 30% of the platelets arriving are fresh in the former setting. Even though in both SL5 and SL6, 50% of the arriving platelets have a remaining life of 1 day, SL5 has more units held in inventory for all the settings due to less outdating and also because 30% of platelets arriving are fresh in SL5. In addition, it is noted that in most cases the total units held in inventory for each setting is the least for the last value rule, followed by the base stock rule.

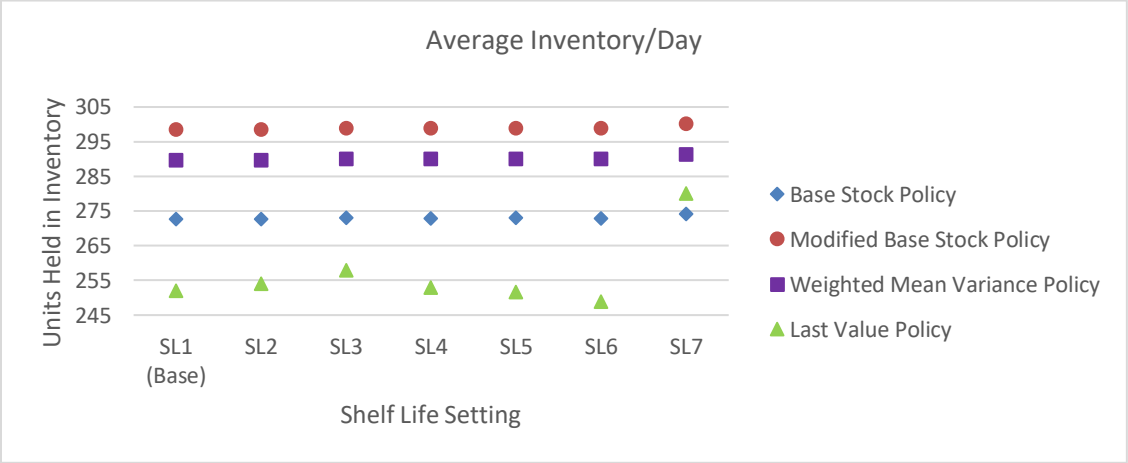


Figure 5.6: Change in Platelet Inventory for Various Shelf Life Settings

Figure 5.7 shows the impact of the shelf life of platelets on units outdated. For setting SL1, the units outdated is greater than those of SL2 since, in the former setting, 30% of the arriving platelets have a remaining shelf life of 1 day. In setting SL3, 70% of the arriving platelets have a shelf life of 2 days or less and hence, there is more outdating in SL3 than SL2. In SL4, 80% of the arriving platelets have a shelf life of 2 days or less leading to a greater wastage compared to SL3. A similar explanation can be given to justify why more units are outdated in SL6 compared to SL5. Outdating is the least for SL7 since all the platelets arriving are fresh. Outdated is the highest

for SL6 because 80% of the arriving platelets are not fresh. We can see that the base stock rule performs the best in most settings for this performance measure.

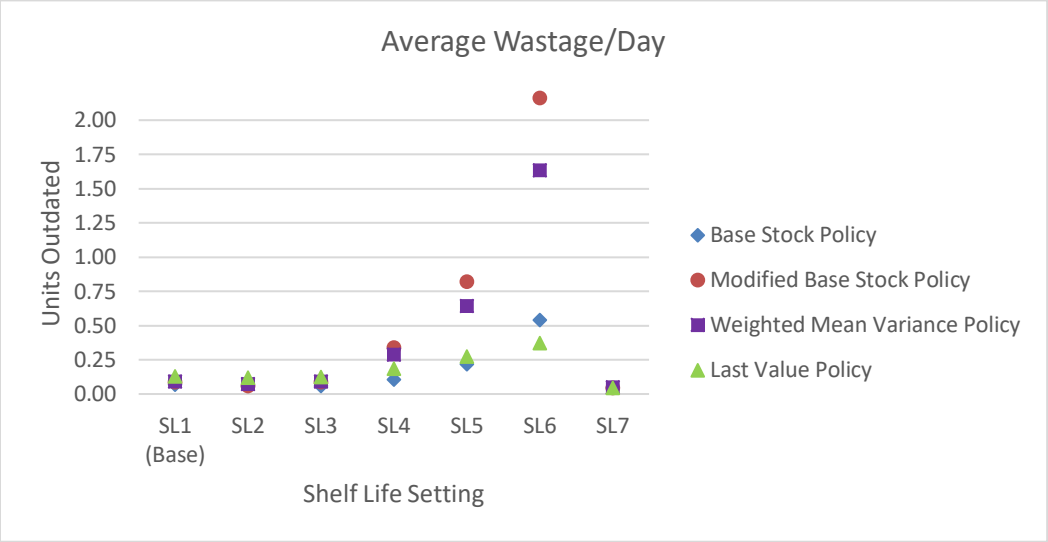


Figure 5.7: Change in Platelet Outdated for Various Shelf Life Settings

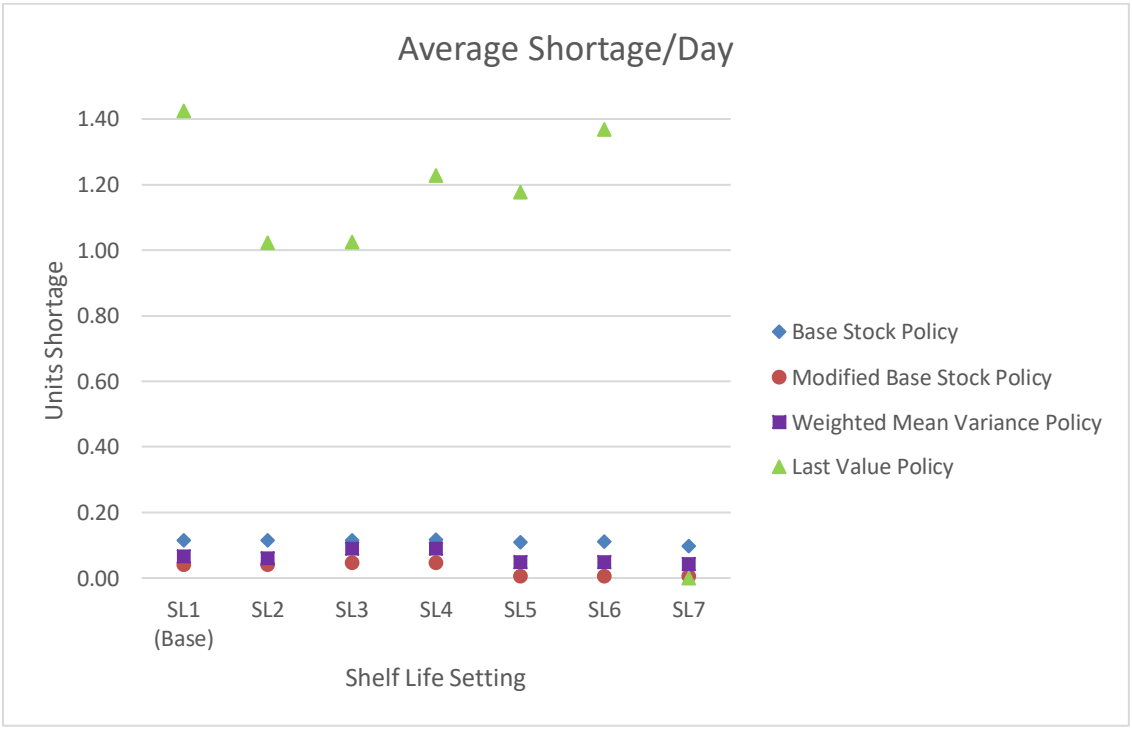


Figure 5.8: Change in Platelet Shortage for Various Shelf Life Settings

Figure 5.8 shows platelet shortages under various shelf life settings for the four rules. For all the rules, the shortage is the least for SL7, since more platelets are held in inventory, which leads to an increase in the demand fulfillment rate. Shortages in SL1 is more than SL2 across all

the rules because, in the latter setting, relatively fresh platelets are arriving at the hospitals and hence, it can fulfill the demand for more days compared to the fulfillment rate of the former. For the same reason, the total units short under SL3 is less than that under SL4. Since the units held in inventory for SL5 is more than SL6, the total units short is less for SL5. For most cases, modified base stock rule yields the least shortage compared to other policies.

Figure 5.9 shows the daily expected total cost obtained for the 4 heuristic policies. The total cost under SL4 is greater than that of SL3, since the units outdated and short are more in the former. The total cost is more under SL6 than that of SL5 for a similar reason. Even though there is less outdating and shortage under SL7, due to the excess units held in inventory, it does not guarantee the lowest total cost across the different shelf life settings. In settings SL1 (base setting), weighted mean-variance policy performs the best. From Figure 5.9, it can be concluded that if 80% of the arriving platelets have a shelf life of 2 or more days, then modified base stock rule performs best. For all the other settings, base stock policy performs the best. Therefore, the decision maker can choose a rule based on the pattern of the shelf life of incoming platelets.

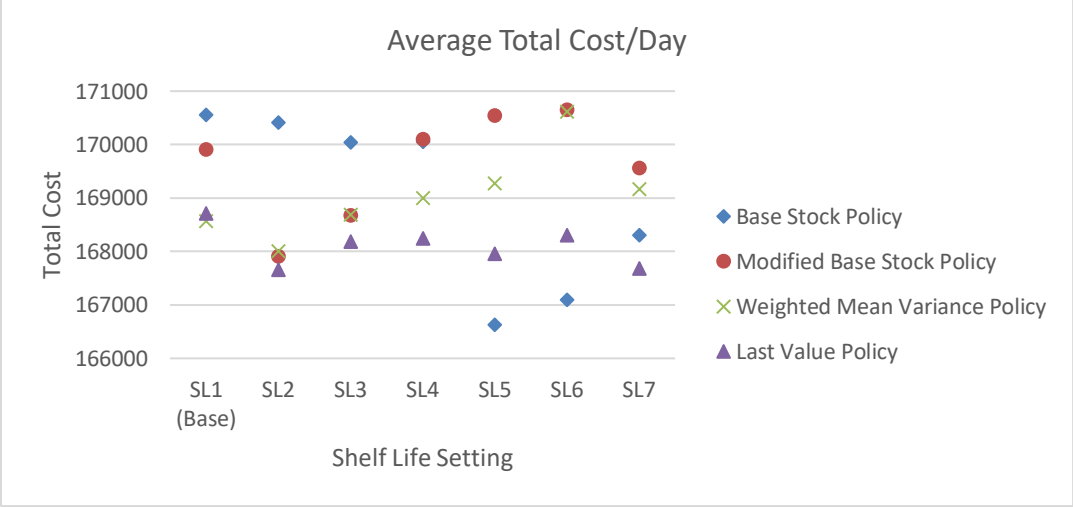


Figure 5.9: Change in the Expected Cost for Various Shelf Life Settings

5.4.3. Changes in Cost Settings

Table 5.8 summarizes the six cost settings used for comparing the 4 policies. Cost setting 1 (CS1) is the base setting for the cost parameters used in Section 5.3.1 (Table 5.2). The other 5 cost settings represent doubling of the values of fixed cost of procurement (FCP), inventory holding cost (IHC), variable purchasing cost (VPC), shortage cost (SC), and outdating cost (OC),

one at a time, compared to CS1 respectively. Thus, in each cost setting, only one of the cost parameters is doubled, while the others are maintained at their base values.

Table 5.8: Cost Settings

Setting	FCP ($/shipment)	IHC ($/unit/day)	VPC ($/unit)	SC ($/unit)	OC ($/unit)
CS1 (Base)	225	130	650	3250	650
CS2	450	130	650	3250	650
CS3	225	260	650	3250	650
CS4	225	130	1300	3250	650
CS5	225	130	650	6500	650
CS6	225	130	650	3250	1300

Table 5.9 details the daily expected total cost for various cost settings. For CS2, CS5 and CS6, the expected cost is not substantially different from that obtained under the base setting (CS1). In all cost settings, except for CS3, weighted mean-variance policy performs the best. As observed from the previous analyses, it is evident that the last value method results in reduced inventory and in CS3, when inventory holding cost is twice the base setting inventory cost, the last value method performs the best. In general, we can also see that the weighted mean-variance rule performs better than modified base stock but the differences are quite small.

Table 5.9: Impact of Cost Settings on Daily Expected Cost

Cost Setting	Base Stock Policy	Modified Base Stock Policy	Weighted Mean-Variance Policy	Last Value Policy	Best Policy
CS1 (Base)	$170,561	$169,913	$168,568	$168,718	Weighted Mean-Variance
CS2	$170,786	$170,138	$168,793	$168,943	Weighted Mean-Variance
CS3	$206,005	$208,732	$206,228	$201,475	Last Value Method
CS4	$305,034	$300,595	$298,972	$299,740	Weighted Mean-Variance
CS5	$170,933	$170,045	$168,786	$173,347	Weighted Mean-Variance
CS6	$170,608	$169,970	$168,630	$168,805	Weighted Mean-Variance

In the base setting, the units purchased and total cost are the least under weighted mean-variance method, while, the shortage is the least under the modified base stock policy and units outdating is the least under the base stock policy (see Table 5.6). Therefore, the cost per unit for

shortage and outdating are varied to find the threshold values at which these policies outperform the weighted mean-variance method. When the shortage cost is set 17 times the base shortage cost, then the modified base stock policy yields a less total cost compared to that under the weighted mean-variance method. Similarly, when the outdating cost is set 200 times the base outdating cost, then the base stock policy performs better than the weighted mean-variance method. This clearly indicates that the performance of weighted mean-variance method is good.

5.5 Managerial Implications

The stochastic programming models proposed in this Chapter will determine the optimal solutions leading to less wastage and shortage. However, their implementations at the hospitals require higher knowledge and skills of the hospital staff. In addition, the computational complexity of the stochastic programming models increases with the increase in time horizon and scenarios. On the other hand, heuristic methods produce near optimal ordering policies in minimal time. Unlike the stochastic programming models that require an optimization software for obtaining a solution, such as, CPLEX to solve complex problems with large variables, the heuristic policies proposed in this study can be coded in an Excel® spread sheet.

An implementation guide to the heuristic policies for hospital use is presented in Table 5.10. The weighted-mean variance (WMV) policy requires the collection of several weeks of demand and the order quantity must be constantly updated with the most recent demand data. Also, explaining the method to compute the order quantity and weights for each daily demand, makes this policy difficult to implement. Under the base stock (BS) and modified base stock (MBS) policies, the hospital administrator needs to know only the order-up-to level S. The value of S remains the same as long as the underlying demand distribution is the same. The optimization model for computing S does not require staff expertise. Also, the model has to be solved only once to determine the order-up-to level. However, the computation of the value of S requires several months of data to determine the underlying demand distribution. On the contrary, the last value method (LVM) only requires prior demand data covering the lead time and review period. The data requirement of the WMV policy is in between the base stock and LVM policies.

Table 5.10: Guide to the Ordering Policies for Hospital Implementation

Criteria	BS	MBS	WMV	LVM
Effort	Low	Low	High	Medium
Implementation	Easy	Easy	Difficult	Medium
Data required	Large	Large	Medium	Small
Staff Expertise	Low	Low	Medium	Medium

Other Managerial Guidelines

Based on the hospital setting, the hospital administrator can decide the appropriate ordering policy that best suits the hospital. We list the following suggestions for the various hospital settings.

- If the demand increases or decreases over time (i.e., if the observed demand has a trend), then the hospital may use the weighted mean-variance or last value ordering policies.
- If the hospital experiences low demand variation, then the weighted mean-variance policy is better. For high demand variation, modified base stock policy is the best performing rule.
- If the blood center is located far away from the hospital, then the cost of emergency procurement (i.e., shortage) would be very high. In such cases, base stock or modified base stock ordering policies would be better.
- If the hospital has limited storage capacity, then it would like to minimize the number of units held in inventory. Hence, last value policy will be the most suitable.
- If more than 80% of the platelets arriving at the hospital are fresh (i.e., have a shelf life of 2 or 3 days), then the modified base stock policy should be adopted.

Chapter 6 : Stochastic Inventory Models for Blood Supply Chain

In this chapter, the stochastic programming model using the (s, S) periodic review policy for hospital inventory management, which was discussed in Chapter 5, is extended to the entire blood supply chain. The formulation of the blood supply chain inventory management problem, with J hospitals and one blood center, as a stochastic programming model, is discussed in Section 6.1. Due to the computational complexity of the model with the increase in the number of scenarios and time horizon, a new genetic algorithm, called modified stochastic genetic algorithm (MSGA) is proposed for larger problems and is discussed in Section 6.2. For smaller problems, the performance of the proposed MSGA is compared with the optimal solution obtained by solving the stochastic programming model directly. This is discussed in Section 6.3.4. For larger problems, the proposed MSGA is also compared against the existing genetic algorithm in the literature and the results are discussed in Section 6.3.5. The coefficient of variation of demand and cost parameters are varied as a part of a sensitivity analysis. Their impacts are analyzed on the performance measures and the best order policy is identified for each supply chain stage. The results are presented in Section 6.4 and Conclusions are presented in Section 6.5.

6.1. Stochastic Integer Programming Model using (s, S) Policy for Blood Supply Chain

A blood supply chain configuration with one blood center and J hospitals is given in Figure 6.1. According to the HIPPA regulations, each hospital can receive blood only from a designated blood center and cannot share or procure blood from other hospitals.

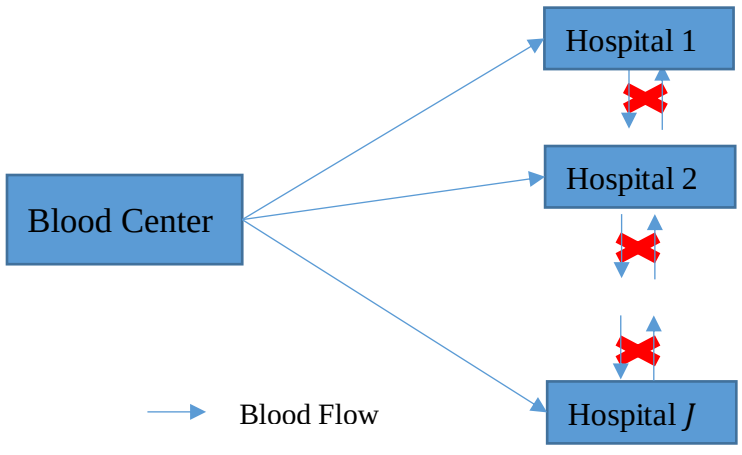


Figure 6.1: Blood Supply Chain with One Blood Center and J Hospitals

6.1.1. Demand Fulfillment at the Blood Center and Hospitals

Demand Fulfillment at the Blood Center on day t (Review period = 1 day)

- Begin with inventory of platelets with one-day and two-day shelf lives.
- Replenish inventory with new platelets arriving from the component lab with three-day shelf life.
- Receive regular demand from all the hospitals.
- Satisfy hospital demands in the following order:
  - Ship platelets to hospital j with one-day shelf life first provided hospital j's lead time is 0 days.
  - Next, ship platelets to hospital j with two-day shelf life (if necessary) provided hospital j's lead time is 0 or 1 day.
  - Finally, ship platelets to hospital j with three-day shelf life (if necessary).
- Receive emergency demand from all hospitals
  - Ship platelets to all hospitals placing emergency demand with one-day shelf life first, followed by two-day and three-day shelf life platelets if necessary.
- Review inventory at the end of the day and place orders for new platelets following (s, S) order policy.

Demand Fulfillment at the Hospital on day t (Review period = 1 day)

- Begin with inventory of platelets with one-day and two-day shelf lives
- Receive platelets from blood center with 1-, 2- and 3-day shelf lives
- Receive platelet demand
- Satisfy platelet demand at the hospital in the following order:
  - Use platelets with one-day shelf life first
  - If insufficient, use two-day shelf life next
  - Finally, 3-day shelf life
- Review inventory at the end of the day and place orders for new platelets following (s, S) order policy.

6.1.2. Model Notations

Model Parameters (known data)

i	Index for shelf life of platelets (i=1,2,3)
j	Index for hospital
ω	Index for scenarios (platelet demand patterns)
t	Index for day
J	Total number of hospitals (i.e., j=1, 2, 3, …, J)
Ω	Total number of scenarios (i.e., ω=1, 2, 3, …, Ω)
T	Time horizon in days (i.e., t=1, 2, 3, …, T)
$TCBSC$	Expected total cost incurred for the entire blood supply chain across the finite time horizon for all scenarios
p^{ω}	Probability of occurrence of scenario ω

Model Parameters associated with Hospital *j*

cH_j^f	Fixed cost of procuring platelets at hospital j ($/shipment)
cH_j^p	Platelet purchasing cost incurred by hospital j ($/unit)
cH_j^h	Inventory holding cost of platelets at hospital j ($/unit/day)
cH_j^{ex}	Cost of expired platelet at hospital j ($/unit)
cH_j^{sh}	Shortage cost at hospital j ($/unit) (Note: This is the cost of procuring one unit of platelet through emergency shipment from the blood center)
$d_{j,t}^{\omega}$	Platelet demand at hospital j for day t under scenario ω (units)
LTH_j	Procurement lead time at hospital j (days). This is the time between placing platelet orders to the blood center and receiving them. (Note: $LTH_j = 0,1$ or 2 only)
RH_j	Review period at hospital j (days)
in_j^i	Initial inventory with shelf life of i days for day 1 at hospital j

Model Parameters associated with the Blood Center

cBC^f	Fixed cost of procuring platelets at the blood center ($/shipment)
cBC^p	Platelet withdrawal and testing cost incurred by the blood center ($/unit)

cBC^h Inventory holding cost of platelet at the blood center ($/unit/day)

cBC^{ex} Cost of expired platelet at the blood center ($/unit)

cBC^{sh} Shortage cost ($/unit) (Note: This is the cost of procuring one unit of platelet through emergency shipment from other blood centers)

$LTBC$ Procurement lead time at the blood center (days). $LTBC$ = Time between placing platelet orders and receiving fresh platelets. It includes blood collection time plus testing time of 2 days.

RBC Review period at the blood center (days)

$inBC^i$ Initial inventory with shelf life of i days for day 1 at the blood center

Key Decision Variables (unknown)

Decision Variables associated with Hospital *j*

$QH_{j,t}^{\omega}$ Quantity of platelet units ordered at the end of day t, under scenario ω, by hospital j

$XH_{j,t,i}^{\omega}$ Platelet units received by hospital j from the blood center, at the beginning of day t, with a shelf life of i days, in scenario ω (note: maximum remaining shelf life of the arriving platelets is 3 days) (i=1,2,3)

$IH_{j,t,i}^{\omega}$ On-hand inventory of platelets at the beginning of day t, with shelf life of i days ($i = 1,2$), under scenario ω, at hospital j. Note: Since platelets have a maximum shelf life of 3 days when they arrive at the hospital, the on-hand inventory at the beginning of day t (carried over from day $t-1$) can have a maximum of 2 days shelf life.

$SHH_{j,t}^{\omega}$ Number of platelet units shortage at the end of day t, under scenario ω, at hospital j (these are procured through emergency shipment by the hospital from the blood center)

$EH_{j,t}^{\omega}$ Number of platelet units outdated (expired) at the end of day t, under scenario ω, at hospital j

$IPH_{j,t}^{\omega}$ Inventory position at the end of day t, in scenario ω, at hospital j

sH_j Re-order point at hospital j

SH_j Order-up-to-level at hospital j

$\Delta H_{j,t}^{\omega}$ — 1 if $IPH_{j,t}^{\omega} \leq sH_j$ (i.e., $\Delta H_{j,t}^{\omega} = 1$ if platelet units are ordered by hospital j to the blood center on day t under scenario ω)
0 otherwise

Key Decision Variables associated with the Blood Center

QBC_t^{ω} Quantity of units ordered by the blood center to the blood drives at the end of day t, under scenario ω. These units will be available at the blood center at the beginning of day $t + LTBC$ (where $LTBC$ is the lead time at the blood center which is the total time taken for blood collection and testing procedures)

XBC_t^{ω} Total platelet units arriving at the blood center from the component lab after completing the testing procedure at the beginning of day t, in scenario ω (Note: All platelets arriving at the blood center will be fresh and have a remaining life of 3 days)

$UBCH_{j,t,i}^{\omega}$ Platelets with shelf life of i days, shipped to hospital j, on day t (i =1,2,3)

$IBC_{t,i}^{\omega}$ On-hand inventory at the beginning of day t, with shelf life of i days, under scenario ω, at the blood center ($i = 1,2$). Note: Since platelets have a maximum shelf life of 3 days, on-hand inventory at the beginning of day t (carried over from day $t - 1$) can have a maximum of 2 days shelf life.

$SHBC_t^{\omega}$ Total Shortage incurred by the blood center at the end of day t, under scenario ω, due to the sum of regular and emergency demands placed by the hospitals to the blood center

EBC_t^{ω} Number of platelet units outdated (expired) at the end of day t, under scenario ω, at the blood center

$IPBC_t^{\omega}$ Inventory position at the end of day t, under scenario ω at the blood center

sBC Re-order point at the blood center

SBC Order-up-to level at the blood center

ΔBC_t^{ω} — 1if $IPBC_t^{\omega} \leq sBC$
0 otherwise

6.1.3. Sequence of Daily Events at the Hospitals and Blood Center

Sequence of daily events at hospital j, for scenario ω, day t: (Refer to Figure 6.2 also)

1. At the beginning of day t, hospital j receives platelet units, $XH^{\omega}_{j,t,i}$, with shelf life of i days, from the blood center. This was shipped from the blood center on day $t - LTH_j$.
2. Hospital receives platelet demand, $d^{\omega}_{j,t}$, on day t.
3. If the demand at hospital j is greater than the total on-hand inventory ($IH^{\omega}_{j,t,1} + IH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,1} + XH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,3}$), then the demand is partially fulfilled with the available on-hand inventory and the on-hand inventory is updated to 0. Shortages of $SHH^{\omega}_{j,t}$ units will be "special ordered" from the blood center and will be fulfilled by the blood center immediately. However, the hospital will incur a high cost for the emergency procurement.
4. If the demand at hospital j is less than the on-hand inventory, then the unutilized platelet units with a shelf life of 1 day are thrown away at the end of the day and incur an outdating cost. The remaining platelets (after discarding the outdated units) are carried over to the next day and the on-hand inventory is updated.
5. At the end of day $t(t = RH_j, 2RH_j, 3RH_j, ..)$, hospital j determines the inventory position $\left(IPH^{\omega}_{j,t}\right)$. If $IPH^{\omega}_{j,t}$ is less than re-order point sH_j, then platelets are ordered to raise the inventory level to SH_j (i.e., $QH^{\omega}_{j,t} = SH_j - IPH^{\omega}_{j,t}$). On the other hand, if $IPH^{\omega}_{j,t}$ is greater than sH_j, then no order is placed (i.e., $QH^{\omega}_{j,t} = 0$). The units ordered at the end of day t will be received by the hospital on the day after its lead time, $t + LTH_j$ (i.e., $\sum_i XH_{j,t+LTH_j,i} = QH^{\omega}_{j,t}$).

It is important to note that, for hospital j, both the reorder point and order-up-to level (sH_j, SH_j) at that hospital will remain the same for all scenarios across the planning horizon.

The sequence of events at the hospital is also illustrated in Figure 6.2.

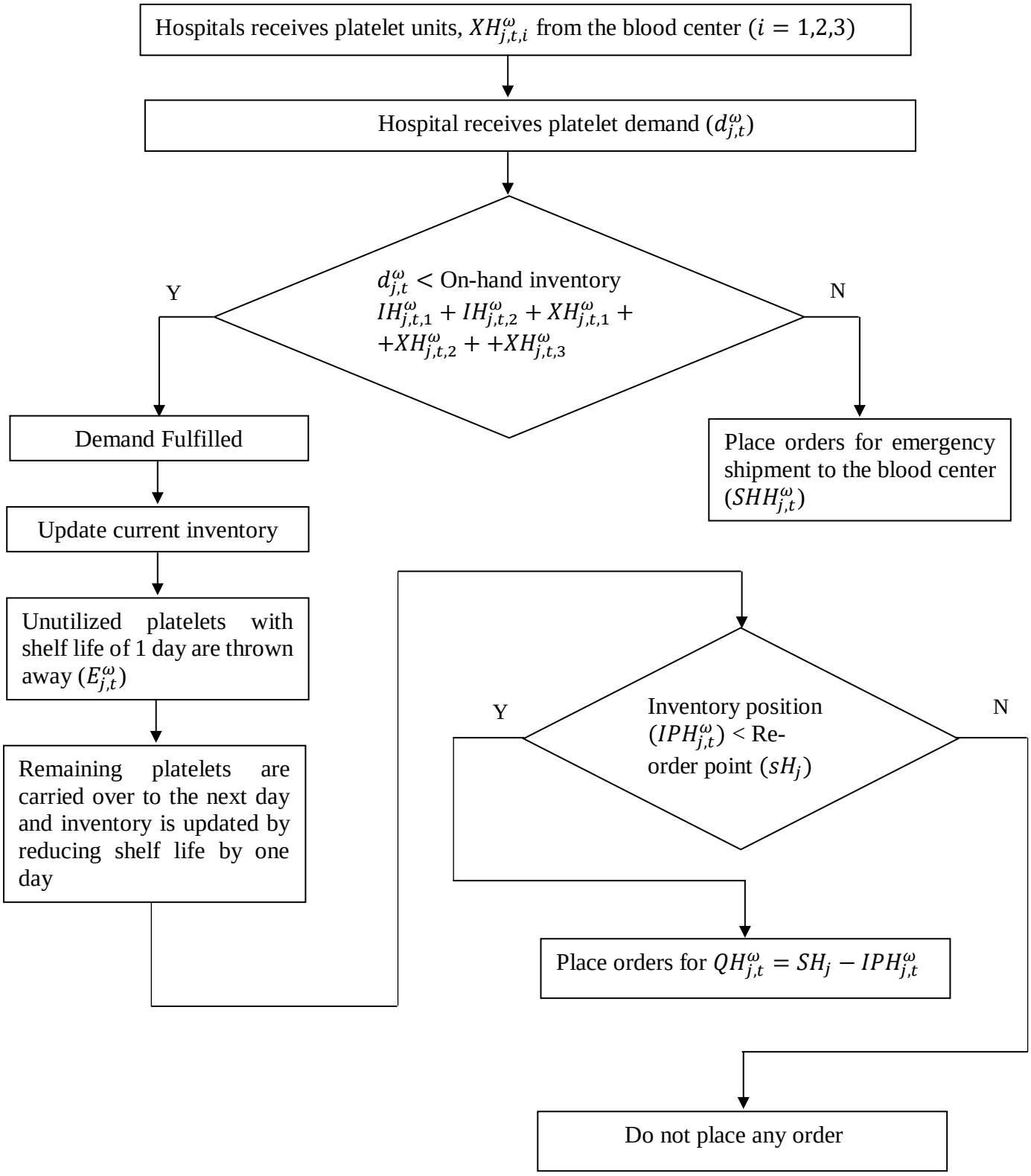
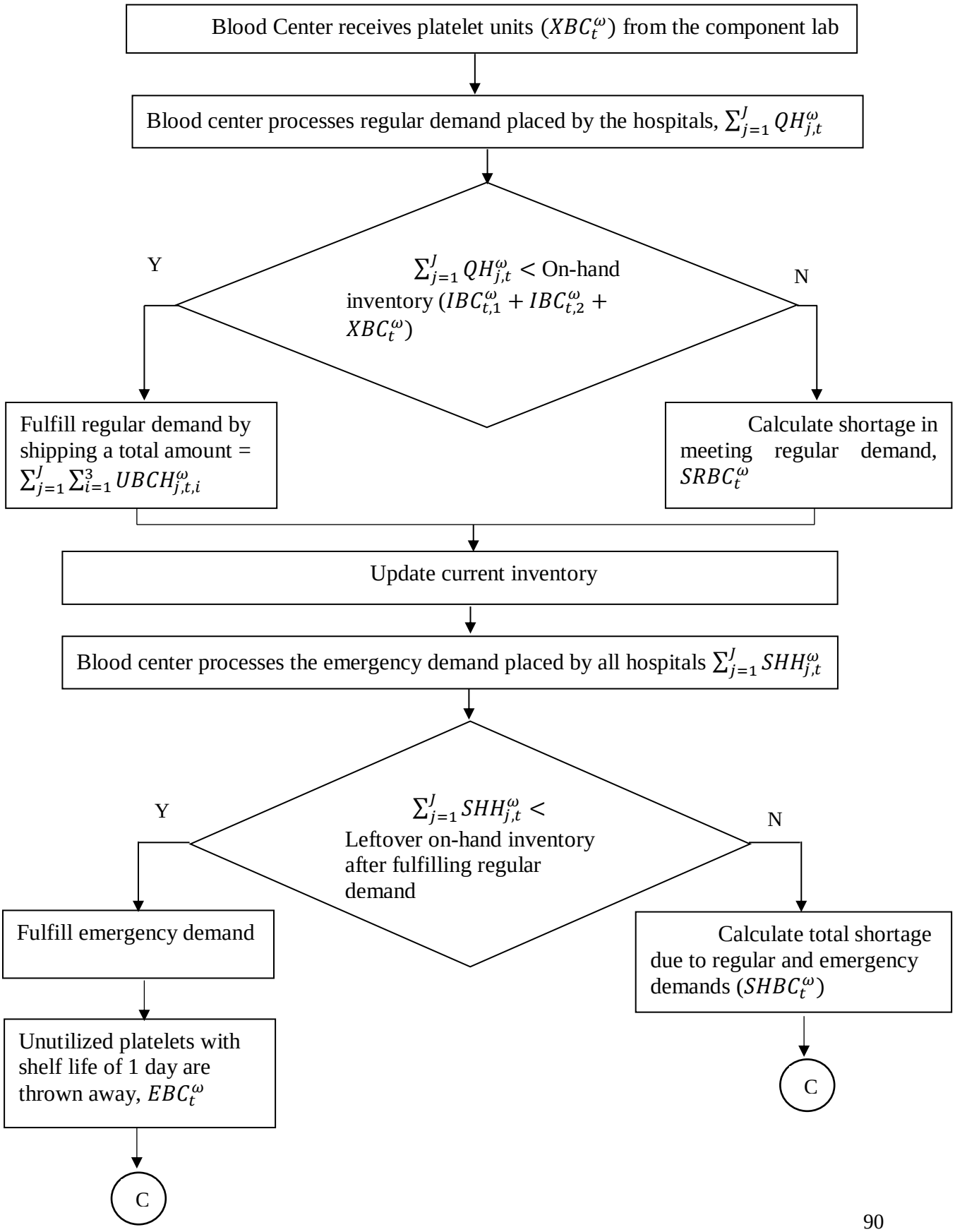


Figure 6.2: Sequence of Events at the Hospital

Sequence of daily events at the blood center, on day t, scenario ω: (Refer to Figure 6.3 also)

1. Fresh platelets with shelf life of 3 days (XBC_t^{ω}) arrive at the blood center from the component lab.
2. The blood center processes the demand that is placed by the hospitals ($\sum_j QH_{j,t}^{\omega}$). Note that this demand is referred to as the *regular demand*.
3. If the sum of the regular demand placed by the hospitals to the blood center is greater than the on-hand inventory, then it is partially fulfilled with the available on-hand inventory and the on-hand inventory is updated to 0. The unfulfilled demand units is procured from other blood centers through emergency procurement, incurring additional cost.
4. Recall that if there is a shortage at hospital j (i.e., if $SHH_{j,t}^{\omega} > 0$), then the hospital places a special order to the blood center and this has to be fulfilled by the blood center immediately. This demand is referred to as the *emergency demand*. We assume that the emergency demand will be fulfilled by the blood center, with the inventory that is available, after fulfilling the regular demand.
5. If the emergency demand is greater than the on-hand inventory at the blood center, then it is partially fulfilled with the available on-hand inventory and the on-hand inventory is updated to 0. The unfulfilled emergency demand units incur the corresponding shortage cost at the blood center and is also procured from other centers through emergency procurement.
6. If the sum of the regular and emergency demands placed by the hospitals are less than the on-hand inventory at the blood center, then the unutilized platelet units with remaining shelf life of 1 day are thrown away at the end of the day and incur outdating cost. The remaining platelets (after discarding the outdated units) are carried over to the next day and the on-hand inventory is updated.
7. At the end of day t ($t = RBC, 2RBC, 3RBC, \ldots$), blood center determines the inventory position ($IPBC_t^{\omega}$) and if $IPBC_t^{\omega}$ is less than re-order point sBC, then platelets are ordered to raise the inventory level to SBC (i.e., $QBC_t^{\omega} = SBC - IPBC_t^{\omega}$). On the other hand, if $IPBC_t^{\omega}$ is greater than the re-order point sBC, then no order is placed (i.e., $QBC_t^{\omega} = 0$). The units ordered at the end of day t is will be received by the blood center on the day after the lead time, $LTBC$, i.e., on day $(t + LTBC)$, hence $XBC_{t+LTBC}^{\omega} = QBC_t^{\omega}$).


Blood Center receives platelet units (XBC_t^{ω}) from the component lab
Blood center processes regular demand placed by the hospitals, $\sum_{j=1}^{J} QH_{j,t}^{\omega}$
$\sum_{j=1}^{J} QH_{j,t}^{\omega}$ < On-hand inventory ($IBC_{t,1}^{\omega} + IBC_{t,2}^{\omega} + XBC_t^{\omega}$)
Y
N
Fulfill regular demand by shipping a total amount = $\sum_{j=1}^{J}\sum_{i=1}^{3} UBCH_{j,t,i}^{\omega}$
Calculate shortage in meeting regular demand, $SRBC_t^{\omega}$
Update current inventory
Blood center processes the emergency demand placed by all hospitals $\sum_{j=1}^{J} SHH_{j,t}^{\omega}$
$\sum_{j=1}^{J} SHH_{j,t}^{\omega}$ < Leftover on-hand inventory after fulfilling regular demand
Y
N
Fulfill emergency demand
Calculate total shortage due to regular and emergency demands ($SHBC_t^{\omega}$)
Unutilized platelets with shelf life of 1 day are thrown away, EBC_t^{ω}
C
C

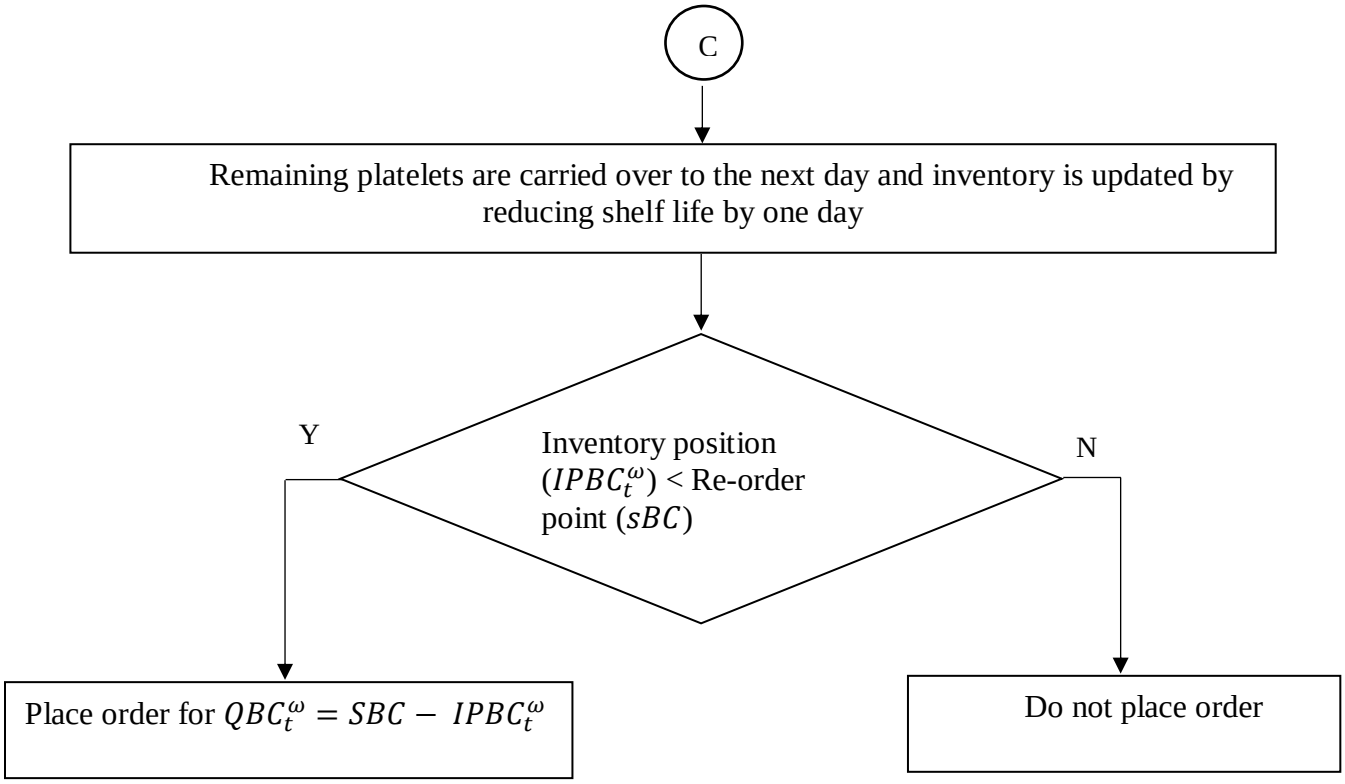


Figure 6.3: Sequence of Events at the Blood Center

Note: At the blood center, both the re-order point and the order up-to-level (sBC, SBC) are the same for all scenarios across the planning horizon.

The sequence of events at the blood center is given in Figure 6.3.

6.1.4 Blood Supply Chain Model Formulation

The blood supply chain model has the following constraints:

(1)Units Received by the Hospital from the Blood Center

The total units received by the hospital from the blood center with shelf life of i days ($XH_{j,t,i}^{\omega}$), will be equal to the units shipped from the blood center on day $t - LTH_j$, with shelf life of $i + LTH_j$ days is given using Equation (6.1). (Note: LTH_j =0,1 or 2 days)

$$XH_{j,t,i}^{\omega} = UBCH_{j,t-LTH_j,i+LTH_j}^{\omega} \qquad \forall t > LTH_j \text{ and } i + LTH_j \leq 3 \qquad (6.1)$$

$$XH_{j,t,i}^{\omega} = 0 \qquad \text{Otherwise} \qquad (6.2)$$

If $LTH_j = 0$ days (negligible lead time), then from Equation (6.1) we have:

- $XH_{j,t,1}^{\omega} = UBCH_{j,t,1}^{\omega}$
- $XH_{j,t,2}^{\omega} = UBCH_{j,t,2}^{\omega}$

- $XH^{\omega}_{j,t,3} = UBCH^{\omega}_{j,t,3}$

If $LTH_j = 1$ day, then,

- $XH^{\omega}_{j,t,1} = UBCH^{\omega}_{j,t-1,2}$
- $XH^{\omega}_{j,t,2} = UBCH^{\omega}_{j,t-1,3}$
- $XH^{\omega}_{j,t,3}$ will not exist since the condition $i + LTH_j \leq 3$ will be violated. Hence, $XH^{\omega}_{j,t,3} = 0$.

If $LTH_j = 2$ day, then,

- $XH^{\omega}_{j,t,1} = UBCH^{\omega}_{j,t-2,3}$
- $XH^{\omega}_{j,t,2}$ and $XH^{\omega}_{j,t,3}$ will not exist since the condition $i + LTH_j \leq 3$ will be violated. Hence, $XH^{\omega}_{j,t,2} = XH^{\omega}_{j,t,3} = 0$

(2) Demand-Inventory Balance at Hospital under Scenario ω

- At hospital j, if demand $d^{\omega}_{j,t}$ is greater than the platelets with shelf life of 1 day (i.e., $IH^{\omega}_{j,t,1} + XH^{\omega}_{j,t,1}$), then the remaining demand denoted by, $DH^{\omega}_{j,t,1}$, is equal to $d^{\omega}_{j,t} - IH^{\omega}_{j,t,1} - XH^{\omega}_{j,t,1}$ and leftover inventory with 1 day shelf life denoted by, $LH^{\omega}_{j,t,1}$ will be 0. On the other hand, if $d^{\omega}_{j,t} \leq (IH^{\omega}_{j,t,1} + XH^{\omega}_{j,t,1})$, then $DH^{\omega}_{j,t,1} = 0$ and $LH^{\omega}_{j,t,1} = IH^{\omega}_{j,t,1} + XH^{\omega}_{j,t,1} - d^{\omega}_{j,t}$. Equation (6.3) is used to calculate $DH^{\omega}_{j,t,1}$ and $LH^{\omega}_{j,t,1}$.

$$d^{\omega}_{j,t} - IH^{\omega}_{j,t,1} - XH^{\omega}_{j,t,1} = DH^{\omega}_{j,t,1} - LH^{\omega}_{j,t,1} \qquad \forall j, t, \omega \qquad (6.3)$$

- If $DH^{\omega}_{j,t,1}$ is positive, then this leftover demand is first fulfilled by platelet units with a shelf life of 2 days (i.e., $IH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,2}$). If $DH^{\omega}_{j,t,1} > IH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,2}$, then leftover demand, $DH^{\omega}_{j,t,2}$, will be equal to $DH^{\omega}_{j,t,1} - IH^{\omega}_{j,t,2} - XH^{\omega}_{j,t,2}$ and leftover inventory with 2 days shelf life, $LH^{\omega}_{j,t,2}$ will be 0. On the other hand, if $DH^{\omega}_{j,t,1} \leq IH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,2}$, then, $DH^{\omega}_{j,t,2} = 0$ and the leftover platelets with 2-day shelf life is given by $LH^{\omega}_{j,t,2} = IH^{\omega}_{j,t,2} + XH^{\omega}_{j,t,2} - DH^{\omega}_{j,t,1}$. Equation (6.4) is used to calculate $DH^{\omega}_{j,t,2}$ and $LH^{\omega}_{j,t,2}$.

$$DH^{\omega}_{j,t,1} - IH^{\omega}_{j,t,2} - XH^{\omega}_{j,t,2} = DH^{\omega}_{j,t,2} - LH^{\omega}_{j,t,2} \qquad \forall j, t, \omega \qquad (6.4)$$

- If $DH^{\omega}_{j,t,2}$ is positive, then it is first fulfilled by fresh platelet units with a shelf life of 3 days (i.e., $XH^{\omega}_{j,t,3}$). If $DH^{\omega}_{j,t,2} > XH^{\omega}_{j,t,3}$, then leftover demand, $DH^{\omega}_{j,t,3}$, will be equal to $DH^{\omega}_{j,t,2} -$

$XH^{\omega}_{j,t,3}$ and leftover inventory with 3 days shelf life, $LH^{\omega}_{j,t,3}$ will be 0. If $DH^{\omega}_{j,t,2} \leq XH^{\omega}_{j,t,3}$, then, $DH^{\omega}_{j,t,3} = 0$ and the leftover platelets with 2-day shelf life is given by $LH^{\omega}_{j,t,3} = XH^{\omega}_{j,t,3} - DH^{\omega}_{j,t,2}$. Equation (6.5) is used to calculate $DH^{\omega}_{j,t,3}$ and $LH^{\omega}_{j,t,3}$.

$$DH^{\omega}_{j,t,2} - XH^{\omega}_{j,t,3} = DH^{\omega}_{j,t,3} - LH^{\omega}_{j,t,3} \qquad \forall j, t, \omega \qquad (6.5)$$

(3) Expired/Outdated Platelets

At the end of day t, hospital j discards the unutilized platelet units with remaining shelf life of 1 day ($LH^{\omega}_{j,t,1}$) and is given by Equation (6.6).

$$EH^{\omega}_{j,t} = LH^{\omega}_{j,t,1} \qquad \forall j, t, \omega \qquad (6.6)$$

(4) Inventory Position and Order Quantity at Hospital

Equation (6.7) is used to calculate the inventory position at the end of day t for hospital j, ($IPH^{\omega}_{j,t}$), which is the sum of the on-hand (i.e., $LH^{\omega}_{j,t,2} + LH^{\omega}_{j,t,3}$) and in-transit inventory (i.e., $\sum_{lt=1}^{LTH_j-1}(QH^{\omega}_{j,lt})$). Under the (s,S) policy, at hospital j, if the inventory position $IPH^{\omega}_{j,t} \geq sH_j$, then no order is placed; otherwise, we order an amount $QH^{\omega}_{j,t} = SH_j - IPH^{\omega}_{j,t}$. These are enforced in the model by Equations (6.8) through (6.12). If $\Delta H^{\omega}_{j,t} = 0$, then $IPH^{\omega}_{j,t} \geq sH_j$ due to Equation (6.8) and Equation (6.9) is inactive. On the other hand, if $\Delta H^{\omega}_{j,t} = 1$, then (6.8) is inactive and $IPH^{\omega}_{j,t} \leq sH_j$ due to Equation (6.9). Also, when $\Delta H^{\omega}_{j,t} = 1$, Equations (6.10) and (6.11), force $QH^{\omega}_{j,t} = SH_j - IPH^{\omega}_{j,t}$ and Equation (6.12) becomes inactive. On the other hand, if $\Delta H^{\omega}_{j,t} = 0$, then Equations (6.10) and (6.11) are inactive and Equation (6.12) forces $QH^{\omega}_{j,t}$ to zero. The order up-to level (SH_j) must be greater than the reorder point (sH_j) at the hospital and is ensured by Equation (6.13).

$$IPH^{\omega}_{j,t} = LH^{\omega}_{j,t,2} + LH^{\omega}_{j,t,3} + \sum_{lt=1}^{LTH_j-1}(QH^{\omega}_{j,t-lt}) \qquad \forall j, t, \omega \qquad (6.7)$$

$$IPH^{\omega}_{j,t} \geq sH_j - M(\Delta H^{\omega}_{j,t}) \qquad \forall j, t, \omega \qquad (6.8)$$

$$IPH^{\omega}_{j,t} \leq sH_j + M(1 - \Delta H^{\omega}_{j,t}) \qquad \forall j, t, \omega \qquad (6.9)$$

$$QH^{\omega}_{j,t} \leq (SH_j - IPH^{\omega}_{j,t}) + M(1 - \Delta H^{\omega}_{j,t}) \qquad \forall j, t, \omega \qquad (6.10)$$

$$QH^{\omega}_{j,t} \geq \left(SH_j - IPH^{\omega}_{j,t}\right) - M(1 - \Delta H^{\omega}_{j,t}) \qquad \forall j, t, \omega \qquad (6.11)$$

$$QH^{\omega}_{j,t} \leq M(\Delta H^{\omega}_{j,t}) \qquad \forall j, t, \omega \qquad (6.12)$$

$$SH_j > sH_j \qquad \forall j \qquad (6.13)$$

(5) Inventory Updates at the Hospital

At the end of each day, the inventory is updated at hospital j using equations (6.14) and (6.15). Note that the ending inventory varies for each hospital based on the scenario.

$$IH^{\omega}_{j,t+1,1} = LH^{\omega}_{j,t,2} \qquad \forall j, t, \omega \qquad (6.14)$$

$$IH^{\omega}_{j,t+1,2} = LH^{\omega}_{j,t,3} \qquad \forall j, t, \omega \qquad (6.15)$$

(6) Platelet Shortages at Hospital

Equation (6.16) gives the shortage at the end of day t ($SHH^{\omega}_{j,t}$) which is the unfulfilled demand, $DH^{\omega}_{j,t,3}$ calculated using Equation (6.5).

$$SHH^{\omega}_{j,t} = DH^{\omega}_{j,t,3} \qquad \forall j, t, \omega \qquad (6.16)$$

(7) Initial Inventory of Platelets at Hospital

The initial inventory at time $t = 1$ at each hospital Equation (6.17) gives the initial conditions at time t = 1 for each scenario, ω

$$IH^{\omega}_{j,1,i} = inH^{i}_{j} \qquad \forall i, j, \omega \qquad (6.17)$$

(8) Platelet Units Ordered and Received at Blood Center

At the blood center, platelets can be ordered only during review periods and not during the other days which is taken care by Equation (6.18). Equations (6.19) and (6.20) are used to calculate the total units available at the blood center at the beginning of day t in scenario ω (XBC^{ω}_{t}) after the testing procedure is complete. This which must be equal to the order quantity placed before the lead time (QBC^{ω}_{t-LTBC}).

$$QBC^{\omega}_{t} = 0 \qquad \text{for all } t \text{ except for } t = RBC, 2RBC, \ldots \qquad (6.18)$$

$$XBC^{\omega}_{t} = QBC^{\omega}_{t-LTBC} \qquad \forall \omega, t > LTBC \qquad (6.19)$$

$$XBC^{\omega}_{t} = 0 \qquad \forall \omega, t \leq LTBC \qquad (6.20)$$

(9) Regular Demand Fulfillment by the Blood Center

The total units shipped to hospital j with shelf life of i days on day t ($UBCH^{\omega}_{j,t,i}$), are set as decision variables (i.e., the model decides the hospital demand fulfillment policy) and they depend on the hospital's lead time. If the lead time of hospital j is 1 day, then platelets with shelf life of 1 day cannot be shipped from blood center to hospital j, to avoid platelet expiration at the time of arrival at the medical center. In other words, if a hospital's lead time is 1 day, then only platelets with shelf life of 2 or 3 days have to be shipped from the blood center. This is ensured by Equations (6.22) and (6.23). Similarly, only platelets with shelf life of 3 days have to be shipped to hospitals

with lead time of 2 days as given in Equation (6.23). However, if the hospital's lead time is negligible (i.e., 0 days), then platelets with any shelf life can be shipped as given in Equations (6.21 – 6.23).

The shortage incurred at the blood center due to the regular demand placed by hospital j ($SRBC_{j,t}^{\omega}$) is calculated using Equation (6.24). As discussed earlier, this shortage will be fulfilled by the blood center by procuring units from other blood centers. In the model, it is assumed that the procured $SRBC_{j,t}^{\omega}$ units will have a shelf life of 3 days. Hence, while calculating the units shipped from the blood center to hospital in the 3-day shelf life category (i.e., $UBCH_{j,t,3}^{\omega}$), $SRBC_{j,t}^{\omega}$ should also be included in addition to $U3_{j,t}^{\omega}$ ($U3_{j,t}^{\omega}$ is the platelet units with shelf life of 3 days from the available inventory shipped to hospital j) as given in Equation (6.25).

$$\sum_j UBCH_{j,t,1}^{\omega} + IBCH_{t,1}^{\omega} = IBC_{t,1}^{\omega} \qquad \forall t, \omega, LTH_j = 0 \qquad (6.21)$$

$$\sum_j UBCH_{j,t,2}^{\omega} + IBCH_{t,2}^{\omega} = IBC_{t,2}^{\omega} \qquad \forall t, \omega, LTH_j = 0{,}1 \qquad (6.22)$$

(In general, $\sum_j UBCH_{j,t,i}^{\omega} + IBCH_{t,i}^{\omega} = IBC_{t,i}^{\omega}$ $\quad \forall t, \omega$ and $i = 1{,}2$, $LTH_j \leq i$)

$$\sum_j U3_{j,t}^{\omega} + IBCH_{t,3}^{\omega} = XBC_t^{\omega} \qquad \forall t, \omega, LTH_j = 0{,}1{,}2 \qquad (6.23)$$

Where $IBCH_{t,i}^{\omega}$ is the leftover platelets at the blood center, with shelf life of i days ($i = 1{,}2{,}3$), after meeting the regular demands of all the hospitals.

$$UBCH_{j,t,1}^{\omega} + UBCH_{j,t,2}^{\omega} + U3_{j,t}^{\omega} + SRBC_{j,t}^{\omega} = QH_{j,t}^{\omega} \qquad \forall t, j, \omega \qquad (6.24)$$

$$UBCH_{j,t,3}^{\omega} = U3_{j,t}^{\omega} + SRBC_{j,t}^{\omega} \qquad \forall t, j, \omega \qquad (6.25)$$

(10) Emergency Demand Fulfillment by the Blood Center

The blood center must not only fulfill the *regular demand* placed by hospital j ($QH_{j,t}^{\omega}$) but also the *emergency demand* placed by that hospital on the same day t ($SHH_{j,t}^{\omega}$). As indicated in the sequence of events section, emergency demand will be fulfilled only with inventory that is remaining after fulfilling the regular demand (i.e., $\sum_j SHH_{j,t}^{\omega}$ will be fulfilled with $\sum_i IBCH_{t,i}^{\omega}$). Equations (6.26) – (6.28) are similar to regular demand-inventory balance equations discussed earlier.

$$\sum_j SHH_{j,t}^{\omega} - IBCH_{t,1}^{\omega} = SBCH_{t,1}^{\omega} - LBC_{t,1}^{\omega} \qquad \forall t, \omega \qquad (6.26)$$

Where $LBC_{t,1}^{\omega}$ is the leftover inventory of platelets, with shelf life of 1 day, after meeting emergency orders of hospitals and $SBCH_{t,1}^{\omega}$ is the remaining shortage to be fulfilled by platelets of lives 2 and 3.

Similarly,

$$SBCH_{t,1}^{\omega} - IBCH_{t,2}^{\omega} = SBCH_{t,2}^{\omega} - LBC_{t,2}^{\omega} \qquad \forall t, \omega \qquad (6.27)$$

$$SBCH_{t,2}^{\omega} - IBCH_{t,3}^{\omega} = SBCH_{t,3}^{\omega} - LBC_{t,3}^{\omega} \qquad \forall t, \omega \qquad (6.28)$$

The total shortage at the blood center due to the emergency demand placed by all hospitals is given by Equation (6.29).

$$SEBC_t^{\omega} = SBCH_{t,3}^{\omega} \qquad \forall t, \omega \qquad (6.29)$$

(11) Inventory Position and Order Quantity at Blood Center

The inventory position at the blood center is calculated after fulfilling the regular and emergency demands placed by all the hospitals. Equations (6.30) – (6.36) are similar to the order quantity calculations done at the hospital (similar to Equations 6.7 – 6.13).

$$IPBC_t^{\omega} = LBC_{t,2}^{\omega} + LBC_{t,3}^{\omega} + \sum_{lt=1}^{LTBC-1}(QBC_{t-lt}^{\omega}) \qquad \forall t, \omega \qquad (6.30)$$

$$IPBC_t^{\omega} \geq sBC - M(\Delta BC_t^{\omega}) \qquad \forall t, \omega \qquad (6.31)$$

$$IPBC_t^{\omega} \leq sBC + M(1 - \Delta BC_t^{\omega}) \qquad \forall t, \omega \qquad (6.32)$$

$$QBC_t^{\omega} \leq (SBC - IPBC_t^{\omega}) + M(1 - \Delta BC_t^{\omega}) \qquad \forall t, \omega \qquad (6.33)$$

$$QBC_t^{\omega} \geq (SBC - IPBC_t^{\omega}) - M(1 - \Delta BC_t^{\omega}) \qquad \forall t, \omega \qquad (6.34)$$

$$QBC_t^{\omega} \leq M(\Delta BC_t^{\omega}) \qquad \forall t, \omega \qquad (6.35)$$

$$SBC > sBC \qquad (6.36)$$

(12) Expired Platelets at Blood Center

At the blood center, the units expired at the end of each day is given using Equation (6.37).

$$EBC_t^{\omega} = LBC_{t,1}^{\omega} \qquad \forall t, \omega \qquad (6.37)$$

(13) Inventory Updates at Blood Center

At the end of the day t, the inventory is updated using Equations (6.38) and (6.39).

$$IBC_{t+1,1}^{\omega} = LBC_{t,2}^{\omega} \qquad \forall t, \omega \qquad (6.38)$$

$$IBC_{t+1,2}^{\omega} = LBC_{t,3}^{\omega} \qquad \forall t, \omega \qquad (6.39)$$

(14) Platelet Shortages at Blood Center

The shortage at the blood center under scenario ω on each day t is the sum of shortage due to regular platelet demand ($\sum_j SRBC_{j,t}^{\omega}$) as well as emergency demand ($SEBC_t^{\omega}$) placed by all the hospitals. This is given using Equation (6.40).

$$SHBC_t^{\omega} = \sum_j SRBC_{j,t}^{\omega} + SEBC_t^{\omega} \qquad \forall t, \omega \qquad (6.40)$$

(15) Initial Inventory of Platelets at Blood Center

Equation (6.41) gives the initial conditions at time t = 1 for each scenario ω at the blood center.

$$IBC_{1,i}^{\omega} = inBC^{i} \qquad \forall i, \omega \qquad (6.41)$$

(16) Non-negativity Constraints

Constraints (6.42) – (6.44) represent non-negativity and binary restrictions in the model.

$$XH_{j,t,i}^{\omega}, DH_{j,t,i}^{\omega}, LH_{j,t,i}^{\omega}, IH_{j,t,i}^{\omega}, IBCH_{j,t,i}^{\omega}, UBCH_{j,t,i}^{\omega}, QH_{j,t}^{\omega}, SHH_{j,t}^{\omega}, EH_{j,t}^{\omega}, IPH_{j,t}^{\omega}, SRBC_{j,t}^{\omega}, LBC_{t,i}^{\omega},$$
$$IBC_{t,i}^{\omega}, LBC_{t,i}^{\omega}, IBC_{t,i}^{\omega}, XBC_{t}^{\omega}, QBC_{t}^{\omega}, SEBC_{t}^{\omega}, SHBC_{t}^{\omega}, EBC_{t}^{\omega}, IPBC_{t}^{\omega}, SBCH_{t}^{\omega}, sH_{j}, SH_{j} \geq 0$$
$$\forall i, j, t, \omega \qquad (6.42)$$

$$sBC, SBC \geq 0 \qquad (6.43)$$

$$\Delta H_{j,t}^{\omega}, \Delta BC_{t}^{\omega} \in (0,1) \qquad \forall j, t, \omega \qquad (6.44)$$

Objective Function:

The objective function is to minimize the total cost incurred at the blood supply chain (i.e., operational cost at the blood center and hospitals). There are 9 cost components along the two-stage blood supply chain:

- Cost incurred by hospital j on day t:
  - Fixed transportation cost: $cH_{j}^{f} \times \Delta H_{j,t}^{\omega}$
  - Variable purchasing cost: $cH_{j}^{p} \times QH_{j,t}^{\omega}$
  - Inventory holding cost: $cH_{j}^{h} \times \left(IH_{j,t,1}^{\omega} + IH_{j,t,2}^{\omega}\right)$
  - Shortage cost: $cH_{j}^{sh} \times SHH_{j,t}^{\omega}$
  - Expiration cost: $cH_{j}^{ex} \times EH_{j,t}^{\omega}$
- Cost incurred by the blood center on day t:
  - Fixed transportation cost: $cBC^{f} \times \Delta BC_{t}^{\omega}$
  - Inventory holding cost: $cBC^{h} \times \left(IBC_{t,1}^{\omega} + IBC_{t,2}^{\omega}\right)$
  - Shortage cost: $cBC^{sh} \times SHBC_{t}^{\omega}$
  - Expiration cost: $cBC^{ex} \times EBC_{t}^{\omega}$

It is to be noted that the platelet testing and processing cost incurred by the blood center is not included in the cost function since the variable procurement costs paid by the hospitals will cover this testing cost.

Equation (6.45) represents the final objective function, which is to minimize the expected cost across all scenarios along the two-stage blood supply chain.

$$\text{Minimize } TCBSC = \sum_{t=1}^{T}[\sum_{\omega=1}^{\Omega}\left[p^{\omega}\times\{\sum_{j=1}^{J}\left[cH_j^f\times\Delta H_{j,t}^{\omega} + cH_j^p\times QH_{j,t}^{\omega} + cH_j^h\times\left(IH_{j,t,1}^{\omega} + IH_{j,t,2}^{\omega}\right) + cH_j^{sh}\times SHH_{j,t}^{\omega} + cH_j^{ex}\times EH_{j,t}^{\omega}\right] + cBC^f\times\Delta BC_t^{\omega} + cBC^h\times\left(IBC_{t,1}^{\omega} + IBC_{t,2}^{\omega}\right) + cBC^{sh}\times SHBC_t^{\omega} + cBC^{ex}\times EBC_t^{\omega}\}\right]] \quad (6.45)$$

It is to be noted that the cost components vary for each hospital depending on the hospital settings.

6.1.5. Complexity of the Stochastic Integer Programming Model for Blood Supply Chain

The problem size of the stochastic mixed integer programming model is given below:

- Total number of decision variables: $(t\times\omega)(24j + 20) + 2j + 2$, out of which $(t\times\omega)(j + 1)$ are binary variables
- Total number of constraints: $(18\times t\times\omega + 3\omega)(j + 1) + j + t$

The stochastic blood supply chain model discussed in Section 6.1.4 is programmed using GAMS® and solved using IBM CPLEX®12.6.0.0 optimizer. The problem was solved for optimality for one blood center and two hospitals, for a planning horizon of 30 days and 15 scenarios. It had 30,306 variables (1350 are binary) and 24,468 constraints. It took 1 hour to solve the problem. The solutions are discussed in detail in Section 6.3. The direct optimization of the blood supply chain model was not feasible for more than 15 scenarios with 2 hospitals or when more hospitals were added to the blood supply chain. Hence, a modified stochastic genetic algorithm (MSGA) technique is proposed and is discussed in Section 6.2. For the smaller problem, the performance of the proposed MSGA is compared against the optimal solution obtained by solving the stochastic program directly in Section 6.3.

6.2. Modified Stochastic Genetic Algorithm (MSGA) for the Blood Supply Chain

The complexity of the stochastic integer programming model increases exponentially as the number of scenarios and time horizon increase. However, the blood center and hospital might be interested in considering hundreds of scenarios with different likelihood of occurrences. Therefore, in this section, a new stochastic genetic algorithm is developed, called modified stochastic genetic algorithm (MSGA) which can solve larger problems with relatively less time.

Genetic algorithm (GA) is a metaheuristic technique based on natural selection and evolution process. Each candidate solution, known as chromosome, consists of a string of genes.

The property of the genes depends on the problem type. The chromosomes are evolved over many generations through the crossover and mutation operations resulting in gradual improvement of the objective function (Reeves, 2003). Over the past decade, GA has been a widely used metaheuristic technique to solve inventory management problems (Maiti et al., 2007; Gupta et al., 2009; Sethupathy et al., 2010; Pasandideh et al., 2011; Amaruchkul and Auwatanamongkol, 2013).

In this study, we propose a new variant of genetic algorithm, called modified stochastic genetic algorithm (MSGA). The proposed genetic algorithm is expected to converge faster due to the different approach taken for selecting the next generation chromosomes (discussed in detail in Section 6.2.7). The performance of MSGA is compared with that of the genetic algorithm proposed by Amaruchkul and Auwatanamongkol (2013) since the latter is one of the very few work in the recent times applying genetic algorithm for (s, S) policy and is referred to as base stochastic genetic algorithm (Base SGA) in this chapter.

6.2.1. Basic SGA steps

Table 6.1: Basic SGA steps (adapted from Amaruchkul and Auwatanamongkol, 2013)

Step	Process
1	Initialize the population
2	While (termination condition is not met) do
2a	Evaluate the fitness value of each member of the population
2b	Select members of the population based on fitness
2c	Perform crossover on pairs of selected members to produce offspring
2d	Perform mutation on the offspring
2e	Replace members of the population with the offspring
3	End

Table 6.1 shows the steps involved in the basic stochastic genetic algorithm (SGA). The generation of initial population (step 1) for the blood supply chain inventory problem is given in detail in Section 6.2.3. Once the initial population is generated, step 2a is to evaluate the fitness of the initial population and the fitness function evaluation procedure is given in Section 6.2.4. Steps 2b and 2c are the crossover and mutation operations (details provided in Sections 6.2.5 and 6.2.6 respectively). In the traditional genetic algorithm, only the offspring produced (as a result of the crossover and mutation operations) are carried over to the next generation. Even if the parents are extremely fit, they are retained in that generation which might result in local optima or slower convergence. Therefore, in the proposed MSGA variant, the selection of the chromosomes to the

next generation (step 2e) is done differently, considering both parent and offspring population and is discussed in Section 6.2.7. Step 2 (steps 2a through 2e) is repeated until the termination criterion is met. The termination process might take place when the maximum number of user specified generations is reached or the difference between the fitness function values between the last two consecutive generations is below a certain threshold error value.

6.2.2. Chromosome Representation

In genetic algorithm, each chromosome consists of several genes and the number of genes in each chromosome depends on the problem type. Since the re-order point and the order-up-to parameters at the blood center and the hospitals ($sBC, SBC, sH_1, SH_1, sH_2, SH_2, \dots, sH_J, SH_J$) are the key decision variables in our study, each chromosome is represented by the structure given in Figure 6.4. The first two genes represent the re-order point (sBC) and order-up-to level (SBC) at the blood center and the consequent pairs of genes represent the re-order point (sH_j) and order-up-to level (SH_j) at hospital j.

sBC	SBC	sH_1	SH_1	sH_2	SH_2	$\cdots$	sH_J	SH_J

Figure 6.4: Structure of Chromosome

In addition, the genes have to be generated such that the conditions $sBC < SBC$ and $sH_j < SH_j$ are satisfied.

Calculation of the upper and lower bounds for the order-up-to level parameter

In this study, it is assumed that the daily patient demand at each hospital j follows a normal distribution with mean $\mu H_{j,D}$ and standard deviation $\sigma H_{j,D}$. Hence, at hospital j, the mean demand during lead time (LTH_j) plus review period (RH_j) denoted by $\mu H_{j,DLTR}$ will be equal to

$$\mu H_{j,DLTR} = \left(LTH_j + RH_j\right) * \mu H_{j,D}$$

and its standard deviation, denoted by $\sigma H_{j,DLTR}$ is equal to

$$\sigma H_{j,DLTR} = \sigma H_{j,D}\sqrt{LTH_j + RH_j}$$

Since the demands at the hospitals are assumed to follow Normal distributions, the demand at the blood center, which is the sum of the demands placed by all the hospitals to the blood center, also follows a normal distribution, with mean $\mu BC_D = \sum_j \mu H_{j,D}$ and standard deviation $\sigma BC_D = \sqrt{\sum_j \sigma H_{j,D}^2}$.

Therefore, the mean demand during lead time ($LTBC$) plus review period (RBC) = $\mu BC_{DLTR} = (LTBC + RBC)\mu BC_D$ and standard deviation of the demand during lead time plus review period = $\sigma BC_{DLTR} = \sigma BC_D\sqrt{LTBC + RBC}$.

(i) Calculation of the lower bounds:

In order to compute the lower bounds, we impose a condition that at least 80% of the demand has to be fulfilled at each stage (i.e., $0.8\times\mu H_{j,DLTR} \leq SH_j\ \forall j$ and $0.8\times\mu BC_{DLTR} \leq SBC$). Also, the earlier conditions $SH_j > sH_j\ \forall j$ and $SBC > sBC$ must be valid. Therefore, the lower bound of SH_j must be $\max\{0.8\times\mu H_{j,DLTR}; sH_j + 1\}\ \forall j$ (as given in Equation 6.46). Similarly, the lower bound of SBC must be $\max\{0.8\times\mu BC_{DLTR}; sBC + 1\}$ (as given in Equation 6.47).

(ii) Calculation of the upper bounds:

The upper bounds for SH_j and SBC are set at $\mu H_{j,DLTR} + 3\sigma H_{j,DLTR}$ and $\mu BC_{DLTR} + 3\sigma BC_{DLTR}$ respectively. This will a good upper bound because 99.73% of the demand falls within three sigma limit under normal distribution.

Equations (6.46) and (6.47) summarize the bounds for SH_j and SBC respectively.

Bounds on SH_j: $\max\{(0.8 * \mu H_{j,DLTR}); (sH_j + 1)\} \leq SH_j \leq \mu H_{j,DLTR} + 3\sigma H_{j,DLTR}$ (6.46)

Bounds on SBC: $\max\{(0.8 * \mu BC_{DLTR}); (sBC + 1)\} \leq SBC \leq \mu BC_{DLTR} + 3\sigma BC_{DLTR}$ (6.47)

6.2.3. Generation of Initial Population

For this study, n distinct parent chromosomes are generated, and based on the literature, n is usually taken as $(4\times J)$ (Sethupathi et al., 2010). Since SBC must be less than or equal to $\mu BC_{DLTR} + 3\sigma BC_{DLTR}$ and $sBC < SBC$, the maximum value that sBC can take must be *strictly* less than $(\mu BC_{DLTR} + 3\sigma BC_{DLTR})$. Similarly, the maximum value that sH_j can take must be strictly less than $\left(\mu H_{j,DLTR} + 3\sigma H_{j,DLTR}\right)$. Therefore, the initial values of sBC and sH_j are selected randomly within $\{0,1,\dots,\mu BC_{DLTR} + 3\sigma BC_{DLTR} - 1\}$ and $\{0,1,\dots,\mu H_{j,DLTR} + 3\sigma H_{j,DLTR} - 1\}$ respectively. If $LBSBC = \max\{(0.8\times\mu BC_{DLTR}); (sBC + 1)\}$, then SBC is randomly selected within $\{LBSBC, LBSBC + 1, LBSBC + 2, \dots, \mu BC_{DLTR} + 3\sigma BC_{DLTR}\}$. Similarly, if $LBSH_j = \max\{\left(0.8\times\mu H_{j,DLTR}\right); (sH_j + 1)\}$, then SH_j is randomly selected within $\{LBSH_j, LBSH_j + 1, LBSH_j + 2, \dots, \mu H_{j,DLTR} + 3\sigma H_{j,DLTR}\}$.

6.2.4. Fitness Function

To determine the fitness function for each chromosome c, the total blood supply chain cost for each chromosome, $TCBSC_c$, is first computed across all scenarios. The total cost is calculated the same way as in the mathematical model (given by Equation 6.45).

Since, the objective is to minimize cost, the fitness function for each chromosome c, $fitness_c$, is given by Equation (6.48):

$$fitness_c = 1/(TCBSC_c) \tag{6.48}$$

It is to be noted that a higher value of fitness function indicates that the chromosome is a better fit, since it results in lower cost.

6.2.5. Crossover Operation

In the traditional genetic algorithm, the genes are independent of each other. However, in the genetic algorithm for determining the (s, S) policy, the condition that $s > S$ must be valid after the crossover operation at both the hospitals and at the blood center (i.e., resultant offspring must have $SBC > sBC$ and $SH_j > sH_j$). Therefore, crossover operator is chosen such that the parent-pair (sBC, SBC) must remain together and the pair (sH_j, SH_j) must also remain together after crossover (i.e., sBC and SBC must remain together and sH_j and sH_j for each hospital j must remain together). An illustration of the crossover operation with two chromosomes is given in Figure 6.5.

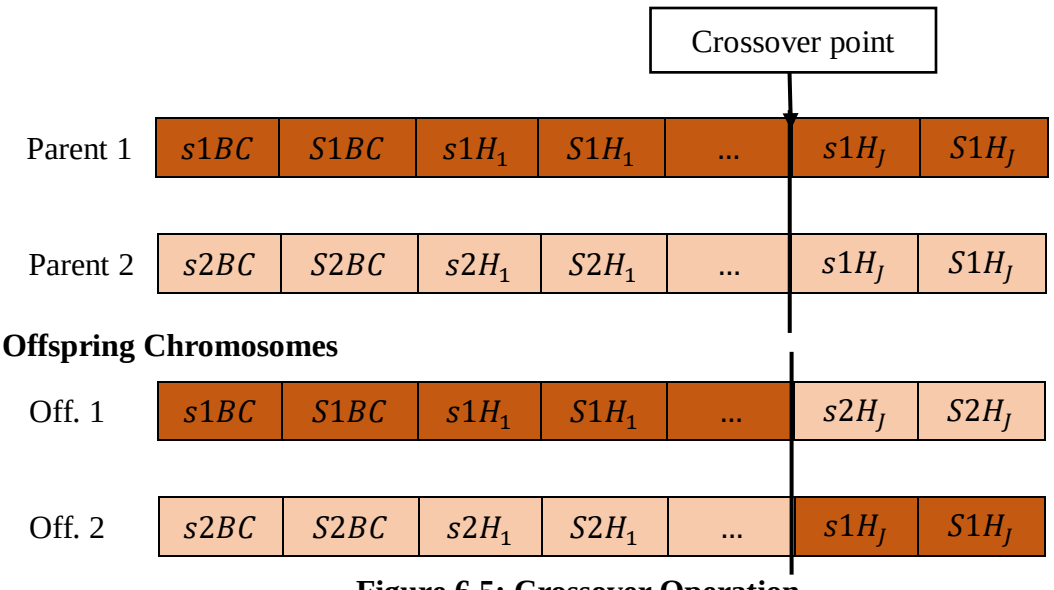


Figure 6.5: Crossover Operation

Note: The crossover point can be randomly chosen in the 2^{nd}, 4^{th}, …, or $(2J)^{th}$ positions. By choosing this way, the parent-pairs (sBC, SBC) and (sH_j, SH_j) remain together even after the crossover operation.

In this study, the crossover rate is set to one (i.e., there will be n distinct offspring produced from the n distinct parents). This is done because the population from which the parents are selected for the next generation will be large (equal to $2n$). The chromosomes selected for the crossover operation is based on the roulette wheel selection, as in the traditional GA given by Goldberg and Holland (1988). The n offspring chromosomes, produced as a result of crossover, are then subjected to mutation operation.

6.2.6. Mutation Operation

If sBC^{new} and sBC^{old} represent the values of sBC before and after mutation respectively, then sBC^{new} is obtained by randomly mutating between 0 and $2\times sBC^{old}$. Also, as discussed earlier, sBC must be strictly less than $\mu BC_{DLTR} + 3\sigma BC_{DLTR}$. Similar restrictions are imposed for mutating sH_j as well. Equations (6.49) and (6.50) represent the alteration of the re-order point genes due to mutation. The chromosomes are subjected to mutation with a mutation probability MP.

$$sH_j^{new} = \max\{sH_j^{old}\times 2 * uH_j; \mu H_{j,DLTR} + 3\sigma H_{j,DLTR} - 1\} \qquad \forall j \qquad (6.49)$$

$$sBC^{new} = \max\{sBC^{old}\times 2\times uBC; \mu BC_{DLTR} + 3\sigma BC_{DLTR} - 1\} \qquad (6.50)$$

where uBC and uH_j are the uniform random variables between 0 and 1.

SH_j and SBC are assigned a random integer within $\{LBSH_j, LBSH_j + 1, LBSH_j + 2, \dots, \mu H_{j,DLTR} + 3\sigma H_{j,DLTR}\}$ and $\{LBSBC, LBSBC + 1, LBSBC + 2, \dots, \mu BC_{DLTR} + 3\sigma BC_{DLTR}\}$ respectively (recall that $LBSH_j = \max\{(0.8\times\mu H_{j,DLTR}); (sH_j^{new} + 1)\}$ and $LBSBC = \max\{(0.8\times\mu BC_{DLTR}); (sBC^{new} + 1)\}$).

It has been observed in the literature that a higher mutation probability (MP) in the initial generations results in a more diversified pool of population and hence increases the chance of obtaining a better solution. However, a high value of MP at the later generations result in slower convergence due to too much of perturbation (Brijesh and Rajendran, 2011). Therefore, in the proposed MSGA variant, the MP at the end of each generation is updated using $MP^{new} = MP^{old}\times MF$, where $MF < 1$ is the mutation factor. Multiplication of MP with the MF ensures that the mutation probability decreases over generations (since $MF < 1$). MF is decided based on

extensive experimentation. It is to be noted that in the traditional genetic algorithm, the mutation probability remains the same across all generations (i.e., $MF = 1$).

After the mutation operation is completed, the fitness of each child produced is evaluated and recorded.

6.2.7. Selection of Next Generation Chromosomes

Drawback of the existing genetic algorithms:

In the traditional genetic algorithm, only the n offspring produced as a result of the crossover and mutation operations are taken to the next generation. Even if the parents producing the offspring are fitter than the children, they are not carried over to the next generation. This might result in the algorithm reaching a local optimum. Therefore, in the proposed MSGA, the n chromosomes taken over to the next generation are selected from the pool of current offspring as well as parent population. The population size will be $2n$ distinct chromosomes (i.e., n parents and n offspring). The chromosomes (either parent or offspring) taken to the next generation are selected based on a probability, which is calculated as a function of their fitness values.

Proposed Chromosome Selection Procedure in MSGA

Recall that $fitness_c$ is the fitness value of chromosome c obtained by Equation (6.48). The probability of selecting chromosome c to the next generation is given by Equation (6.51).

$$pr(next\_gen_c) = \frac{fitness_c}{\sum_{c=1}^{2n} fitness_c} \tag{6.51}$$

Where $c = 1$ to n represents the parent chromosomes and $c = n + 1$ to $2n$ represents the offspring chromosomes.

The fitness value of all the parent and offspring chromosomes are considered for making the selection. A greater value of the fitness function ensures a greater chance of the chromosome being selected to the next generation. It is also possible to select a bad chromosome to the next generation, but with a very small probability. This idea is derived from the simulated annealing metaheuristic in which a bad solution is also accepted and taken to the next iteration with a small probability (Laarhoven and Aarts, 1987).

6.2.8. Termination Criteria

In the proposed MSGA, the generation process is stopped when the number of generations reaches a maximum user specified value. The parameters ((sH_j, SH_j) and (sBC, SBC)) that yield the least total cost across all the generations is selected as the final solution.

6.2.9. Steps of the Modified Stochastic Genetic Algorithm (MSGA)

Step 1: Generate the initial population (n chromosomes); Initialize current generation to 1.

Step 2: Calculate the total cost across all demand scenarios for each chromosome c ($TCBSC_c$)

Step 3: Evaluate the fitness function for each chromosome c ($fitness_c$)

Step 4: If current generation $<$ maximum generation, then do steps 4a through 4g; otherwise go to Step 5.

Step 4a: Perform crossover operation on the parent chromosomes

Step 4b: Perform mutation operation on the parent chromosomes

Step 4c: Update mutation probability (i.e., set $MP^{new} = MP^{old} \times MF$)

Step 4d: Calculate the total cost for the n offspring

Step 4e: Evaluate of the fitness function for the n offspring

Step 4f: Select parent chromosomes for the next generation based on the fitness function of the parents and offspring in the current generation

Step 4g: Increment generation by 1 and repeat Step 4.

Step 5: Current generation has reached the prescribed maximum value. Terminate the algorithm. The value of the chromosome with the least total cost across all the generations and the corresponding (s, S) policies for the blood center and the hospitals will be the final solution obtained from the MSGA.

In summary, the main difference between the proposed MSGA and the genetic algorithm proposed by Amaruchkul and Auwatanamongkol (2013) are as follows:

(1) Gradual decrease in mutation probability over generations (step 4c) to ensure faster convergence as a result of reduced perturbation.

(2) Selection of chromosomes for the next generation considering even the parent population in the current generation (step 4f).

6.3. Computational Results

In this section, the performance of the modified stochastic genetic algorithm (MSGA) is compared with that of the optimal solution obtained for smaller problems using a case study. For larger problems, the proposed MSGA is compared against an existing genetic algorithm in the literature.

For the purpose of conducting the analysis, a blood supply chain configuration with two hospitals and one blood center is considered. The lead time of hospital-1 is negligible (i.e., close

to the blood center), while the lead time of the other hospital is assumed to be 1 day (i.e., located away from the blood center).

6.3.1 Input Parameters

The input parameters for the hospitals and the blood center used for the case study are given in Table 6.2. The impact of varying the input parameters is studied in Section 6.4.

6.3.1.1. Demand Parameters at the Hospitals

The blood demand data reported by Tetteh (2008) for a hospital at New York for 122 days is fitted to a normal distribution N~(200,32). For hospital-2, the demand parameters are assumed to be half of those of hospital-1. In other words, the demand for hospital-2 follows Normal distribution with mean 100 and standard deviation of 16. The effect of varying the demand parameters is discussed in Section 6.4.

6.3.1.2. Cost Settings

The fixed and variable purchasing cost parameters are obtained from a regional medical center in Pennsylvania and from the literature (Civelek et al., 2015). The inventory holding cost (IHC) in the literature is calculated based on the cost of storing platelets in the agitator and the electricity cost. Because platelets are very expensive, IHC must also include the working capital tied up in inventory. Therefore, at both the blood center and hospitals, IHC is taken as 20% of their purchasing/testing cost. The shortage cost is assumed to be five times the variable purchasing cost and the outdating cost is taken as the purchasing cost based on the ratios given in the literature (Hill, 2011; Haijema, 2013). Table 6.2 summarizes the cost data used for the analysis. The effect of varying the cost parameters is discussed in Section 6.4.

Table 6.2: Input Parameters

Parameter	**Values**		
Time Horizon (days)	30		
Number of Scenarios	15		
Parameter	**Hospital 1**	**Hospital 2**	**Blood Center**
Lead Time (days)	0	1	5
Review Period (days)	1	1	1
Fixed Cost of Procurement ($/shipment)	113	225	1125
Inventory Holding Cost ($/unit/day)	130	130	108
Variable Purchasing Cost ($/unit)	650	650	538
Shortage Cost ($/unit)	3250	3250	2690
Outdating Cost ($/unit)	650	650	538
Platelet Demand	N~(200,32)	N~(100,16)	-

Since the lead times of hospital-1 and hospital-2 are considered to be 0 and 1 day respectively, the fixed transportation cost at hospital-1 is considered to be half of that of hospital-2. For the purpose of simplicity, all other cost parameters are considered the same at both the hospitals and are summarized in Table 6.2.

6.3.2. Complexity of the Stochastic Programming Model

The stochastic blood supply chain model discussed in Section 6.1 is programmed using GAMS® and solved using IBM CPLEX®12.6.0.0 optimizer. For the input parameters given in Table 6.2, the stochastic blood supply chain model was able to run in its fullest efficiency for only 15 scenarios. The model had the following features:

- Total number of decision variables: 30306, out of which 1350 are binary variables
- Total number of constraints: 24468
- Solution time: approximately 1 hour

6.3.3. Calculation of the upper and lower bounds for order-up-to levels at the blood center and hospitals for the modified stochastic genetic algorithm (MSGA)

Following the procedure given in Section 6.2.2, we get the bounds as follows:

At Hospital-1

From Table 6.2, $\mu H_{1,D} = 200, \sigma H_{1,D} = 32, LTH_1 = 0$ days and $RH_1 = 1$ day.

$\mu H_{1,DLTR} = (LTH_1 + RH_1) \times \mu H_{1,D} = 200$

$\sigma H_{1,DLTR} = \sigma_D \times \sqrt{LTH_1 + RH_1} = 32$

Therefore, upper bound of $SH_1 = \mu H_{1,DLTR} + 3\sigma H_{1,DLTR} = 296$

Lower bound of $SH_1 = 0.8 \times \mu H_{1,DLTR} = 160$

At Hospital-2

$\mu H_{2,D} = 100, \sigma H_{2,D} = 16, LTH_2 = 1$ day and $RH_2 = 1$ day.

$\mu H_{2,DLTR} = (LTH_2 + RH_2) \times \mu H_{2,D} = 2 \times 100 = 200$

$\sigma H_{2,DLTR} = \sigma_D \times \sqrt{LTH_2 + RH_2} = 16 \times 1.414 \cong 23$

Therefore, upper bound of $SH_2 = \mu H_{2,DLTR} + 3\sigma H_{2,DLTR} = 269$

Lower bound of $SH_2 = 0.8 \times \mu H_{2,DLTR} = 160$

At Blood Center

$LTBC = 5$ and $RBC = 1$

$\mu BC_D = \mu H_{1,D} + \mu H_{2,D} = 200 + 100 = 300$

$\sigma BC_D = \sqrt{\sigma H_{1,D}{}^2 + \sigma H_{2,D}{}^2} = \sqrt{32^2 + 16^2} = \sqrt{1280} \cong 36$

$\mu BC_{DLTR} = (LTBC + RBC) \times \mu BC_D = 6 \times 300 = 1800$

$\sigma BC_{DLTR} = \sigma BC_D \times \sqrt{LTBC + RBC} = 36 \times 2.449 \cong 88$

Therefore, upper bound of $SBC = \mu BC_{DLTR} + 3\sigma BC_{DLTR} = 2064$

Lower bound of $SBC = 0.8 \times \mu BC_{DLTR} = 1440$

6.3.4. Comparison of the Optimal Solution by the Stochastic Integer Model with MSGA

The proposed MSGA is coded in Matlab® on a computer with 8GB RAM, Intel i5 2.50 GHz processor. To illustrate the performance of the MSGA, five performance measures are considered; Units purchased, units held in inventory, units shortage, units outdated and expected total cost.

As discussed in Section 6.3.2, the stochastic programming mathematical model was able to run efficiently for only 15 scenarios. For the same 15 demand scenarios, MSGA is run and the expected total cost, units outdated, shortage and purchased for 30 days are recorded. The two solutions are then compared in Table 6.3.

6.3.4.1. Demand Fulfillment at the Blood Center

In the stochastic integer programming model, the number of units with shelf life of i days to ship to hospital j, on day t ($UBCH_{j,t,i}^{\omega}$) is determined by the model. However, in the genetic algorithm, the allocation rule has to be given by the users to the model. Therefore, the stochastic integer model results are analyzed first to understand the allocation policy developed by the model.

Based on the observation made from the optimal solution, in most scenarios, the allocation rule, when there is a shortage at the blood center, is as follows:

All platelets with shelf life of 1 day ($IBC_{t,1}^{\omega}$) are allocated to hospital 1, since, hospital-1 has a lead time of 0 days. If there exist a leftover demand placed by hospital-1, then the remaining inventory is proportionately split among the demand placed by both the hospitals.

Let us consider a numerical example to illustrate the allocation rule:
Assume the following platelet data:

- Platelets with shelf life of 1 day at the blood center: 200 units
- Platelets with shelf life of 2 days at the blood center: 100 units
- Platelets with shelf life of 3 days at the blood center: 200 units
- Demand placed by hospital-1: 450 units
- Demand placed by hospital-2: 200 units
- Lead time at hospital-1: 0 days
- Lead time at hospital-2: 1 day

Note that the total demand of 650 units at the hospitals exceeds the available inventory of 500 units. Since, the lead time of hospital-1 is 0, all platelets with 1-day life (200 units) are allocated to hospital-1. Platelets with shelf life of 2 and 3 days have to be proportionately split among the two hospitals based on their remaining demands. The remaining unfulfilled demand of hospital-1 is 250 (i.e., 450 – 200) units and the demand at hospital-2 is 200 units.

Therefore, percentage of demand of hospital-1: $\frac{250}{(250+200)} = 0.56$; Percentage of demand of hospital-2: $\frac{200}{(250+200)} = 0.44$.

The platelets with shelf life of 2 and 3 days are then partitioned among the two hospitals using the calculated percentage values. Platelets with two-day shelf life shipped to hospital-1: 100*0.56 = 56 and platelets with two-day shelf life shipped to hospital-2: 44. Similarly, units shipped to hospitals 1 and 2 with three-day shelf life are 112 and 88 respectively.

<u>Allocation rule followed by the blood center:</u>

If the lead time of hospital j is negligible (i.e., if $LTH_j^{\omega} = 0$ days), estimate the percentage of platelets to allocate to hospital j with remaining life of 1 day, on day t ($PR_{j,t,1}^{\omega}$).

$$PR_{j,t,1}^{\omega} = \frac{QH_{j,t}^{\omega}}{\sum_{j \,\epsilon J'} QH_{j,t}^{\omega}}$$

where J' is the set of all hospitals with negligible lead time (i.e., $LTH_j^{\omega} = 0$). $PR_{j,t,1}^{\omega}$ is the percentage of total platelets with shelf life of 1 day allocated to hospital j on day t $PR_{j,t,1}^{\omega}$ will be 0 for hospitals with $LTH_j^{\omega} \geq 1$

In order to allocate platelets with shelf life of 2 days, we have to consider two types of demand; (1) Demand for hospitals with lead time of 1 day and (2) Remaining unfulfilled demand of hospital j whose lead time is 0 days (i.e., remaining demand after consuming the 1-day platelets).

$$PR_{j,t,2}^{\omega} = \frac{QH_j^{\omega} - PR_{j,t,1}^{\omega} \times QH_j^{\omega}}{\sum_{j \in J''}(QH_j^{\omega} - PR_{j,t,1}^{\omega} \times QH_j^{\omega})}$$

where J'' is the set of all hospitals with $LTH_j^{\omega} \leq 1$

Note: According to step (a), $PR_{j,t,1}^{\omega}$ will be 0 for hospitals whose lead time is 1 day. Therefore, $PR_{j,t,2}^{\omega}$ for these hospitals will become:

$$PR_{j,t,2}^{\omega} = \frac{QH_j^{\omega}}{\sum_{j \in J'}(QH_j^{\omega} - PR_{j,t,1}^{\omega} \times QH_j^{\omega})}$$

Similarly, the percentage of platelets to be allocated to hospital j with shelf life of 3 days is given below.

$$PR_{j,t,3}^{\omega} = \frac{QH_j^{\omega} - PR_{j,t,1}^{\omega} \times QH_j^{\omega} - PR_{j,t,2}^{\omega} \times QH_j^{\omega}}{\sum_{j}(QH_j^{\omega} - PR_{j,t,1}^{\omega} \times QH_j^{\omega} - PR_{j,t,2}^{\omega} \times QH_j^{\omega})}$$

For the parameter settings given in Table 6.2, the daily performance measures for each scenario are compared for smaller problems and their average values are given in Table 6.3.

From Table 6.3, it can be observed that the total cost obtained by MSGA is $ 598,059 with a gap of 15% from the optimal. At the blood center, the average units purchased under the mathematical model is 315 units which is 5% more than the mean demand. This happens because the blood center is not only responsible for fulfilling the regular demand but also the emergency demands placed by the hospitals. Due to the large quantity purchased, shortage is less at the blood center, in spite of the outdating under the optimal policy. At each of the two hospitals, almost the same number of units are purchased under the mathematical model and MSGA and is approximately equal to its mean demand. Since the lead time of hospital-2 (1 day) is more than that of hospital-1 (negligible), there is more outdating in hospital-2 compared to hospital-1, resulting in more shortage. It can also be observed that base stock periodic review policy is followed at the blood center under MSGA.

Table 6.3: Average Performance Measures for Smaller Problems (t=30,ω=15)

Supply Chain Stage	Performance Measure	Stochastic Integer Programing Model	MSGA
Hospital-1	Units Shortage	2	1
	Units Outdating	3	2
	Units Holding	62	59
	Units Purchased	194	195
	sH_1	246	198
	SH_1	258	248
Hospital-2	Units Shortage	3	2
	Units Outdating	4	2
	Units Holding	29	26
	Units Purchased	101	103
	sH_2	267	265
	SH_2	268	268
Blood Center	Units Shortage	2	15
	Units Outdating	25	16
	Units Holding	74	165
	Units Purchased	315	317
	sBC	1469	1918
	SBC	1710	1919
Overall Measures	Total Cost/day	$ 518,902	$ 598,059 (Gap from optimal: 15.25%)
	Computational Time	1 hour	7 minutes

6.3.5. Comparison of MSGA and Base SGA for Larger Problems

As discussed earlier, for larger problems, the performance of the proposed MSGA is compared with the genetic algorithm proposed by Amaruchkul and Auwatanamongkol (2013), which is referred to as Base stochastic genetic algorithm (Base SGA) in this chapter. Amaruchkul and Auwatanamongkol (2013) is one of the very few work in the recent times applying genetic algorithm for (s, S) policy. To evaluate the effectiveness of MSGA for larger problems, 500 scenarios are considered with a planning horizon of 100 days.

For the settings presented in Table 6.2, the results obtained using MSGA and base SGA for larger problems are given in Table 6.4. It can be seen that the objective function value (total cost) obtained by the MSGA is better than that of the base SGA. Even though the gap is quite small, the actual difference between the cost values is more than $6500 (i.e., using MSGA, savings

per day per scenario is more than $6500). At both the hospitals and the blood center, shortage is more under the base SGA, due to the less units purchased compared to MSGA.

Table 6.4: Average Performance Measures for Larger Problems (t=100,ω=500)

Supply Chain Stage	Performance Measure	MSGA	Base SGA
Hospital-1	Units Shortage	1	1
	Units Outdating	1	1
	Units Holding	53	84
	Units Purchased	201	200
	sH_1	198	246
	SH_1	248	258
Hospital-2	Units Shortage	1	2
	Units Outdating	1	1
	Units Holding	28	29
	Units Purchased	103	102
	sH_2	202	232
	SH_2	225	262
Blood Center	Units Shortage	9	28
	Units Outdating	5	3
	Units Holding	152	34
	Units Purchased	204	173
	sBC	1918	1469
	SBC	1924	1710
Overall Measures	Total Cost/day	$ 539,728	$ 546,406
	Convergence Time	29 minutes	32 minutes

6.4. Sensitivity Analysis

In this section, the impact of the cost parameters and the coefficient of demand variation on the total cost measure is studied.

6.4.1 Impact of Cost Parameters

The fixed transportation cost (FTC), inventory holding cost (IHC), variable purchasing cost (VPC), shortage cost (SC) and outdating cost (OC) at the blood supply chain are varied. Table 6.5 summarizes the 17 cost settings used for the sensitivity analysis. Cost setting 1 (CS1) is the baseline setting used in Section 6.3. Cost settings 2 to 9 (CS2 – CS9) represent multiplying the values of cost parameters by 0.5 one at a time, compared to CS1 respectively. Similarly, cost

settings 10 to 17 (CS10 – CS17) represent multiplying the values of cost parameters by 1.5 one at a time, compared to CS1 respectively. Thus, in each cost setting, only one of the cost parameters is changed, while the others are maintained at their base values. The problems are solved under each cost settings by both MSGA and base SGA. The average values of the daily total cost are compared in Table 6.6.

Table 6.5: Cost Setting

Cost Setting	Cost incurred at Blood Center			Cost incurred at Hospital				
	IHC	SC	OC	FTC (H1,H2)	IHC	VPC	SC	OC
CS1 (base)	108	2690	538	(113,225)	130	650	3250	650
CS2	54	2690	538	(113,225)	130	650	3250	650
CS3	108	1345	538	(113,225)	130	650	3250	650
CS4	108	2690	269	(113,225)	130	650	3250	650
CS5	108	2690	538	(57,113)	130	650	3250	650
CS6	108	2690	538	(113,225)	65	650	3250	650
CS7	108	2690	538	(113,225)	130	325	3250	650
CS8	108	2690	538	(113,225)	130	650	1625	650
CS9	108	2690	538	(113,225)	130	650	3250	325
CS10	162	2690	538	(113,225)	130	650	3250	650
CS11	108	4035	538	(113,225)	130	650	3250	650
CS12	108	2690	807	(113,225)	130	650	3250	650
CS13	108	2690	538	(170,338)	130	650	3250	650
CS14	108	2690	538	(113,225)	195	650	3250	650
CS15	108	2690	538	(113,225)	130	975	3250	650
CS16	108	2690	538	(113,225)	130	650	4875	650
CS17	108	2690	538	(113,225)	130	650	3250	975

From Table 6.6, it can be observed that the MSGA performs better than the base SGA for 12 out of the 17 cost settings. MSGA performs better with more than 25% deviation for CS7 and CS15. In both these settings, the purchasing cost at hospital is altered from the baseline setting. Hence, it can be concluded that MSGA remains robust with respect to change in unit purchasing cost. Also, for 6 out of the 17 scenarios considered, the performance of MSGA is better than the base SGA by more than 10%. For 5 scenarios, the base SGA performs better than the MSGA and with nearly 4% deviation on average.

Table 6.6: Impact of Cost Parameters on the Objective Function

Cost Setting	MSGA	Base SGA	% Deviation of Base SGA from MSGA	Best Performing Rule
CS1	$546,406	$539,728	-1.22%	Base SGA
CS2	$516,142	$566,338	8.86%*	MSGA
CS3	$516,445	$505,094	-2.20%	Base SGA
CS4	$529,875	$612,095	13.43%*	MSGA
CS5	$542,047	$532,751	-1.72%	Base SGA
CS6	$521,725	$574,605	9.20%*	MSGA
CS7	$328,896	$450,284	26.96%*	MSGA
CS8	$524,095	$545,214	3.87%	MSGA
CS9	$532,526	$594,535	10.43%*	MSGA
CS10	$549,391	$646,444	15.01%*	MSGA
CS11	$606,701	$558,650	-7.92%*	Base SGA
CS12	$536,113	$602,640	11.04%*	MSGA
CS13	$533,370	$542,758	1.73%	MSGA
CS14	$584,584	$543,621	-7.01%*	Base SGA
CS15	$736,568	$1,050,801	29.90%*	MSGA
CS16	$537,424	$576,005	6.70%	MSGA
CS17	$533,541	$589,252	9.45%*	MSGA

*Indicates that there exist a significant difference in the performance of the two methods at α=0.05.

6.4.2 Impact of Demand Variation

The coefficient of variation (CV) is the ratio of the standard deviation to the mean of the platelet demand. CV at both the hospitals is increased from 0.1 to 0.5 in steps of 0.1 and the objective function values under MSGA and base SGA are recorded in Table 6.7. From the results, it is evident that the performance of MSGA is significantly better than the base SGA for CV values greater than 40%. In other words, when there is more uncertainty in platelet demand, MSGA performs better. When CV is less than 30%, it can be seen that the gap between the base SGA and the MSGA is decreasing with increase in CV and in fact, for CV=30%, SGA performs better than MSGA.

Table 6.7: Impact of Demand Parameters on the Objective Function

CV Setting	MSGA	Base SGA	% Deviation of Base SGA from MSGA	Best Performing Rule
CV = 10%	$496,208	$502,854	1.32%	MSGA
CV = 20%	$561,747	$567,760	1.06%	MSGA
CV = 30%	$656,420	$650,527	-0.91%	Base SGA
CV = 40%	$749,299	$824,690	9.14%*	MSGA
CV = 50%	$860,272	$941,228	8.60%*	MSGA

*Indicates that there exists a significant difference in the performance of the two methods at α=0.05.

6.5. Conclusions

In this chapter, inventory management at the entire blood supply chain is studied to minimize outdating and shortage of platelets. Stochastic integer programming model under a (s, S) policy is developed to determine the ordering policy. The computational complexity of the model with the number of scenarios and time horizon appears to increase exponentially and hence, a new variant of genetic algorithm is proposed, called modified stochastic genetic algorithm (MSGA) for solving the stochastic program. The proposed MSGA overcomes the drawbacks of the traditional GA such as long convergence time and high probability of obtaining a local optimum. For smaller problems, the performance of MSGA is compared against that of the true optimal solution. For larger problems with 100 scenarios and 500 days horizon, MSGA and the existing genetic algorithm proposed in the literature are compared and the results are presented. Sensitivity analysis is performed by varying the cost and demand parameters. The results indicate that MSGA performs better than the existing genetic algorithm under most cost and demand settings. For future work, different allocation policies at the blood centers can be studied. Also, multi-criteria optimization techniques, discussed in Chapter 4, can be used to develop the inventory policies for the blood supply chain under conflicting performance measures (inventory, versus outdating and shortages).

Chapter 7 : Conclusions and Future Work

Blood supply chain deals with the delivery of different components of blood, (Red Blood Cells (RBC), White Blood Cells (WBC) and platelets suspended in a liquid substance called plasma) from the donor to the hospitals and surgery centers for patient treatment. The whole blood is collected at several collection sites from various donors and is then sent to blood centers where blood is separated into different components and tested for infection. Several hospitals and surgery centers place orders to the blood centers for the various blood components, depending upon their needs to serve their patients.

Among the blood components, platelets have a very short shelf life of 5 days and after the 2-day testing procedure, they only have a remaining life of 3 days. Due to the demand uncertainty and short shelf life of platelets, there are significant wastage and shortage of platelets. It has been reported that about 20% of the total platelet unit collected are outdated in the US and western European countries and nearly 500 surgeries are canceled each day due to the shortage of blood. Therefore, it is necessary to develop inventory ordering policies such that both the outdating and shortage of platelets are reduced.

In this dissertation, deterministic single objective inventory model is first developed to determine the number of platelet units to order and time between orders at the hospital. The model is extended to deterministic multiple objective inventory management at the hospital. All these models assume demand to be known. The models are later extended incorporating demand uncertainty for hospital inventory management. Finally, stochastic inventory models for the entire blood supply chain with a single blood center and multiple hospitals are developed. The models are illustrated using a real case-study data.

7.1. Theoretical Contributions

In the past research work on the inventory management of perishable items and blood in specific, reducing platelet wastage is seldom considered due to the extremely short shelf life of platelets. In addition, published articles on platelet inventory management have assumed infinite supply at the blood center, which is not the case in reality. The blood supply chain models developed in this dissertation consider platelet shortages at the blood center while determining the ordering policies.

According to Dillon *et al.* (2017), most research on blood inventory management assume that the demand is deterministic. However, Haijema et al., (2007) highlighted the necessity to consider blood demand uncertainties, since 50% of the total blood requested by the physicians are not transfused due to uncertainty. Therefore, stochastic programming models under demand uncertainty have been developed to determine ordering policies at individual hospitals as well as at the entire blood supply chain.

In the research work done on the platelet inventory management, it is mostly assumed that the platelets arriving at the hospital are fresh, with a shelf life of 3 days, which is not necessarily true in practice. Based on our interaction with the technicians and pathologist at a regional medical center, the arriving platelets have different shelf lives. In fact, 50% of the platelets arriving have only 1-day life. The analysis presented in Chapter 5 clearly indicates that the inventory policies proposed in the literature are not valid, unless hospitals assume that they receive only fresh platelets from the blood center. The hospital inventory models developed in this dissertation have relaxed this assumption and considered platelets with varying shelf-lives. In addition, the impact of shelf life on the platelet wastage and shortage is also analyzed.

There has been very little previous work on blood inventory management for the entire blood supply chain. In Chapter 6, stochastic programming models and meta-heuristic techniques have been developed for determining the ordering policies for the entire blood supply chain. In addition, the models consider two types of demands placed by the hospitals to the blood center. The first type of demand (referred to as the regular demand) is placed by the hospital at the end of each day and will be received after the lead time. The second type of demand (referred to as the emergency demand) have to be supplied by the blood center to the hospital immediately. The stochastic programming models developed in Chapter 6 is one of first research work to incorporate the real-life sequence of events in the blood supply chain.

7.2. Methodological Contributions

Most of the research on inventory management of platelets assume that the shortage cost is five times the outdating cost (Haijema, 2007; Haijema, 2009; van Dijk, 2009; Gunpinar and Centeno, 2015; Rajendran, 2016a, 2016b). However, shortage cost cannot be quantified in reality. Moreover, better inventory models can be developed if conflicting criteria such as outdating and shortage, holding cost and ordering cost are included. In this dissertation, multiple criteria mathematical programming (MCMP) models for platelet inventory management have been

developed and solved using three MCMP solution techniques - preemptive goal programming, non-preemptive goal programming and weighted objective method. The results obtained from the three MCMP techniques can assist the hospital management in deciding how many platelet units to purchase based on their operational settings.

The stochastic programming model for hospital inventory management under the (s, S) policy is developed in Chapter 5. The performance of the models under the (s, S) policy is compared against the other ordering policies and have proven to be better than the others under several performance measures. Also, the model under the (s, S) policy is computationally less complex and reaches optimality in less time.

In Chapter 6, a new variant of the genetic algorithm, called modified stochastic genetic algorithm (MSGA) is proposed for determining the order-up-to level and re-order points at the hospitals and the blood center. In the MSGA, a new selection method is developed for generating the chromosomes for the next generation. The chromosomes that are carried over to the next generation are selected based on a probability, which is calculated as a function of their fitness value. A greater value of the fitness function ensures a greater chance of being selected to the next generation.

7.3. Contributions to Practice

Hospitals might be interested in following a simple ordering policy without compromising patient care. In Chapter 5, a (s, S) periodic review policy has been developed for ordering platelets at the hospitals. Under this policy, at the end of each review period, the inventory position is recorded. If the inventory position is below the reorder point s, then an order is placed to bring the inventory to level S. If the inventory position is greater than or equal to the reorder point s, then no platelets are ordered at that time. This simple policy is easy to follow by the hospitals and also performs better than other ordering policies.

In addition, four heuristic policies have been developed for hospital inventory management (base stock, modified base stock, weighted mean-variance and last value policies). These policies can be implemented easily using an Excel spreadsheet and can act as decision support systems to hospital administrators.

We also developed the following recommendations for the hospital's inventory management:

- If there is a trend in platelets demand (increasing/decreasing), then the hospital should use the weighted mean-variance or last value ordering policies.
- If the hospital experiences low demand variation, then the weighted mean-variance policy is better. For high demand variation, modified base stock policy is the best performing rule.
- If the blood center is located far away from the hospital, then the cost of emergency procurement (i.e., shortage) would be very high. In such cases, base stock or modified base stock ordering policies would be better.
- If the hospital has limited storage capacity, then the last value policy will be the most suitable. This would result in minimizing the inventory of platelets.
- If more than 80% of the platelets arriving at the hospital are fresh (i.e., have a shelf life of 2 or 3 days), then the modified base stock policy should be adopted.

7.4. Future Research Directions

The following are the potential future work:

- **Multiple Criteria Approaches for managing the Blood Supply Chain:** As discussed earlier, it is difficult to quantify the cost of shortage and outdating at any stage of the blood supply chain. Therefore, goal programming and weighted objective techniques developed for hospital inventory management in Chapter 4, can be extended to the entire blood supply chain. In addition, other multiple criteria techniques such as compromise programming and interactive approaches which directly involve the decision maker in the solution process, can also be used for making order policy decisions at the blood supply chain.
- **Platelet Demand for Two Types of Patients:** Hospitals place platelet demand under two age categories. 'Young' (fresh) platelets are usually required by patients in the oncology and hematology departments, while 'any' age platelets are required by other departments such as traumatology and general surgery (Haijema et al., 2007). The models developed in this dissertation can be extended considering these two types of patient demands.
- **Vehicle Routing Policies for Blood Supply Chain:** Vehicle routing policies can be studied for the two stages in the blood supply chain. The first stage is during the collection of blood from the donors in the blood drives. The blood that is collected at blood drives

have to be transported to the blood center within 4-6 hours of collection. Therefore, blood have to be collected from several drives and efficiently transported to the blood center within the limited time window. The other stage is during the delivery of blood components from blood centers to hospitals. In some cases, blood components have to be transported for several hundred miles from the blood centers to hospitals and hence, it is necessary to schedule vehicles such that the overall transportation cost is reduced.

- **Closed-Loop Blood Supply Chain:** Blood can be sent back to blood center due to reasons such as bacterial contamination or when excess units are ordered. In these cases, the reverse shipment cost has to be considered in the model. However, none of the previous research takes into account the reverse shipment cost and the associated reduction in inventory.
- **Prediction Analytics for Blood Products:** Predicting demand for blood components is essential since the demand is increasing and the supply is not increasing enough to meet the demand. Also, advanced information can increase blood collection efforts if more blood is required, and blood collection can be limited, if less units are needed (Frankurter et al., 1974). Predicting demand of perishable items such as blood is specifically challenging because of the limited shelf life. Therefore, predictive analytic tools such as random forest, artificial neural network or regression can be used for demand prediction considering several input factors such as weather, day of the week and month of the year.
- **Ordering Policies considering Multiple Blood Products:** Ordering policies can be developed for the entire platelet supply chain considering the flow of multiple blood products, such as red blood cells, white blood cells, platelets and plasma, along the blood supply chain.
- **Collaboration and Platelet Sharing:** A collaborative hospital network can be proposed in which each hospital can fulfill its patient demand from its inventory, but can also receive an additional amount of platelet units from other collaborating hospitals, which have excess platelet available that day. As a result, the extent of platelet demand fulfillment is increased due to excess platelet units shared by the collaborating hospitals. This collaboration in a hospital network will reduce platelet shortage and outdating. Currently, the government policies do not allow sharing of platelets among different hospitals. The results from this work may reveal potential benefits of platelet sharing and act as a catalyst to change government policies.

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Appendix
Forecasting Data and Seasonality Index

Day 1 average	193.6923077
Day 2 average	211.6153846
Day 3 average	198
Day 4 average	183.7692308
Day 5 average	182.6923077
Day 6 average	165.7692308
Day 7 average	158.3076923
Overall average	184.8351648

$$\text{Seasonality index for day } i = \frac{\text{average demand during day } i}{\text{overall average of demand for all periods}}$$

$$\text{Seasonality index for day 1} = \frac{193.6923}{184.8352} = 1.047919$$

$$\text{Seasonality index for day 2} = \frac{211.6153846}{184.8352} = 1.144887$$

$$\text{Seasonality index for day 3} = \frac{198}{184.8352} = 1.071225$$

$$\text{Seasonality index for day 4} = \frac{183.7692308}{184.8352} = 0.994233$$

$$\text{Seasonality index for day 5} = \frac{182.6923077}{184.8352} = 0.988407$$

$$\text{Seasonality index for day 6} = \frac{165.7692308}{184.8352} = 0.896849$$

$$\text{Seasonality index for day 7} = \frac{158.3076923}{184.8352} = 0.\ 85648$$

Vita

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