ABSTRACT

OPTIMAL ALLOCATION OF BLOOD PRODUCTS

by
Godson A. Tetteh

The high cost of collection and the short shelf life of apheresis platelets demand efficient inventory management to reduce outdates and shortages. Apheresis platelets are licensed for seven days, and blood centers are keen on knowing the consequences of various product collection and distribution strategies. To reduce outdates, inventory managers typically distribute the older units first, thereby following first-in first-out (FIFO) policy; however, hospital blood banks would prefer that the blood center issues out the freshest units first, equivalent to a last-in first-out (LIFO) policy. This study addresses the optimal distribution policy to achieve a desired outdate, shortage and average age of apheresis platelets.

A comprehensive literature review was conducted on previous models studied to efficiently distribute blood products. However, most of the research on blood inventory management has been restricted to the hospital blood bank level in terms of ordering policies and inventory levels. This study takes the approach from the perspective of the inventory manager at the regional blood center. The inventory manager needs a reliable forecast of the quantity and timing of future blood supply (collection from donors) and blood demand from hospital blood banks to make an effective decision on blood inventory control. A forecasting method is used in this study to predict collection and demand for Single Donor Platelets (SDPs), and solves the blood inventory problem using a heuristic method and a Linear Programming (LP) with a rolling horizon method to find

the near optimal issuing policy, the expected average age, outdate rate, and shortage rate of a blood product from the perspective of the blood center.

It is concluded that regional blood centers can distribute with a 'mixed' FIFO/LIFO strategy and not significantly affect outdates or ability to cover shortages. For the LP model with a rolling horizon schedule, the inventory manager at the blood center would have to use forecast windows of five to achieve good issuing policies.

A simulation study comparing the heuristic method and an LP-based with a rolling horizon method indicated that LP models with forecast windows of five and heuristics methods with a 'mixed' FIFO/LIFO strategy can be used to optimize this inventory problem.

OPTIMAL ALLOCATION OF BLOOD PRODUCTS

by
Godson A. Tetteh

A Dissertation
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Transportation Engineering

Interdisciplinary Program in Transportation Engineering
May 2008

APPROVAL PAGE

OPTIMAL ALLOCATION OF BLOOD PRODUCTS

Godson A. Tetteh

Dr. Jian Yang, Dissertation Advisor — Date
Associate Professor of Industrial and Manufacturing Engineering, NJIT

Dr. Athanassios K. Bladikas, Committee Member — Date
Associate Professor of Industrial and Manufacturing Engineering, NJIT

Dr. Lazar Spasovic, Committee Member — Date
Professor of Civil and Environmental Engineering, NJIT

Dr. Adefemi Sunmonu, Committee Member — Date
Associate Professor of Mathematics, York College, CUNY, NY

Dr. Steven I-Jy. Chien, Committee Member — Date
Professor of Civil and Environmental Engineering, NJIT

BIOGRAPHICAL SKETCH

Author: Godson A. Tetteh

Degree: Doctor of Philosophy

Date: May 2008

Undergraduate and Graduate Education:

- Doctor of Philosophy in Transportation Engineering,
  New Jersey Institute of Technology, Newark, NJ, 2008

- Master of Science in International Transportation Management
  State University of New York (SUNY) Maritime College, Bronx, NY, 2002

- Master Mariner – Class 1 Deck Officer,
  Regional Maritime Academy, Accra, Ghana, 1997

Major: Transportation Engineering

Presentations and Publications:

Godson Tetteh,
"Lean Six Sigma Theory and Practice,"
Speaker at the American Society for Quality NY-NJ Metropolitan Section 59th Annual Conference, Newark, NJ, October 2007.

Godson Tetteh, Christopher Baldwin and Alan Blomquist,
"Forecasting Single-Donor Platelets and Inventory Practice,"
Abstract AP98 Selected for Poster Presentation at AABB 2007 Annual Meeting Anaheim (California) *Transfusion*, Vol. 47 No. 3S, September 2007, p. 258A.

Godson Tetteh and Christopher Baldwin,
"Inventory Management with 7-Day Apheresis Platelet,"
Abstract A19-020D Selected for Oral Presentation at AABB 2006 Annual Meeting Miami (Florida) *Transfusion*, Vol. 46 No. 9S, September 2006, p. 172A.

To my beloved wife, Barbara, and our dear son,

Josh Gideon Tetteh

ACKNOWLEDGMENT

To God be the glory, great things HE has done! "I can do all things through Christ which strengthens me." Without HIM I can do nothing.

I would like to thank my dissertation supervisor, Dr. Jian Yang for his support and encouragement throughout this study. Special thanks are given to Dr. Athanassios Bladikas, Dr. Lazar Spasovic, Dr. Steven Chien and Dr. Adefemi Sunmonu for their valuable advice as committee members. I will say a special 'Thank you' to Dr. Adefemi Sunmonu for helping to develop the visual basic script for the Linear Programming analysis.

I acknowledge with thanks the assistance of Dr. Christopher Baldwin (New York Blood Center) in the initial stages of this dissertation, and Ms. Betsy McQuail (Vice President, New York Blood Center) for granting the permission to use NYBC data for the analysis. This is a debt I cannot fully repay.

Special thanks are given to Mark Wiley of LINDO Systems, Inc., for the license to use LINGO software for the Linear Programming analysis.

I thank my fellow graduate students and faithful friends both near and far for their encouragement in one way or the other.

TABLE OF CONTENTS

Chapter		Page
1	INTRODUCTION	1
	1.1 Background	1
	1.2 Problem Statement	4
	1.3 Dissertation Organization	7
2	LITERATURE REVIEW	8
	2.1 Forecasting Blood Supply and Demand	8
	2.2 Blood Inventory Management	10
	2.3 A Linear Programming Method for Obtaining Optimal Issuing Policy	13
	2.4 Rolling Horizon Schedule	14
3	FORECASTING PLATELET COLLECTION AND DEMAND	16
	3.1 Overview	16
	3.2 Choice of Forecasting Method	17
	3.3 Empirical Study Design and Methodology	20
	3.4 Empirical Study Results	21
	3.5 Verifying Empirical Study Result	22
4	BLOOD INVENTORY MANAGEMENT	28
	4.1 Overview	28
	4.2 Mathematical Model for Blood Inventory Management	29
	4.3 Parameters	30
	4.4 Heuristic Method using Microsoft Excel	30
	4.5 Case Study I	32

TABLE OF CONTENTS
(Continued)

Chapter	Page
4.5.2 Limitation of the Heuristic Model	34
4.6 Linear Programming (LP) method using the LINGO optimization software	34
4.6.1 Decision Variables	34
4.6.2 Constraints	35
4.6.3 Objective Function	35
4.7 Main Factors Effecting Inventory Model	36
4.8 Rolling Horizon Schedule	38
4.8.1 A Computational Study	39
4.8.2 Computational Results	40
5 STOCHASTIC MODEL	43
5.1 Overview	43
5.2 Problem Formulation	44
5.3 Data Collection and Analysis	44
5.4 Random Variable Generation and Model Validation	45
5.5 Simulation	47
5.5.1 For the Linear Programming (LP) with Rolling Horizon Solution	48
5.5.2 For the Heuristic Model	48
5.6 Stochastic Empirical Study	49
5.7 Case Study II	53
5.7.1 Stochastic Approach	54
5.7.2 Simulation Result	55

TABLE OF CONTENTS
(Continued)

Chapter	Page
5.7.4 Average Outdate Rate	57
5.7.5 Average Age of Products Shipped	57
5.7.6 Discussion	58
6 CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER STUDIES	59
6.1 Conclusions	59
6.2 Further Studies	60
APPENDIX A FORECAST OUTPUT OF QUANTITY RELEASE (R) AND DEMAND/SALES (D) FOR JULY 2006	62
APPENDIX B TABLE CONSTANTS FOR CONTROL CHARTS	63
APPENDIX C 92 DAY FORECAST AND ACTUAL QUANTITY RELEASE (R) AND DEMAND/SALES (D)	64
APPENDIX D LINGO MODEL	65
APPENDIX E LINGO OUTPUT	66
APPENDIX F HEURISTIC METHOD USING MICROSOFT EXCEL	67
APPENDIX G FACTORS WITH LEVELS FOR DOE ON OBJECTIVE FUNCTION	70
REFERENCES	71

LIST OF TABLES

Table		Page
4.3	Results of Case Study I	33
4.5	Factors with Levels for Design of Experiments (DOE)	36
5.4	Average Daily Total and Standard Deviation (Group A)	50
5.5	Average Daily Total and Standard Deviation (Group B)	52
5.6	Average Daily Total and Standard Deviation (Group C)	52
5.7	Revenue Schedule for 5 Day and 7 Day Platelets	53
5.8	Comparison of the 5 Day and 7 Day Models	55

LIST OF FIGURES

Figure		Page
3.1	Days to donation vs. number of appointments.....	17
3.2	Box plots comparing monthly SDP appointments.....	18
3.3	Regression results from MINITAB	20
3.4	Normal probability plot – forecasted released products.....	25
3.5	Control chart test results – forecasted released products.....	25
3.6	Control chart test results – forecasted sales.....	26
4.1	Network representation of inventory problem.....	29
4.2	Heuristic method using Microsoft Excel.....	31
4.4	Effect of change in demand on outdates and shortages.....	33
4.6	Analysis of variance (ANOVA) of factors.....	37
4.7	Factors' effect on objective function.....	37
4.8	IMR chart for forecast release error.....	41
4.9	IMR chart for forecast demand/sales error.....	41
4.10	Rolling horizon results.....	42
5.1	Discrete frequency distribution for released quantity R.....	46
5.2	Discrete frequency distribution for released quantity D.....	46
5.3	Flow chart of stochastic inventory simulation model.....	47
5.7	Comparison of heuristic and LP-rolling horizon methods.....	51
5.9	Average daily total benefit – 7 Day vs. 5 Day Group A	55
5.10	Average daily total benefit – 7 Day vs. 5 Day Group C	56
5.11	7 Day average outdate rate	57

CHAPTER 1

INTRODUCTION

"For the life of the flesh is in the blood" (Leviticus 17:11) - a quotation from the Bible stresses the importance of human blood.

1.1 Background

Blood transfusion therapy is an important aspect of the medical care system, and it has been stated that "one in three infants, teens, and adults of all ages will need blood transfusion at one point of their life"[1]. In the New York metropolitan area, about 4000 newborn babies, trauma victims, cancer patients, transplant patients, and surgery patients need blood transfusion each day. To meet this demand, blood collection centers and hospital blood banks must maintain desirable inventory levels to ensure that blood demand is adequately met and appropriate measures are taken to minimize blood waste. Since human blood is a perishable product, there is a need for effective and efficient management of the blood supply. To ensure effective use of the limited blood resources, blood utilization and inventory management policies must be practiced by the blood collection centers, hospital blood banks, and physicians ordering transfusions.

Blood products are supplied in the United States mainly by the American Red Cross (ARC) and independent community blood centers that belong to America's Blood Centers (ABC). The ARC, blood banks, and blood centers charge hospitals a service fee to cover the costs for drawing, processing, testing, and distributing the blood. Blood centers make strenuous efforts to recruit volunteer donors to replenish the blood supply. It is important that every pint of blood donated should end up as a transfusable product.

---

[1] See NYBC pamphlet "Donate Blood now. People can't live without it."

The blood supply chain is made up mainly of blood donors, regional blood centers, (community blood banks, or hospital blood bank donor rooms), hospital blood banks, and patients at the hospital. The blood center or hospital blood bank donor room collects blood in units of one pint from donors at a collection site. The collected blood undergoes a series of typing and screening tests, is inventoried at the Blood Center or Blood Bank, and then shipped to a hospital blood bank or transfusion facility at the latter's request to satisfy present or expected demand for transfusions. Collection of blood is an important function in the supply chain. Blood donations are collected by (1) scheduled visits to organizations, schools, or churches where donors have already pledged to give blood or telemarketers book platelet donors at scheduled times, (2) walk-in donors to blood center's facilities, and (3) invited donors from a campaign. However, an uncertain percentage of donors that pledge to donate blood may not be able to donate due to health reasons, may defer their visit, or may not show up at all. Hence the amount to be collected can only be estimated.

The primary blood products are whole blood, packed red blood cells, packed red blood cells leukocytes reduced, fresh frozen plasma, plasma cryoprecipitate, and platelets (apheresis and random). Packed red blood cells (RBCs), plasma, and random platelets (RDP) may be extracted from a whole blood unit drawn from a donor and prepared by centrifugal or gravitational separation.

Platelets are needed to support cancer therapy, treatment of blood disorders, organ transplants, and open-heart surgery. Deficiencies in platelet number and function in a patient may have unpredictable effects that may range from major life-threatening hemorrhage to clinically insignificant prolongation of the bleeding time. Platelets are

transfused to patients whose platelet count is much lower than the normal range of 150,000 - 400,000 per μL due to illnesses including cancer, leukemia, or certain blood disorders. The platelet count criteria for transfusing platelets depends upon many factors including but not limited to the clinical state of the patient and whether any invasive procedures are going to be performed.

Apheresis platelets (SDPs) as well as random donor platelets (RDPs) have a lifetime of five (or seven) days from collection depending on the technology used for collection and the storage bag used. Apheresis platelets are a high-value product compared to random platelets. Even though it is more expensive to obtain one unit of SDPs than to prepare a random platelet from whole blood, SDPs can offer definite advantages to recipients, including increased consistency of dose, decreased patient exposure to disease transmission, speed of availability, and the possibility for matched platelet transfusions (McLeod, Price and Weinstein, 2003).

Apheresis platelets account for about 60 percent of the total blood product sales of a blood center. Because of their relatively high cost of collection and their short shelf-life, the overall management of apheresis platelet collection programs can have substantial consequences for a blood center and the hospitals that rely upon it. This dissertation addresses some of the problems associated with the efficient allocation and inventory management of apheresis platelets in a blood center.

1.2 Problem Statement

Forecasting blood demand (D) and collection (C) is a prerequisite for inventory control. However, the uncertainty of the variable to be predicted is so high that standard forecasting techniques lead to unsatisfactory results. Past data indicate that demand and collection exhibit a lumpy pattern at certain times, and have both a trend and seasonality. During holidays, many donors do not show up for blood drives. With this high degree of uncertainty, some hospital blood banks tend to overstock their inventory towards the lean season consequently creating a lumpy demand prior to a holiday. This "chaotic effect" of historical demand tends to introduce large errors in the forecast and either over estimate and increase the product outdate rate, or under estimate demand and create product shortages.

Sometimes blood supplies to hospital blood banks are rationed during lean seasons. This could skew the forecast if it was mainly based on past sales data instead of actual demand. For example, blood centers may have an adequate record of sales, but if a hospital requested a number of products that were not available, the blood center may supply only a limited amount during these so called lean seasons. The negotiation between the hospital and the blood center may not have been monitored, and as a result, the record of sales could be a poor reflection of the actual demand.

Hospitals have contractual agreements for scheduled or 'standing order' deliveries with the blood center to satisfy a hospital's demand. Most single donor platelet standing orders however do not specify the ABO type distribution of the platelets but simply specify the number of platelets.

A hospital blood bank is concerned with maintaining a sufficient inventory of platelets to meet variable daily demand of transfusions and reaches a working compromise between the outdate and shortage rates. Sometimes supplemental or 'emergency' orders are made by the hospital blood bank for a specific type of blood product when there is a shortage of that specific type. A typical break-down of an annual order from blood banks indicated that 78 percent were of the standing orders and 22 percent were supplemental or emergency orders.

Since the blood supply is derived from volunteer donors, its collection and availability is uncertain. Outdating a product is undesirable, but the uncertainties in supply and demand can result in a number of blood products that exceed their shelf-life. Due to the short shelf-life for Single Donor Platelets (SDPs), over-collecting on a particular day could necessitate outdates, if the demand is less than the supply for that period. It is also uncertain how many scheduled donors will actually show up and keep their appointments. Since SDPs are produced by using automated cell-separator devices, the system is constrained by the number of apheresis machines available. Each unit collected is first tested for 2 days, and expires either 5 or 7 days after collection depending on the type of storage bags used. A blood center must decide how many platelet units to collect each day to satisfy demand for the period without outdating a large fraction of the platelets.

To reduce outdates, the blood center would prefer to distribute the older units' first thereby following first-in first-out (FIFO) policy. However, the hospital blood bank ordering products would prefer that the blood center issues the freshest unit first and follow a last-in first-out (LIFO) policy. As a matter of fact, there have been instances

where hospital blood banks have insisted on a fresher product than that being offered by the blood center. Hence the blood center cannot apply a strict use of the FIFO policy. Single Donor Platelets (SDPs) used to expire on the fifth day following collection. However, Gambro BCT was recently granted Food and Drug Administration (FDA) permission to extend the shelf-life of SDPs from five to seven days following collection. What will be the optimum issuing policy that will reduce outdate and shortage rates from the perspective of the blood center? Who will benefit from the 7-Day platelet production - the blood center or the blood banks? What will be the average age of the products distributed by the blood center?

The primary objective of this dissertation is to address the following fundamental inventory management problems for the optimum allocation of blood products with special reference to Single Donor Platelets (SDPs):

1. Determine a forecasting method to predict Single Donor Platelets (SDP) collection and demand.

2. Determine how the blood center can achieve its goal of fulfilling blood demand and minimizing inventory costs by reducing outdates and shortages of platelets (SDPs) using:

   - A heuristic method using Microsoft Excel to obtain the optimal 'mixed' FIFO/LIFO policy,

   - A linear programming method using a rolling horizon schedule to obtain the optimal policy,

   - A stochastic model to compare the above two methods.

1.3 Dissertation Organization

This dissertation is organized into six chapters. The background, the inventory problem, and the primary objectives are stated in the first chapter. A thorough literature review, covered in Chapter 2, summarizes findings from previous studies on forecasting blood supply and demand, blood inventory management, the linear programming method for obtaining an optimal issuing policy, and rolling horizon schedule. Chapter 3 includes a forecasting method to predict the collection and demand for Single Donor Platelets (SDPs), and the verification of the forecasting method. In Chapter 4, the blood inventory problem is solved using a heuristic and a Linear Programming (LP) with rolling horizon method. The total benefit, expected average age, outdate rate, and shortage rate of a blood product are obtained from the heuristic and the Linear Programming (LP) with rolling horizon methods, and the results are evaluated. Chapter 5 contains a stochastic model to compare the heuristic with the Linear Programming (LP) with rolling horizon methods, and a discussion of the 5 - Day and 7 - Day inventory models. Conclusions and recommendations for further studies are finally presented in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

Most research on blood inventory management has been restricted to the hospital blood bank level in terms of ordering policies and inventory levels.

This study focuses on inventory manager at level of a regional blood center which takes blood orders from hospital blood banks. The literature review is classified into

(1) Forecasting blood supply and demand;

(2) Blood inventory management;

(3) Linear Programming to obtain an optimal issuing policy;

(4) Rolling horizon schedule.

2.1 Forecasting Blood Supply and Demand

A reliable forecast of the quantity and timing of future blood supply (collection from donors) and blood demand from hospital blood banks is needed to manage inventory at the Regional Blood Center and make an effective decision on blood inventory control. Forecasting blood supply and demand can be based on quantitative approaches (for example, using historical data to predict the future using regression or time series analysis) and qualitative approaches (using expert judgment or management assumptions).

Frankfurter, Kendall, and Pegels (1974) used a short-term computerized blood inventory level forecast and provided management the tool to control blood inventory levels by eliminating blood shortages and excessive expirations. The forecasting model was made of blood transfusion

forecasts using an exponential smoothing model (this method exponentially decreases weights of past data); blood expiration forecasts using an exponential function with empirically derived parameters; blood collection forecasts using historical data; and blood inventory projection based on the transfusion forecast, predicted expirations, and forecasted collections.

Gardner Jr. (1979) tested the Box-Jenkins forecasting models (which uses a variable's past behavior to select the best forecasting model from a general class of models including auto-regressive, moving average, autoregressive-moving average (ARIMA)), and multiple regression models to forecast the aggregate number of blood tests to be conducted at a laboratory each month as a function of time. He found that the regression models gave significantly better forecast errors for both short and long range horizons. Pereira (2004) used three time-series (namely autoregressive integrated moving average (ARIMA), the Holt-Winters family of exponential smoothing models, and one neural-network-based) methods to investigate the forecasting of demand for red blood cell transfusion.

Even though forecasting is a precondition for decision making in inventory practice, few studies have focused on the interactions between forecasting and inventory decisions. Croton (1972), Lee and Adam (1986), and Watson (1987) concluded that forecast errors can distort projections of customer service in distribution inventories. Gardner Jr. (1990) in a study on the impact of forecasting on inventory decisions in a large physical distribution system concluded that the forecasting model choice is an important factor in determining the amount of investment to support any target level of customer service. Analyzing the characteristics of the inventory demand time series to identify alternative forecasting models, and the experimental design to test forecasting models are relevant to the main topic of this dissertation.

Time series forecast errors can be calculated using: Mean-Squared Error (MSE) which is the absolute error that squares the difference between the actual historical data and the forecast fitted data predicted by the model; Root Mean-Squared Error (RMSE) which is the average of the absolute values of the forecast errors; Mean Absolute Deviation (MAD) which is an error statistic that averages the absolute value of the difference between the actual historical data and the forecast-fitted data predicted by the model; Mean Absolute Percent Error (MAPE) which is a relative error statistic measured as an average percent error of the historical data points. Whybark (1973) and Gardner Jr. (1990) in their experimental design to deal with outliers and jump shifts in a time series forecasting system used control limits set at plus and minus three standard deviations of demand, which is similar to a Shewhart (1939) control chart to determine when the forecasting model will no longer be feasible. This procedure made marginal improvements in the ability to forecast demand.

2.2 Blood Inventory Management

The optimal allocation of blood inventory could be described as a problem of finding an issuing policy which either maximizes or minimizes a function of the inventory level and actions over time. Optimal selection of an issuing policy with conditions under which either FIFO (first in, first out) or LIFO (last in, first out) are used have generated a lot of interest especially with perishable products like blood. Hospitals ordering blood products from blood banks or blood centers insist on receiving the freshest blood product, thereby forcing the blood bank or center to practice LIFO. In contrast, the blood bank or center will prefer to send out the older units first (FIFO) to minimize outdate and shortage of blood products.

Derman and Klein (1958) formulated an optimal sequence to remove items from a

stockpile of finite units of varying ages. The stockpile consisting of n items was associated with the *i-th* item having an age (length of time in the stockpile) S_i *(1, 2,..., n)*. The total field life (a function *L(S)* of the age) of the stockpile depends on the sequence in which items are removed from the stockpile, as an item was issued only when the previous item issued had expired.

They stated that if a complete knowledge of the function *L(S)* was available, then optimal policies for any given situation could be obtained by a consideration of all *n factorial (!)* different orderings and the consequent selection of the best, or the use of an algorithm would lead to the solution. Derman and Klein in their study took the approach to specify conditions on the "field life" of the item in the stockpile for which issuing either the oldest units first (FIFO) or the newest units first (LIFO) was optimal. First-in-first-out (FIFO) and last-in-first-out (LIFO) issuing policies in practice are the most easily understood and the most easily implemented inventory policies, and only knowledge of the relative ages of the items in the inventory are required. However, there are limitations to their study; (1) there was no penalty or installation costs associated with the issuance of an item from the stockpile, (2) new items were never added to the stockpile after the process started.

Pierskalla (1965) in a study on the analytic results of Derman and Klein (1958) eliminated and modified some of the assumptions to obtain a LIFO or FIFO issuing optimal policies. In perishable product inventory systems where the issuing of the stock to meet demand was controlled by the consumer, the movement of units through the system was found to obey a LIFO issuing policy (Cohen and Pekelman (1978)).

Brodheim et al. (1975) evaluated a class of inventory distribution policies for deliveries of perishable products with variable demand, which was modeled as a Markov chain. Fries (1975) and Nahmias (1982) determined independently the optimal ordering policy for a product

with a general lifetime of *m* periods by solving a dynamic programming equation. Chazan and Gal (1977) used a similar approach to Cohen (1976), but daily demand was modeled as a discrete random variable so that starting stock levels formed a discrete state space Markov chain.

Numerous theoretical models have been developed using dynamic programming models (Prastacos, 1981), queuing models (Graves, 1982), and Markov chain models (Chazan and Gal, 1977), to solve the blood inventory problem. Simulation models (Cohen and Pierskalia, 1979) have been used also to determine the operating characteristics curves and decision rules for setting optimal blood inventory levels. Prastacos (1984) carried out a comprehensive review of the theory and practice of blood inventory management and the models developed to address some of the issues faced at the hospital levels, and stated that "because of the assumption that *all units demanded are used* in these analytical research on general perishable products, the analytical results obtained are not directly applicable to blood inventory management." Due to this drawback blood bankers turned to empirically-obtained results in combination with their own experience. Jennings (1968, 1973) used empirical results using data from a Massachusetts hospital to derive the trade-off curves showing outdate vs. shortage as functions of the inventory level.

Some of the recent studies on perishables include the use of an estimator for the probability that an item will be sold in a period to determine the outdate and shortage operating curves in an inventory problem with a fixed lifetime (Omosigho, 2002). Sirelson and Brodheim, (1991) used a computer planning model for blood platelet production and distribution. Haijema et al. (2007) in a study combined a Markov dynamic programming (MDP) and simulation approach to optimize blood platelet production.

2.3 A Linear Programming Method for Obtaining Optimal Issuing Policy

From the theoretical solution of Derman and Klein (1959), Linear Programming (LP) may be one of the methods that may be useful in obtaining the optimal issuing policy. Linear Programming (LP) deals with situations in which a function is to be optimized (for example, maximize a benefit function, or minimize a cost function), where the objective function is linear, and the constraints are linear equalities or inequalities.

Linear programming is an important field of optimization in operations research. Historically, ideas from linear programming have inspired many of the central concepts of optimization theory, such as duality, decomposition, and the importance of convexity and its generalizations. A number of algorithms for other types of optimization problems work by solving Linear Programming problems as sub-problems.

The main algorithm used in solving Linear Programming problems is the Simplex method. Four major drawbacks (Schulze, 1998) of the simplex method are:

- *Initialization*, when there is a problem of finding the initial feasible solution with which to start the simplex method;
- *Iteration*, when there may be difficulty in choosing an entering or leaving variable;
- *Degeneracy* or *Cycling* could be encountered when the simplex method gets "stuck" during iteration and finds itself repeating without changing the value of the solution and therefore not changing the value of the objective function; and
- *Termination*, when the simplex method terminates by finding that the problem is infeasible or unbounded or goes through endless, repeating sequences of non-optimal solutions.

The importance of linear programming derives in part from its ability to be used in many applications including agricultural economics (Kuang, 1972), solving the multi-commodity flow problem (McBride, 1998), planning and scheduling in yogurt production (Entrup, Günther, Van

Beek, Grunow, and Seiler, 2005), inventory management, portfolio and finance management, human and machine resource allocation, scheduling and transportation assignments. Likewise, linear programming is heavily used in microeconomics and business management, either to maximize the income or minimize the costs of a production scheme.

The main advantage of linear programming as an optimization method is that an optimal solution is always found, if one exists.

2.4 Rolling Horizon Schedule

A *rolling horizon schedule* is the product of solving a finite horizon multi-period model and implementing the first period's decision only. A period later, the multi-period model is updated as relevant information is obtained and the process is repeated.

For the inventory manager to obtain the optimal issuing policy, he/she would have to depend on forecasts for blood supply and demand into the future. However, forecasts further into the future are prone to error. For multi-period problems like the inventory problem, decision(s) for the first period or the first few periods are of importance to the decision maker.

Rolling horizon research dates back to the studies of Modigliani and Hohn (1955), and Wagner and Whitin (1958). Forecasting and rolling horizon have been studied in dynamic problems for inventory management, production planning, capacity expansion and warehousing (Chand, Hsu, Sethi, 2002). Baker and Peterson (1979) found the longer the planning horizon the better the rolling horizon performance of the static models.

Hence, one investigates given that the forecast window interval length has been determined *a priori*, what impact the underestimate or overestimate of the blood supply and demand would have on a rolling horizon inventory problem.

The next chapter explores a forecasting method to predict the collection and demand for Single Donor Platelets (SDPs) and the verification of the forecasting method.

CHAPTER 3

FORECASTING PLATELET COLLECTION AND DEMAND

3.1 Overview

Forecasting platelet demand and collection is important for inventory control, but, the uncertainty of the variable to be predicted is so high that standard forecasting techniques lead to unsatisfactory results. Platelet donors are normally contacted by telephone or email and an appointment is booked for a particular day of donation. Even though there are 'walk-ins' without appointment, their number is insignificant.

Plateletpheresis is a process to obtain platelets from blood drawn from a single donor (SDP) using a blood cell separator. Apheresis, which is the use of automated cell-separator devices, may be described as a process by which blood is removed from a subject and is continuously separated into layers. The desired component is retained, while the remainder is returned to the donor. After the donation, the hematology laboratory receives the 'platelet-rich-plasma' samples from the platelet apheresis procedure to determine each product's platelet count and concentration.[2] The product of the volume and concentration will produce the 'yield'. The hematology laboratory then informs the component laboratory of the availability of successful "raw" products, indicating those that can be split into 'doubles' or 'triples'. After splitting, the product volumes are determined by weighing each split product and the platelet count is measured to obtain the qualified single donor platelet products, which will now be known as the released product R_t.

---

[2] New York Blood Center-SOP, "Daily Quality Control Procedures for Single Donor Platelets Collected by Apheresis" 04.0048 July 2003

3.2 Choice of Forecasting Method

The dataset comprises observations for SDP appointments and production in the New York/ New Jersey region for a period of 12 months. To get an idea of the sample properties, Figure 3.01 graphically depicts Days to Donation, d, and the corresponding number of SDP appointments, A, for a particular day of the week from the historical data.

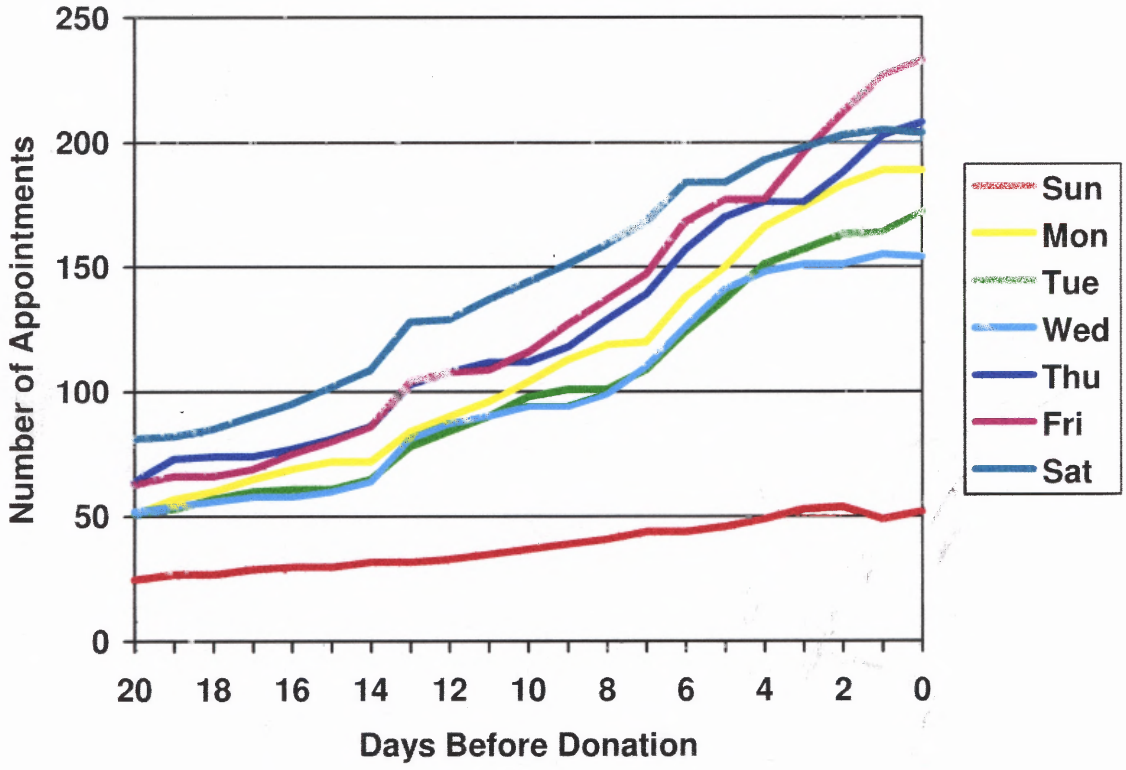

Figure 3.1 Days to donation vs. number of appointments.

To gain some insight, the graphs in Figure 3.1 show that there are differences in the filling rate of the appointments depending on the day of the week (for example, Sundays (Sun) are the lowest filling rate).

A fitted line plot using a linear regression model for all days of the week had a p-value < 0.0005 which indicated a good fit to the data. A visual inspection of the plot revealed that the

data were randomly spread about the regression line, implying no systematic lack-of-fit. This provided some preliminary evidence for a linear relationship between the Days to Donation, *d*, and the corresponding number of SDP appointments, *A*. Secondly, the mean SDP Appointments in January were statistically similar with the mean SDP appointments in all other months as depicted in Figure 3.2.

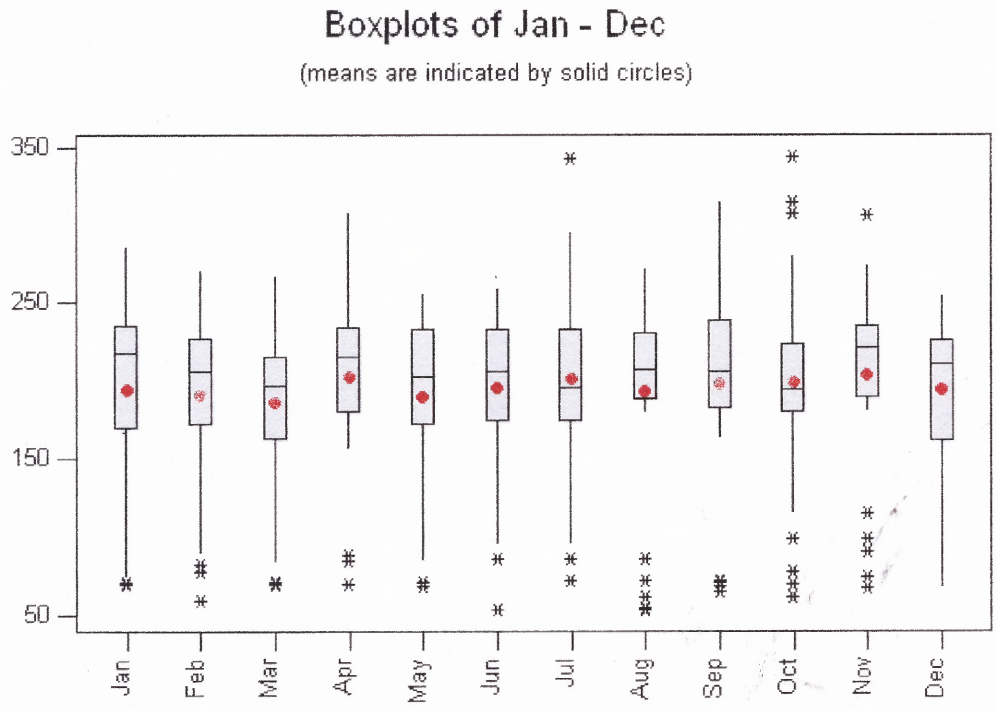

Figure 3.2 Box plots comparing monthly SDP appointments.

The one way analysis of variance (ANOVA) test with the null hypothesis that there were no differences among the mean SDP appointments, and the alternative hypothesis that there were differences in the mean SDP appointments had a p-value of 0.992. Hence, the mean SDP appointments in January are equivalent to the mean SDP appointments in all the months.

Based on the historical data analysis, it was assumed that blood supply (collection and production) was stable and similar throughout the year. A similar analysis of blood demand from

historical data exhibited the same characteristics, hence demand was assumed to be constant throughout the year. Some of the observed factors that affected blood supply (collection) were

1. The inventory manager had limited control of the blood supply (collection) by shifting blood donors from days the appointments are over-booked to days that are under-booked based on a forecast.

2. Location and population of the blood drive.

Future studies could investigate how the limited control strategies of the inventory manager affect blood supply (collection) and demand. This study assumed that blood supply and demand are constant throughout the year based on the historical data analysis. Other prediction models could be used if blood supply and demand is not uniform.

3.3 Empirical Study Design and Methodology

The standard bivariate (two variables) linear regression model can be represented as follows:

$$A_t = \beta_0 + \beta_1 d + \varepsilon \tag{3.1}$$

where A_t is the number of appointments for day t, β_0 is the intercept, β_1 is the slope, d is the days to donation, and ε is the error term. The regression results are shown in Figure 3.3.

Number of Appointments = 216 - 7.18*Days to Donation

Predictor	Coef [3]	SE Coef [4]	T [5]	P [6]
Constant	216.139	2.359	91.63	0.000
d_7	-7.1805	0.2018	-35.59	0.000

S [7] = 5.599 R-Sq [8] = 98.5% R-Sq [9] (adj) = 98.4%

Analysis of Variance

Source	DF [10]	SS [11]	MS [12]	F [13]	P [14]
Regression	1	39701	39701	1266.54	0.000
Residual Error	19	596	31		

Figure 3.3 Regression results from MINITAB.

[3] This is the coefficient in a regression equation. Coefficients are the estimates of the parameters in a regression equation. The coefficients are used, along with the independent variables, to calculate the fitted value of the dependent variable.
[4] Standard Error Coefficient
[5] T statistic
[6] P-values are often used in hypothesis tests, where you either reject or fail to reject a null hypothesis. The p-value represents the probability of making a Type 1 error, which is rejecting the null hypothesis when it is true. The smaller the p-value, the smaller is the probability that you would be making a mistake by rejecting the null hypothesis.
[7] This is the estimated standard deviation about the regression line.
[8] This is Root Square, also called the coefficient of determination.
[9] This is Root Square adjusted for degrees of freedom.
[10] Degrees of Freedom
[11] Sum of Squares
[12] Mean of Squares
[13] F-test. An F-test is usually a ratio of two numbers, where each number estimates a variance. An F-test is used in the test of equality of two populations. An F-test is also used in analysis of variance, where it tests the hypothesis of equality of means for two or more groups. For instance, in an ANOVA test, the F statistic is usually a ratio of the Mean Square for the effect of interest and Mean Square error. The F-statistic is very large when MS for the factor is much larger than the Mean Square for error. In such cases, reject the null hypothesis that group means are equal. The p-value helps to determine statistical significance of the F-statistic.
[14] P-value

The estimator of the parameters $\{\beta_0, \beta_1\}$ of the best fitting line of the regression model is the least squares (LS) line which minimizes the sum of squared errors function $\sum_t \varepsilon_t^2$.

Based on historical data, a regression equation for SDP appointments[15] for days before the scheduled date of donation was established. The regression equation generates Projected Appointment Forecast. To calculate the Released Forecast[16], the Projected Appointment Forecast was multiplied by the Product per Appointment (PPA)[17]. The Product per Appointment (PPA) value was obtained from past data by evaluating the current or known number of appointments and the number of products released after laboratory testing.

The p-value (<0.0005) in the Analysis of Variance in Figure 3.3, indicates that the relationship between the *d* (predictor) and *A* is statistically significant at an α-level of 0.05. This is also shown by the p-value for the estimated coefficient of *d*, which is 0.0005. The R-square value shows that *d* explains 98.4% of the variance in *A*, indicating that the model fits the data extremely well.

3.4 Empirical Study Results

Regression equations for each day of the week were obtained as follows:

- Number of Appointment (Sundays) = 53.4113 - 1.4935*Days to Donation
- Number of Appointment (Mondays) = 186.896 - 7.44675 *Days to Donation
- Number of Appointment (Tuesdays) = 167.087 - 6.53247 *Days to Donation

---

15 SDP appointments with platelet donors are scheduled two weeks ahead of time.

16 Released forecast is the expected number of platelets to be released by the laboratory.

17 Product per appointment (PPA) is the ratio of the released product R_t and the number of donor appointments that produced the products.

- Number of Appointment (Wednesdays) = 159.554 - 6.03636 *Days to Donation
- Number of Appointment (Thursdays) = 199.364 - 7.42208 *Days to Donation
- Number of Appointment (Fridays) = 219.398 - 8.87792 *Days to Donation
- Number of Appointment (Saturdays) = 216.139 – 7.18052 *Days to Donation

The regression equation for each day of the week was then used to obtain the Projected Appointments. To calculate the Release Forecast, the Projected Appointment Forecast was multiplied by the Product per appointment (PPA), which has to be further reduced by the non hematology reject rate (which includes incomplete donations, contaminants, etc). The Sales Forecast uses the moving average of the maximum and minimum value of sales from the previous three weeks. The deviation between the actual variable and the forecast was monitored and verified as indicated in section 3.5 below.

3.5 Verifying Empirical Study Results

Since forecasting is the act of predicting the future either based on historical data or speculation about the future, there is a need to compare the forecasted value with the actual to determine if the forecasting methodology is effective and efficient.

Shewhart (1939) developed a theory of statistical quality control and concluded that there were two components to variations that were displayed in all processes. The first component (*common causes*) that appeared to be inherent in the process was a steady component or had random variation. The second component (*special causes*) was an intermittent deviation to assignable causes and includes unusual events. When these unusual events are noticed and proper action is taken to handle, the special causes can usually be removed or adjusted. Shewhart

(1939) developed the standard control chart test based on three sigma limits to separate the steady component of variation (*common causes*) from assignable causes (*special causes*).

Statistical Process Control (SPC) is made up of a set of tools and activities that help make statistically valid decisions. A process is said to be in statistical control when special causes do not exist. The SPC tools were used to verify if the aforementioned forecasting tool was efficient in predicting SDP collection and demand. Control Charts are SPC tools used to help recognize the presence of *special causes* or *common causes* in the process.

Control charts track the process by plotting data over time and see whether there are within three standard deviations from the average. Normally one would desire at least 20 data points. When a point falls outside these limits, the process is said to be out of control or the process is unpredictable. When a process is in control/predictable, the control chart pattern should exhibit "natural characteristics", a reflection of data randomness. To determine if a process has special causes present, certain criteria will have to be met. A special cause is assumed to be present if one or more of the following occurs:

- One point is more than 3 standard deviations from the center line,
- Nine points in a row are on the same side of the center line,
- Six points in a row are all increasing or all decreasing,
- Fourteen points in a row are alternating up and down,
- Two out of three points in a row are more than 2 standard deviations from the center line (same side),
- Four out of five points in a row are more than 1 standard deviation from the center line (same side),
- Fifteen points in a row are within 1 standard deviation of the center line (either side),
- Eight points in a row are more than 1 standard deviation from the center line (either side).

For individual measurements like the variance for Quantity of Released Products, and Demand (Sales), an *I* or *X* Chart is preferred. A moving range (*MR*) chart normally accompanies these charts, hence the term *I-MR* or *X-MR* chart.

For an individual measurement control chart, the process average is the mean of the n data points:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{3.2}$$

The adjacent values are used to determine the moving range (*MR*):

$$MR_1 = | x_2 - x_1 | \quad MR_2 = | x_3 - x_2 |, \ldots \tag{3.3}$$

The average moving range (MR) is defined as

$$\overline{\text{MR}} = \frac{\sum_{i=1}^{m} MR_1}{m} = \frac{(MR_1) + (MR_2), \ldots (MR_m)}{m} \tag{3.4}$$

Charting parameter for the individual values are:

Center Line $CL = \bar{X}$,

Upper Control Limit (UCL)

$$UCL = \bar{\bar{X}} + \frac{3(\overline{MR})}{d_2} = \bar{\bar{x}} + 2.66(\overline{MR}) \tag{3.5}$$

Lower Control Limit (LCL)

$$LCL = \bar{\bar{X}} - \frac{3(\overline{MR})}{d_2} = \bar{\bar{x}} - 2.66(\overline{MR}) \tag{3.6}$$

where the 2.66 factor is $3/d_2 - 3$ since three standard deviations are used, and d_2 makes a center line correction and is obtained from the Table Constants for Control Charts in Appendix B.

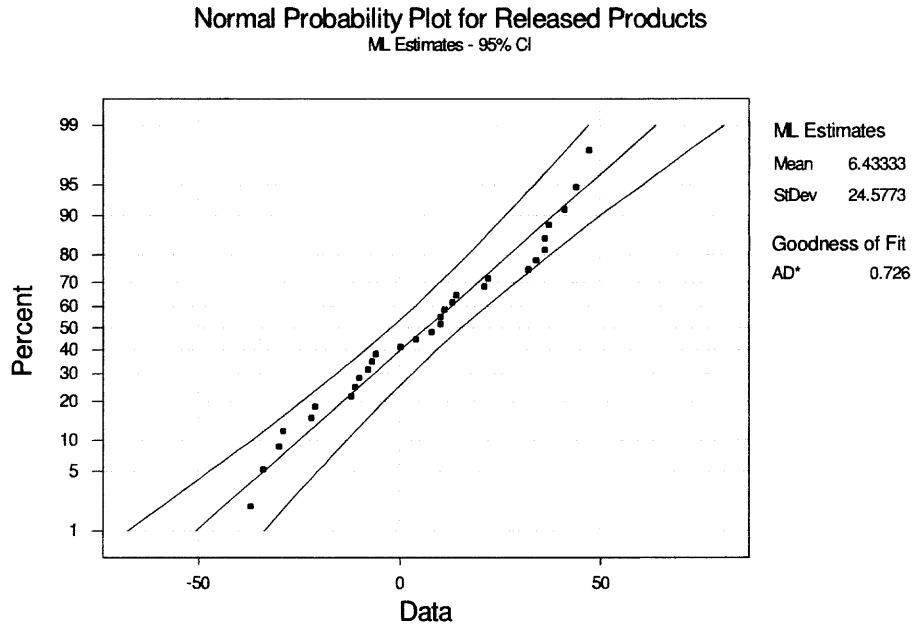

Figure 3.4 Normal probability plot – forecasted released products.

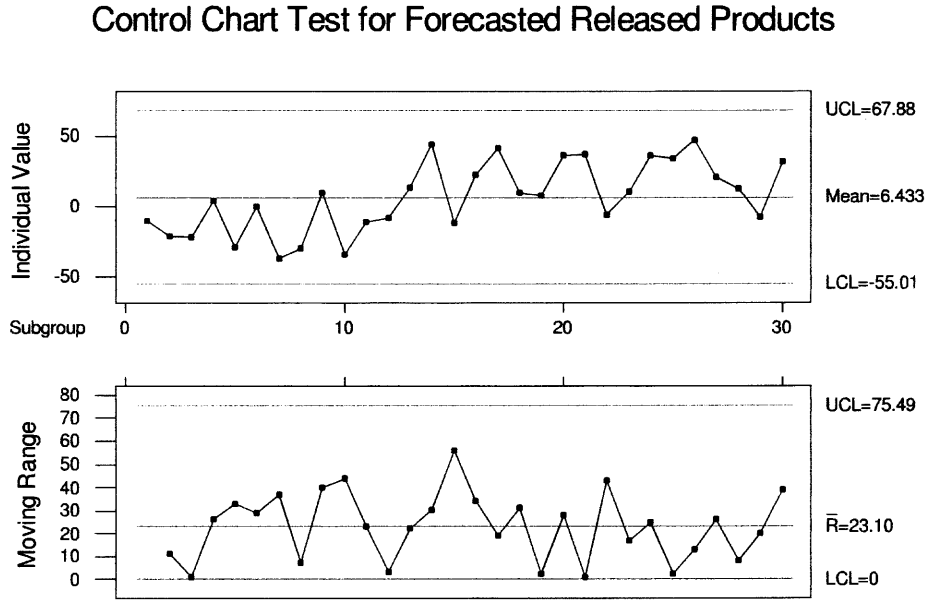

Figure 3.5 Control chart test results – forecasted released products.

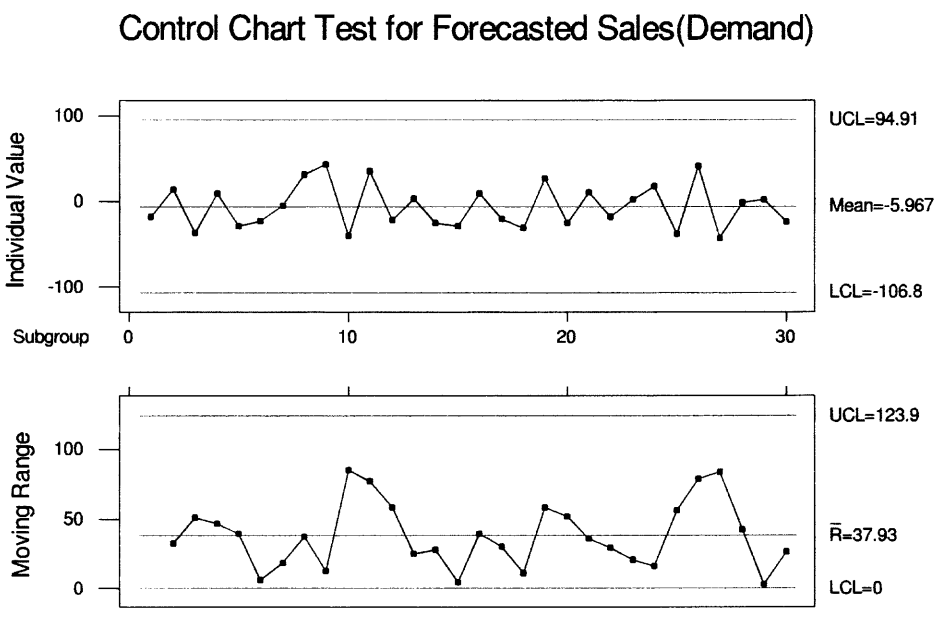

Figure 3.6 Control chart test results – forecasted sales.

The forecasted value, actual value and deviation for Released SDP products and the demand[18] (Sales) are presented in Appendix A for analysis. The Normal Probability Plot of the variances from the Released Forecast and Actual products released are depicted in Figure 3.4.

The example in Figure 3.4 shows points that form an approximately straight line, which demonstrates that it was reasonable to assume that the data was from a normal distribution. To determine if the forecast methodology was within process control as aforementioned, the MINITAB statistical software was used, and the results are displayed in Figures 3.5 and 3.6. The *ImR* computer plots shown in Figures 3.5 and 3.6 indicate no out-of-control or unpredictable conditions for the forecasted released products and sales. Thus, there are no special causes. However, the common causes or random nature characteristics are present and displayed by the

[18] Sales assumed to be equal to demand for the purpose of this paper only.

up-and-down swings. One could conclude that the methodology was appropriately predicting quantity of SDP products to be released and sales (demand) for each period.

CHAPTER 4

BLOOD INVENTORY MANAGEMENT

4.1 Overview

Blood inventory managers are faced with the problem of meeting demand and at the same time balancing the minimizing of outdates and the shortage of blood products. The relationship between outdates and shortage of blood is a trade-off curve and a function of the inventory level. If the quantity collected and released is increased, the outdate rate will increase and the shortage rate will be reduced, and vice versa. Also, the blood center would have to decide whether to fill daily demand with the older units first (FIFO policy) or to send the fresher units first (LIFO policy). Most hospital blood banks insist on receiving the freshest unit in the inventory as the efficacy of the blood unit decreases with time. However, if the blood center follows a strict LIFO policy, the outdate rate will increase.

To illustrate the FIFO and LIFO issuing policies, suppose that a hospital orders 10 blood units from the blood center having a total of 19 units with different expirations (3 expiring today, 5 with 1 day remaining before expiration, 5 with 2 days remaining before expiration, and 6 with 3 days remaining before expiration). The blood center following the FIFO policy will then ship to the hospital 3 units expiring today, 5 units with 1 day remaining, and 2 units with 2 days remaining. If the blood center in the above example is following the LIFO policy, it will ship 4 units with 2 days remaining on them, and 6 units with 3 days remaining. However, if the blood center practices 50% FIFO and 50% LIFO, it will ship out 3 units expiring today, 2 units with 1 day remaining, and 5 units with 3 days remaining.

4.2 Mathematical Model for Blood Inventory Management

The inventory network in Figure 4.1 below depicts released quantity $\mathbf{R_1}$ entering the inventory system as (1,1); the Beginning Inventory is made of (1,1), (2,1), and (3,1) which is equivalent to (j, t) where j = age of the unit, and t = day or period. $(x_{1,1})$, $(x_{2,1})$, $(x_{3,1})$ are units moved from the Beginning Inventory to fill Demand D_1. The units that remain in the inventory y_{3t} will outdate the next day $(t+1)$.

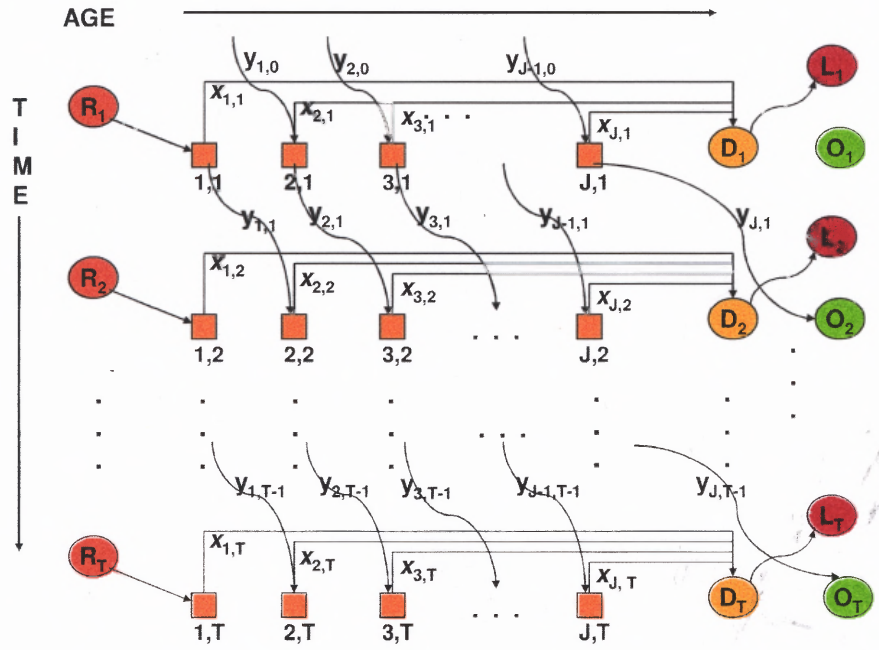

Figure 4.1 Network representation of inventory problem.

To formulate the mathematical inventory model, assume R_t amount of blood is released on day t after testing to fulfill demand from a hospital blood bank.

Hospital demand $\mathbf{D_t}$ can be filled with the units in inventory y_{jt} where j is the unit age (1, 2…7 for product expiring after age 7) at time t in days. There is a social benefit $(\mathbf{W_j})$ for fulfilling hospital demand $\mathbf{D_t}$, a lost sale due to unfulfilled demand attracted a penalty $(\mathbf{P})$, a

holding cost ($\mathbf{H_j}$) for the storage cost for carrying one unit of inventory for one time period, and an outdate cost (**O**) for an expired unit. All these parameters are assumed to be deterministic.

4.3 Parameters

The parameters for the inventory problem are:

$\mathbf{R_t}$ Quantity of blood product released into inventory on day t after laboratory testing,

$\mathbf{D_t}$ Quantity of blood demand from hospital blood banks on day t,

$\mathbf{W_j}$ Social benefit for satisfying demand with age-j product,

P Penalty for not satisfying blood demand,

$\mathbf{H_j}$ Holding cost for blood product at age j,

O Outdate cost for an expired unit

The released units $\mathbf{R_t}$ enters the inventory at age 1 on day t as y_{1t}. The quantity of units moved from the inventory, y_{jt}, at age j to fulfill demand, $\mathbf{D_t}$ at time t with a social benefit $\mathbf{W_j}$ are represented by (x_{jt}); and a lost sale, $\mathbf{L_t}$ occurs when demand was not fulfilled with the current inventory, y_{jt}, with a penalty of **P**.

To solve the inventory problem two methods were employed:

(1) A heuristic method using Microsoft Excel with 'mixed' FIFO/LIFO policy,

(2) A Linear Programming (LP) method using the LINGO optimization software.

4.4 Heuristic Method using Microsoft Excel

A Microsoft Excel spreadsheet was set up for the heuristic method of the inventory problem as indicated in Figure 4.2. To begin, the deterministic parameters social benefit ($\mathbf{W_j}$), holding cost ($\mathbf{H_j}$), lost sale penalty ($\mathbf{L_t}$), outdate cost (**O**), have to be entered. The Warning level or days

indicate that the total beginning inventory is less than the average demand order and expressed as a percentage, the issuing policy indicates the order percentages to be filled according LIFO and FIFO issuing policy.

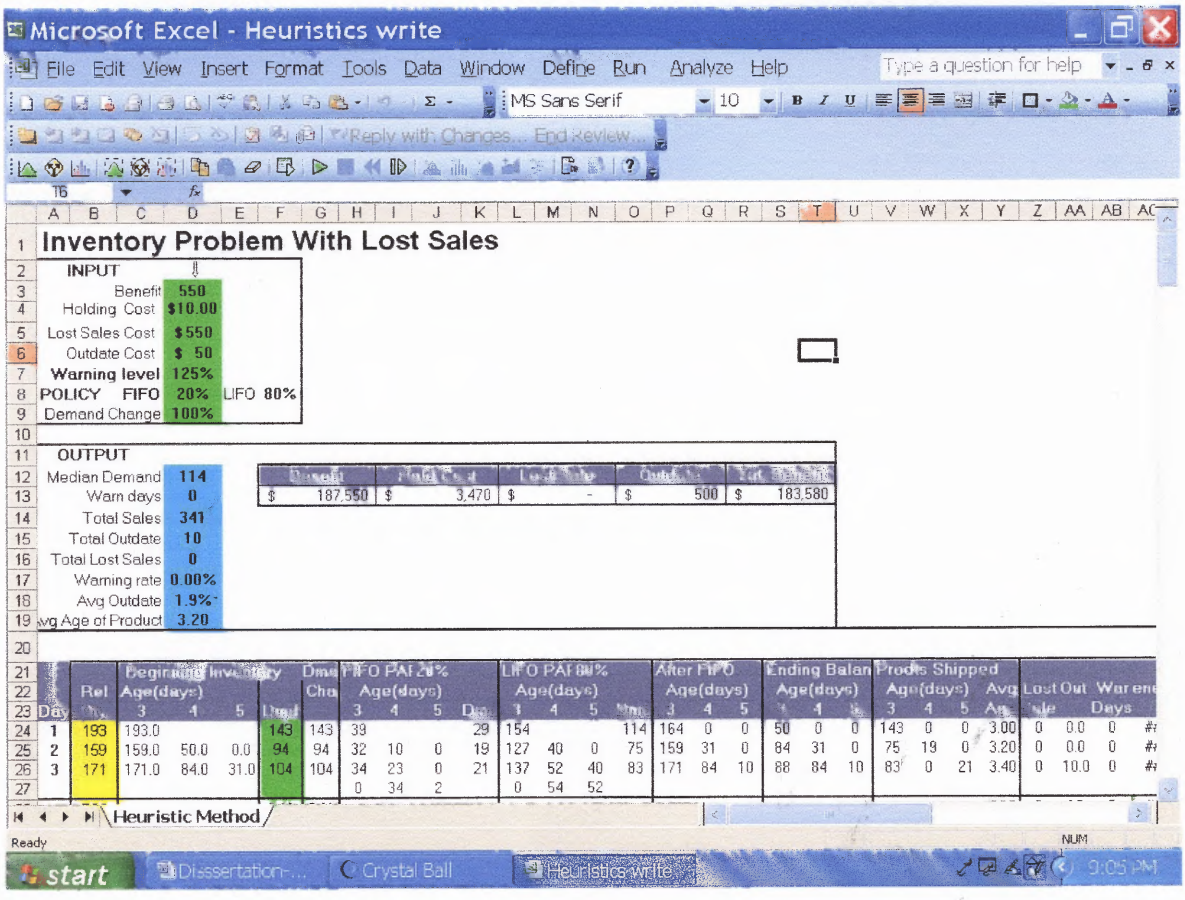

Figure 4.2 Heuristic method using Microsoft Excel.

Rows 21 to 23 in Figure 4.2 contain the headings in the spreadsheet which are: Day (cell A23), Released Quantity (cell B23), Beginning Inventory with Ages 3, 4, 5 (cells C23-E23), Demand (cell F23), FIFO Part % (cells G23-I23), LIFO Part % (cells L23-M23), After FIFO (cells P23-R23), Ending Balance (cells S23-U23), Age of Products Shipped (cells V23-X23), Average Age (cell Y23), Lost Sale (cell Z23), Outdate (cell AA23), Warning Days (cell AB 23).

The Day column is filled through out for all periods. The Released Quantity represents the aggregate platelets released which enters the Beginning Inventory as Age 3; ages 4 and 5 are obtained from previous period ending balances. The demand ($\mathbf{D_t}$) is the aggregate demand from the data given. For further details of the Microsoft excel spreadsheet formulation see Appendix F.

4.5 Case Study I

A blood center must determine whether to send out the 'fresher' or 'older' single donor platelets (SDP) first to meet daily demand of blood products. Assuming the revenue for filling one unit of demand was $550; lost sales have a penalty of $550 per unit due to unrealized revenue and loss of goodwill from customers, holding one unit in inventory will cost $10 per day, and a unit that has expired costs $50. Assuming the SDP will expire after 5 days of collection and will take 2 days for laboratory testing (thus product shelf-life is 3 days). The objectives are:

(1) To determine how the blood center can maximize welfare (revenue less lost sale, outdate, and holding cost) by fulfilling SDP demand using the released quantities $\mathbf{R_t}$ and demand $\mathbf{D_t}$ data provided for a period of 365 days and varying the issuing policy.

(2) To alert the blood center when the sum of units in inventory is less than 125% of the average demand. Calculate the warning rate (defined as when the sum of the beginning inventory is less than the anticipated demand), the outdate rate, and average age of SDPs shipped to hospital blood banks.

4.5.1 Approach

To use the heuristic method with the Microsoft Excel spreadsheet formulation (Appendix F) and data provided for the released quantities $\mathbf{R_t}$ and demand $\mathbf{D_t}$, the issuing policy variable for the FIFO is changed from 0% to 100%. The total benefit, product outdate, age of product distributed,

and days when the blood center inventory fell under a threshold (125% of average daily order) are then tracked.

Table 4.3 Results of Case Study I

FIFO	LIFO	Total Benefit	Warn Rate	Avg Outdate	Avg Age
0%	100%	28,533,675	45.2%	11.0%	3.15
10%	90%	29,461,512	43.0%	9.7%	3.22
20%	80%	30,131,751	40.3%	8.8%	3.28
30%	70%	30,666,105	30.7%	8.1%	3.37
40%	60%	31,239,333	20.0%	7.3%	3.50
50%	50%	31,673,266	12.3%	6.7%	3.65
60%	40%	31,864,459	6.9%	6.4%	3.80
70%	30%	32,012,946	4.1%	6.2%	3.98
80%	20%	32,093,711	0.8%	6.1%	4.18
90%	10%	32,094,483	0.6%	6.0%	4.38
100%	0%	**32,095,210**	0.3%	5.9%	4.58

The results for the Total Benefit, Warning Rate, Average Outdate Rate and Average Age were as shown in Table 4.3. The maximum total benefit occurs at an issuing policy of 100 percent FIFO with a warning rate of 0.3 percent, outdate rate of 5.9 percent and an average age of 4.58 days.

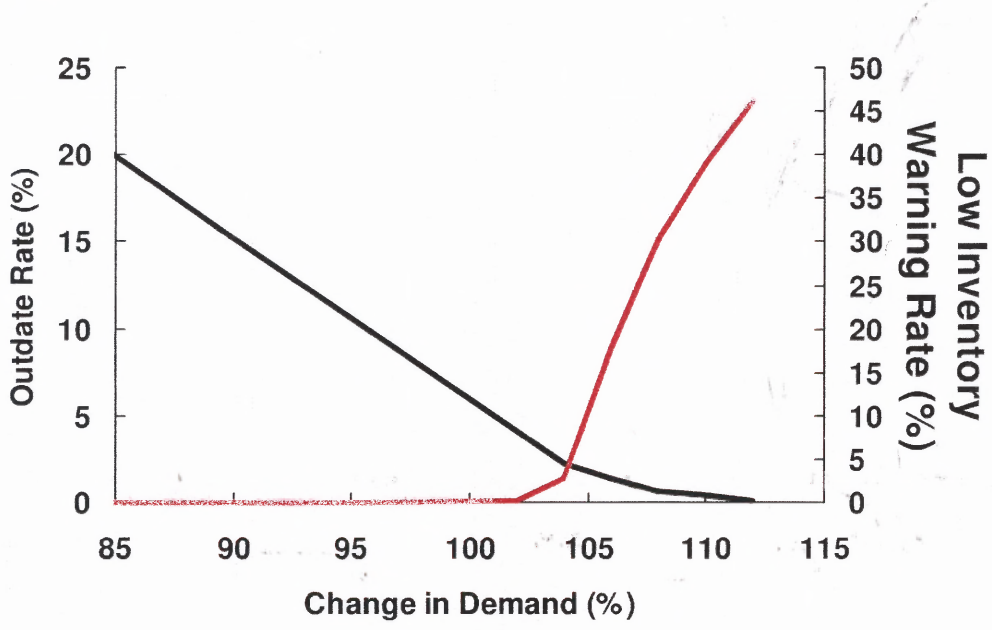

Figure 4.4 Effect of change in demand on outdates and shortages.

Figure 4.4 shows the effect of change in demand on outdates and shortages. When demand was varied from 85 to 115 percent of the current level the outdates declined from 20 to 0 percent. The Low Inventory Warning Rate rose sharply after demand becomes 104 percent of the current level as indicated in Figure 4.4 all being equal *(ceteris paribus).*

4.5.2 Limitation of the Heuristic Model

To operate the heuristic model, one needs to input the FIFO/LIFO policy, the released quantities $\mathbf{R_t}$ and the demand $\mathbf{D_t}$ for the entire period, *T*. The limitation to the heuristic model is that once the FIFO/LIFO policy is specified, it will be carried throughout the entire inventory system thereby achieving a near optimal allocation.

4.6 Linear Programming (LP) method using the LINGO optimization software

One other method of solving the inventory problem is Linear Programming (LP) - a tool for solving optimization problems. Linear programming model components include decision variables, model constraints and an objective function.

4.6.1 Decision Variables

The decision variables under one's control and influence are the total number of units (x_t) moved to fill demand, the left over (y_t) in the inventory after fulfilling demand, and the lost sale ($\mathbf{L_t}$) due to unfulfilled demand.

y_{jt} *Inventory level of blood product at age j at the end of day t*

x_{jt} *Quantity of blood product at age j used to fill demand on day t*

$\mathbf{L_t}$ *Quantity of unsatisfied blood demand on day t*

4.6.2 Constraints

Constraints on the values of the decision variables are as follows:

The sum of the units (x_{jt}) moved in the inventory to fill demand and lost sale L_t are equal to the demand. Hence

$$\sum_{j=1}^{J} x_{jt} + L_t = D_t \qquad \forall j = 2,3,...J : t = 1,2,...T-1 \tag{4.7}$$

The ending inventory for t-1 should be equal to the sum of the inventory level of blood product (y_{jt}) and the quantity of blood product used to fill demand (x_{jt}) at age j (from $j=2$ to J) on day t. Hence,

$$x_{jt} + y_{jt} - y_{j-1,t-1} = 0 \qquad \forall j = 2,3,...J : t = 1,2,...T-1 \tag{4.8}$$

A unit released (R_t) will enter the inventory at age 1. Therefore,

$$x_{1t} + y_{1t} = R_t \qquad \forall\ t = 1,2,...T \tag{4.9}$$

where j, the age of the blood product was 1 day old.

4.6.3 Objective Function

The blood center would like to maximize the total benefit (social benefit less holding cost, lost sales cost and outdate cost). Hence the values of (x_t), and (y_t) that would generate the largest value should be obtained. Letting z represent the value of the objective function,

$$Max\ z = \sum_{t=1}^{T}(\sum_{j=1}^{J} W_j x_{jt} - \sum_{j=1}^{J-1} H_j y_{jt} - PL_t - Oy_{Jt}) \tag{4.10}$$

The LP formulation can be written as

$$Max\ z = \sum_{t=1}^{T}(\sum_{j=1}^{J} W_j x_{jt} - \sum_{j=1}^{J-1} H_j y_{jt} - PL_t - Oy_{Jt}) \tag{4.11}$$

s.t.

$$\sum_{j=1}^{J} x_{jt} + L_t = D_t \qquad \forall\ t = 1,2,...T$$

$$x_{jt} + y_{jt} - y_{j-1,t-1} = 0 \qquad \forall\ j = 2,3,....J : t = 1,2,...T-1$$

$$x_{1t} + y_{1t} = R_t \qquad \forall\ t = 1,2,...T$$

$$x_{jt}, y_{jt}, L_t \geq 0$$

The inventory problem is solved using the LINGO optimization software presented in Appendix D, and the output is included in Appendix E.

4.7 Main Factors Effecting Inventory Model

The social benefit W_j, holding cost H_j, lost sale cost P, and outdate cost O, were parameters of the inventory model which had assigned values. Hence there was a need to investigate the sensitivity of the model to the values of these parameters.

Table 4.5 Factors with Levels for Design of Experiments (DOE)

	Level 1	Level 2	Level 3
Benefit	500	640	675
Holding Cost	1	5	10
Lost Sale	600	3000	6000
Outdate Cost	4	250	450

The design of experiments (DOE) methodology was used to investigate the effect of these parameters on the objective function. Three quantitative levels were chosen, each in relation to the actual production costs to the four parameters or factors as indicated in Table 4.5. A full factorial design was used with no replications producing 81 runs, the results of which are included in Appendix G.

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Benefit	2	2	3.83443e12	7615.509	<.0001
Holding cost	2	2	4051883337	8.0474	0.0010
Lost Sale	2	2	6.99211e12	13886.92	<.0001
Outdate Cost	2	2	755255602	1.5000	0.2334
Benefit*Holding cost	4	4	1510518683	1.5000	0.2171
Benefit*Lost Sale	4	4	1510518683	1.5000	0.2171
Holding cost*Lost Sale	4	4	0.04938272	0.0000	1.0000
Benefit*Outdate Cost	4	4	755263082	0.7500	0.5629
Holding cost*Outdate Cost	4	4	1510511204	1.5000	0.2171
Lost Sale*Outdate Cost	4	4	1510511204	1.5000	0.2171

Figure 4.6 Analysis of variance (ANOVA) of factors.

When the model was run, the factors and their subgroup effects on the objective function were analyzed using analysis of variance (ANOVA) techniques. The interaction effect was considered to be statistically significant if its magnitude was large relative to the other column effects. The JMP software was used to obtain the results shown in Figure 4.6. Figure 4.6 indicates that social benefit, holding cost, and lost sale, have p-values < 0.05 and therefore very convincing significance of influence on the objective function. The factors' effect on the objective function is shown in Figure 4.7.

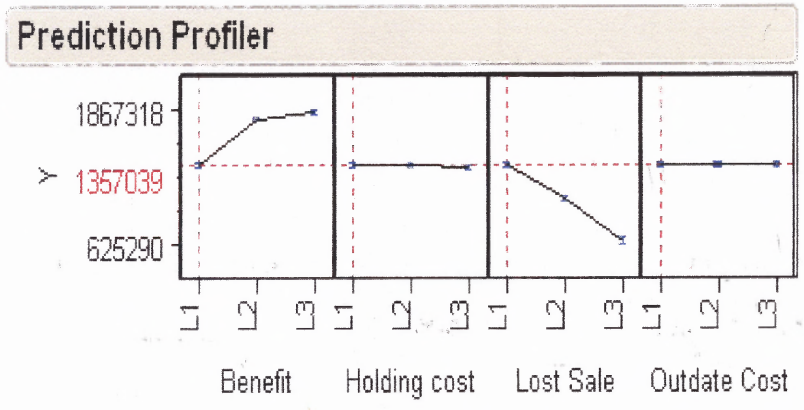

Figure 4.7 Factors' effect on the objective function.

The prediction profiler shows that the social benefit W_j, and the lost sale cost P have a significant influence on the objective function as indicated in Figure 4.7. The prediction profiler gives a closer look at the best settings that produce the response target (objective function).

4.8 Rolling Horizon Schedule

So far it was assumed that the inventory manager needs to forecast the released quantity $\mathbf{R_t}$, the daily demand $\mathbf{D_t}$, and decide on the optimum distribution policy to optimize the blood product inventory system. The optimum solution was provided for a horizon of length, T. However forecasts for periods further into the future are likely to be in error and of a poorer quality, and to take this into consideration '*rolling horizon schedules*' are used as a common business practice.

In principle, some incremental benefit will be realized by extending the planning horizon since a greater amount of relevant data is brought into the analysis. The concern here is to analyze the total benefits derived from longer horizons. "The optimization of finite-horizon models is backed implicitly by the belief that these solutions will be optimal, or at least very good, when implemented on a rolling basis" (Baker and Peterson, 1979).

The rolling horizon schedule aimed to split a long horizon of length, T, into several sub-problems with a forecast window, N, (where $N < T$). The total number of sub-problems would be $T - N + 1$.

The algorithm for the rolling schedule is:

1. Begin with $t = 0$ with y_{j0} known for $j = 1$ to J.
2. Increment t by 1, and assume that the aggregated released quantity R_t and D_t are known and y_{jt-1} would migrate to $y_{j+1,t'}$. At $t' = t + 1$ to $t + N - 1$ the forecasted values for $R_{t'}$ and $D_{t'}$ are utilized. Solve for the finite-horizon problem from periods t to $t + N - 1$, and record only the first period action as period t action.
3. Check to see if $t = T - N + 1$. If yes, then implement the whole solution, then stop;

if $t \neq T - N + 1$, then implement the first solution and return to step 2.

4. Compute the model until the $t = T$ and the objective function (total benefit) is obtained.

4.8.1 A Computational Study

Inventory managers must make decisions daily based on an appropriate model horizon to plan for the optimal issuing policy. Solutions resulting from a shorter horizon period may be suboptimal over the long run. This raises the question of how far ahead a forecast the inventory manager needs to optimize the inventory problem in the long term. The answer is not obvious. Either the inventory manager may use the actual quantity released $\mathbf{R}_t$ and actual demand $\mathbf{D}_t$ only or include some forecast values of $\mathbf{R}_t$ and $\mathbf{D}_t$ to optimize the inventory, assuming **R** and **D** are known at the beginning.

To investigate rolling horizon schedules, the forecasted and actual quantity released, $\mathbf{R}_t$ and demand, $\mathbf{D}_t$ for 92 periods listed in Appendix C were generated using the forecasting model of Chapter 3. The first period in the static test was assumed to have actual values of $\mathbf{R}_t$ and $\mathbf{D}_t$ and the rest of the periods have forecasted values of $\mathbf{R}_t$ and $\mathbf{D}_t$. The quality of a set of implemented rolling-horizon decisions is evaluated by comparing a forecast window, $N = 1, 2, 5, 7$, and 92 for the inventory model with period, $T = 92$ days using equation 4.11. The concern here is that the forecast error in the static solution calculated may be suboptimal over the entirety of the rolled horizons. For example, in $N = 1$, with $T = 92$, the number of runs $R = (T-N+1) = 92$ using actual values of $\mathbf{R}_t$ and $\mathbf{D}_t$ throughout the 92 runs ; for $N = 2$, $R = 91\ldots$ and for $N = 92$, R =1.

The revenue for filling one unit of demand was \$600 for a product at age 3, \$550 for a product at age 4, \$500 for a product at age 5, \$450 for a product at age 6, \$400 for a product at

age 7, lost sales attract a penalty of $100 per unit due to unrealized revenue and loss of goodwill from customers, holding one unit in inventory will cost $10 per day, and a unit that has expired costs $50.

The total benefit or the objective function of equation 4.11 was taken into consideration to compare the rolling horizon outcomes of $N = 1, 2, 5, 7,$ and 92.

4.8.2 Computational Results

Shewhart (1939) control charts were used to track the forecasting statistics of the quantity released $\mathbf{R}_t$ and demand $\mathbf{D}_t$ over time and to detect the presence of *special causes* as explained in Chapter 3. *Special causes* result in variation that can be detected and controlled. Common cause variation, on the other hand, is inherent in the forecasting methodology or process.

A process is in control when only common causes affect the process output. A process is in control when data points fall within the bounds of the control limits, and the points do not display any nonrandom patterns.

Each of the eight tests for special causes described in Chapter 3, which detect a specific pattern in data plotted on the Individuals chart and Moving Range (*I-MR*) control chart, were used to evaluate the forecasting error for quantity released $\mathbf{R}_t$ and demand $\mathbf{D}_t$. The occurrence of a pattern suggests a *special cause* for the variation, one that needs to be investigated. The Upper/Lower control limits are three standard deviations above/below the center line (mean) respectively.

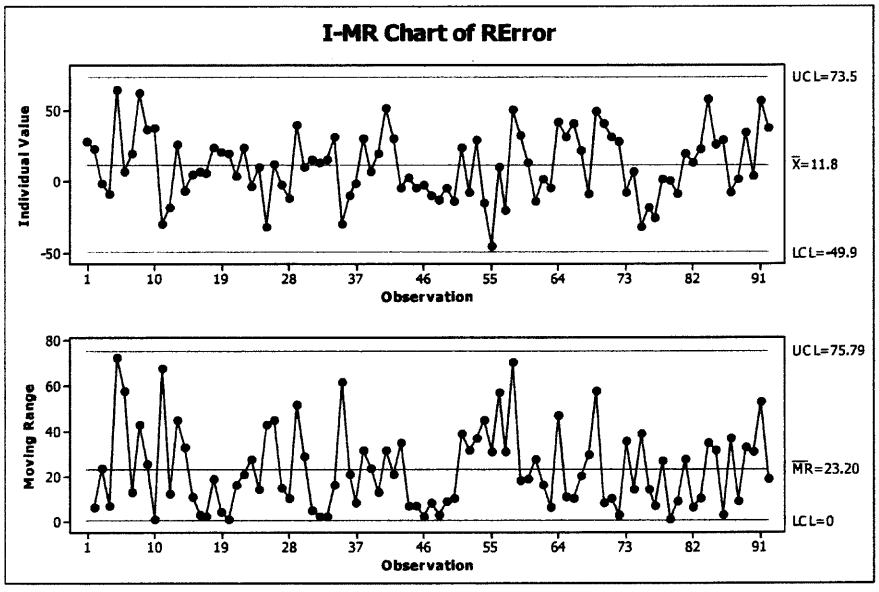

Figure 4.8 *IMR* chart for forecast release error.

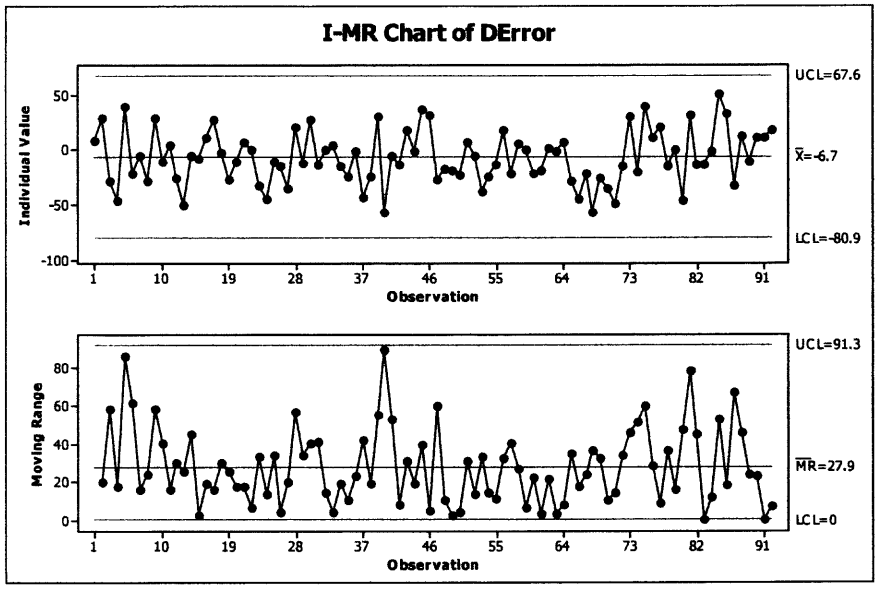

Figure 4.9 *IMR* chart for forecast demand/sales error.

Figures 4.8 and 4.9 indicate that there were **no data points** outside the control limits exhibiting a nonrandom pattern, suggesting that one could accept results from the forecasting method. Hence, the rolling horizon method was used for the inventory problem. Using the LP

inventory model equation 4.11 and the LINGO optimization software the value of the objective function (Total Benefit) and the average daily total benefit was calculated for N = 1, 2, 5, 7, and 92 as summarized in Figure 4.10.

N	Daily Total Benefit	Percent
1Day	106,347	99.66%
2Day	106,388	99.70%
5Day	106,484	99.79%
7Day	106,676	99.97%
92Day	106,707	100.00%

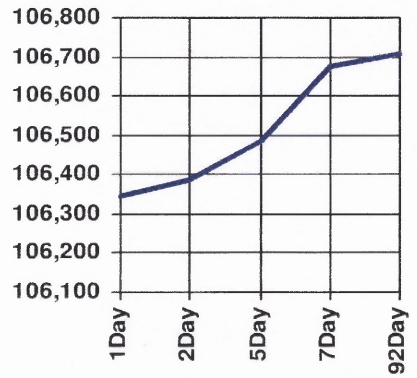

Figure 4.10 Rolling horizon results.

N = 92 was compared with a horizon window N = 1, 2, 5, and 7 and the following percentages 99.66, 99.70, 99.79, and 99.97 were obtained respectively. Even though for N = 1 actual $\mathbf{R}_t$ and $\mathbf{D}_t$ were used for the calculation, this option generated the least daily total benefit. It was observed that the objective function increases as the forecast window, N, approaches the length the horizon length, T, which supports the findings of Baker and Paterson, (1979).

Thus the inventory manager at the blood center would have to use forecast windows N greater than 1 to achieve better issuing policies.

CHAPTER 5

STOCHASTIC MODEL

5.1 Overview

In Chapter 4 linear programming (LP) was combined with the rolling horizon technique and a heuristic method was used to solve the inventory management problem. For simplicity, the released blood quantity $\mathbf{R}_t$ and demand $\mathbf{D}_t$ had been assumed to be known with certainty. However, in real life, $\mathbf{R}_t$ and $\mathbf{D}_t$ were not known with certainty. Hence, a situation when $\boldsymbol{R}$ and $\boldsymbol{D}$ over a given time period are random was considered.

A mathematical model formulated should reflect the questions that the analyst wants answered about the real system by using analytic methods of mathematics or by simulation methods. Analytic models are often difficult to build and solve. However, simpler analytic models can be used to verify the parameters and assumptions of a simulation model. Attempts to use analytical models to solve such inventory systems usually require so many simplifying assumptions that the solutions are likely to be inferior or inadequate for implementation.

Simulation, which is a technique that imitates a real-world system operation, can be used to test a variety of solution methods and models. A major advantage of simulation is its algorithmic nature, which makes it easier for the non-mathematical audience to understand and appreciate the model. A static simulation model represents a system at a particular time, for example the Monte Carlo simulation model. A dynamic simulation model represents a system as it evolves over time.

The main elements in a simulation analysis are problem formulation, data collection and analysis, random variable generation, model simulation, and simulation results and analysis.

5.2 Problem Formulation

The objective is to maximize the social benefit of fulfilling the Single Donor Platelets (SDP) demand from hospitals. The blood center would have to decide to move fresher products (LIFO issuing policy – improve customer service), move older products (FIFO – to reduce outdate rate) or use the so called 'mixed or hybrid' FIFO/LIFO strategy to fulfill demand.

The exogenous (input) variables are the released quantity $\boldsymbol{R}$ and demand $\boldsymbol{D}$ which are random in character. Parameters are the social benefit ($\mathbf{W_j}$), the lost sales penalty due to unfulfilled demand (**P**), the holding cost ($\mathbf{H_j}$) for the storage of one unit of inventory for one time period, the outdate cost (**O**) for expired products and the issuing policy. Since the released product $\boldsymbol{R_t}$ and demand $\boldsymbol{D_t}$ take on a finite number of values, they were modeled as discrete random variables. The system performance measures include the expected Total Benefit, Lost Sales (or Warning Rate), Average Outdate, and Average Age of products moved to fulfill demand.

Earlier in Chapter 4 a Linear Programming (LP) method combined with a rolling horizon schedule and a heuristic method using pure FIFO, pure LIFO or so-called 'mixed' FIFO/LIFO strategy were established, to solve the inventory problem.

5.3 Data Collection and Analysis

Data used in this study were collected at the New York Blood Center with permission from the Vice President Core Operations. To limit the scope of the study, the released product $\boldsymbol{R_t}$ and demand $\boldsymbol{D_t}$ are an aggregate of any of the eight *ABO-Rh* types of platelets. There is a need to specify the probability distributions for the input random variables $\boldsymbol{R_t}$ and $\boldsymbol{D_t}$ to carry out a simulation of the inventory system.

Data collection analysis is a critical step in a discrete time simulation model. One could specify the historical data distributions by using an empirical distribution based on the historical data or, using the standard techniques of statistical inference to "fit" a theoretical distribution (Poisson, Discrete Uniform...) form to the historical data observed and then perform a hypothesis test to determine goodness-of-fit (Law and Kelton 1982).

Data were collected for 547 days (one and a half years) for both the released product $\boldsymbol{R_t}$ and the demand $\boldsymbol{D_t}$. An *ANOVA* test for each sample for $\boldsymbol{R_t}$ and $\boldsymbol{D_t}$ for each day of the week indicated that they were significantly different by day. A histogram was used to ascertain the probability distribution for $\boldsymbol{R}$ and $\boldsymbol{D}$ for each day of the week. The *system inputs* $\boldsymbol{R}$ and $\boldsymbol{D}$ were therefore modeled as discrete distributions for a 7-day cycle and for T days for the stochastic inventory model.

5.4 Random Variable Generation and Model Validation

The random variables $\boldsymbol{R}$ and $\boldsymbol{D}$ are characterized by their probability distributions. The Crystal Ball® software was used for random variable generation. Figures 5.1 and 5.2 depict the custom distribution for the $\boldsymbol{R}$ on Sunday (Su) and the demand (Dmd) $\boldsymbol{D}$, respectively. Crystal Ball® defined the terms on the custom distribution as "*Relative probability meaning the sum of the probabilities that does not have to add up to 1. So the probability for a given value is meaningless by itself; it makes sense only in relation to the total relative probability. For example, if the total relative probability is 3 and the relative probability for a given value is 1, the value has a probability of 0.33*".

Figure 5.1 Discrete frequency distribution for released quantity *R*.

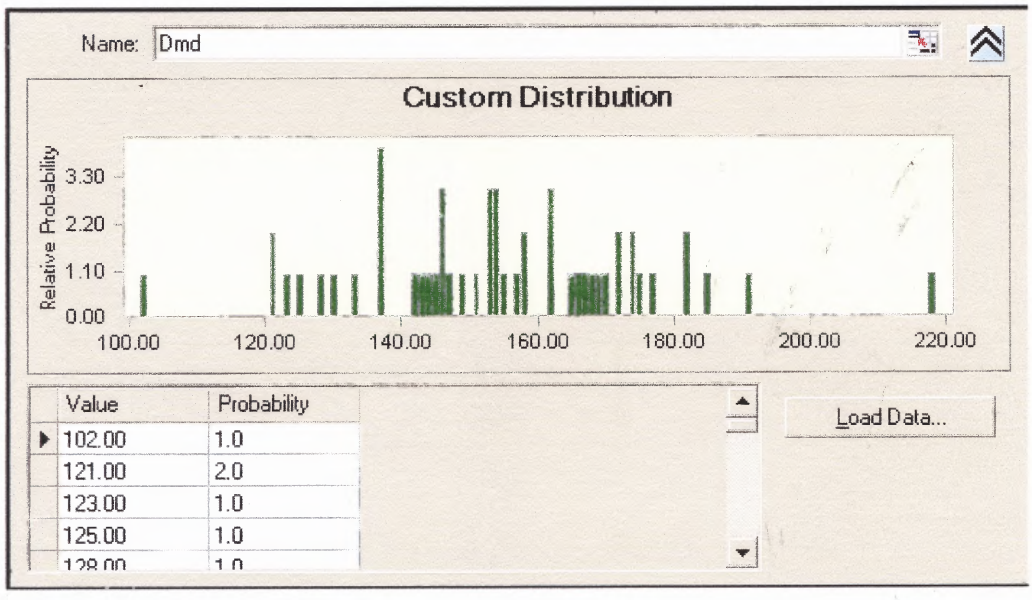

Figure 5.2 Discrete frequency distribution for demand *D*.

The Crystal Ball® software uses the multiplicative congruential generator defined by modulo $(2^{31} - 1)$ to generate random variables, which have been found to be efficient (Law and Kelton, 1982). The generator has a period of length 2,147,483,646. This means that the cycle of random

numbers repeats after several billion trials. Crystal Ball® uses a single Random Number Generator (RNG) to produce values for all of the assumptions defined in the excel spreadsheet model. The software then uses a sampling method known as Latin hypercube sampling, to select the $\boldsymbol{R}_t$ and $\boldsymbol{D}_t$ values.

5.5 Simulation

For the simulation exercise the same ($\boldsymbol{R}$, $\boldsymbol{D}$) sequence is used as input for the Linear Programming (LP) with rolling horizon and the heuristic ('mixed' FIFO/LIFO) methods. Random variables for $(\boldsymbol{R}, \boldsymbol{D})_t$ were generated using the Crystal Ball software for cycle = 7, and T = 365 days. The average daily total benefit was used as a performance measure to compare the LP - based rolling horizon with forecast window, N and the heuristic 'mixed' policy methods. The flow chart of the stochastic inventory simulation model is presented in Figure 5.3.

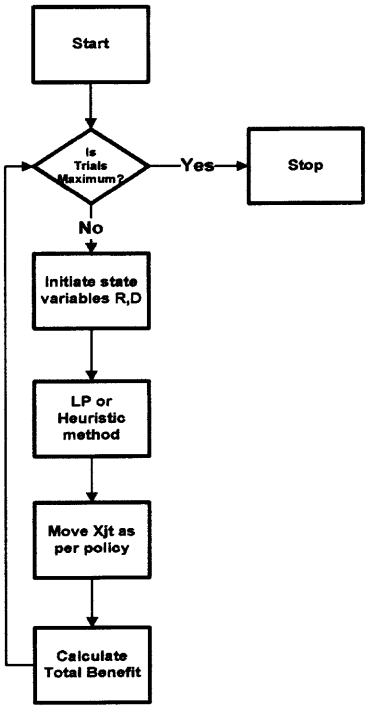

Figure 5.3 Flow chart of stochastic inventory simulation model.

The random variables generated for $(\boldsymbol{R}, \boldsymbol{D})_t$ for T days were used as inputs for the LP with rolling horizon or 'mixed' FIFO/LIFO policy method, for calculating the Total Benefit, Outdate Rate and Average Age of products shipped to fulfill demand $\boldsymbol{D}$.

5.5.1 For the Linear Programming (LP) with Rolling Horizon Solution

The LP with rolling-horizon schedule could have many variants, with different look-ahead windows of length, N. The *Rolling horizon schedule* was split into several sub-problems with a forecast or look-ahead window length, N, (where $N < T$) for the entire horizon, T. The total number of sub-problems would be $T\text{-}N + 1$ for each forecast window, N. Thus a finite horizon multi-period model was solved and the first period's decision only was implemented. The quantity of blood product at age j used to fill demand on day t (X_{jt}) was recorded for each run. For the Linear Programming (LP) with rolling horizon schedule method equation 4.11 was used with forecast window length, $N = 1, 3, 5, 7,$ and 9 days.

5.5.2 For the Heuristic Model

The same data used for the LP with rolling-horizon schedule model as described above were used for the heuristic model. The 'mixed' FIFO/LIFO issuing policy at ten percent intervals was used and the performance measures recorded.

5.6 Stochastic Empirical Study

A blood center would have to decide the way to fulfill daily demand of blood products. Historical data were provided for 50 months for both the daily released quantity $\boldsymbol{R}$ and demand $\boldsymbol{D}$. There are three groups of revenue schedule for fulfilling demand of blood products.

The revenue schedule for filling one unit of demand was: \$600 for a product at age 3, \$550 for a product at age 4, \$500 for a product at age 5, \$450 for a product at age 6, \$400 for a product at age 7 for Group A Samples; \$520 for a product at age 3, \$510 for a product at age 4, \$500 for a product at age 5, \$490 for a product at age 6, \$480 for a product at age 7 for Group B Samples; and \$500 for a product at age 3, \$500 for a product at age 4, \$500 for a product at age 5, \$500 for a product at age 6, \$500 for a product at age 7 for Group C Samples. The lost sales attract a penalty \$100 per unit due to unrealized revenue and loss of goodwill from customers, holding one unit in inventory will cost \$10 per day, and a unit that has expired costs \$50 for Groups A, B, and C Samples.

The objective is to determine how the blood center can maximize average daily total benefit (revenue less lost sale, outdate, and holding cost) by fulfilling SDP demand using the released quantity $\boldsymbol{R}$, demand $\boldsymbol{D}$, and the revenue schedule for Groups A, B, and C, and make comparison between the heuristic model with 'mixed' FIFO/LIFO issuing policy and the LP based rolling horizon schedule with forecast window, $N = 1, 3, 5, 7$, and 9 days.

Stochastic Empirical Results and Analysis

In the empirical study the heuristic model was compared with the 'mixed' FIFO/LIFO issuing policy and the LP based rolling horizon schedule with forecast windows, N = 1, 3, 5, 7, and 9 days and their impact on the inventory problem.

The primary concern was to compare each average total benefit. Tables 5.04, 5.05 and

5.06 display the average daily total benefit, the standard deviation and the percent of the maximum average daily total benefit for group samples A, B, and C, respectively.

Table 5.4 Average Daily Total and Standard Deviation (Group A)

Method	Average Daily Total Benefit	Std. Dev	Percent
N=1	$96,829	5763	94.2%
N=3	$100,584	2384	97.8%
N=5	$102,240	744	99.4%
N=7	$102,756	718	99.9%
N=9	**$102,808**	**760**	
FIFO=0/LIFO=100	**$101,868**	**846**	**99.1%**
FIFO=10/LIFO=90	$100,979	796	98.2%
FIFO=20/LIFO=80	$99,112	1186	96.4%
FIFO=30/LIFO=70	$96,488	1609	93.9%
FIFO=40/LIFO=60	$93,172	1870	90.6%
FIFO=50/LIFO=50	$89,455	2044	87.0%
FIFO=60/LIFO=40	$85,721	2253	83.4%
FIFO=70/LIFO=30	$81,887	2468	79.7%
FIFO=80/LIFO=20	$78,113	2831	76.0%
FIFO=90/LIFO=10	$74,555	3699	72.5%
FIFO=100/LIFO=0	$71,197	4658	69.3%

The results of Table 5.4 indicate that the LP with rolling horizon schedule and a forecast window length, N = 9 for Group A produced the maximum average daily total benefit ($102,808). This value was used as a base to compare the other methods and the results are shown in dollar amount and as a percent of the maximum. Thus, the results from the LP with a rolling horizon and forecast window length, N = 1, 5, 7, 9 and from the heuristic 'mixed' policy with FIFO = 0/LIFO = 100, 10/90, 20/80, 30/70, 40/60, 50/50, 60/40, 70/30, 80/20, 90/10, and 100/0, were respectively 94.2, 97.8, 99.4, 99.9, 100, 99.1, 98.2, 96.4, 93.9, 90.6, 87.0, 83.4, 79.7, 76.0, 72.5, and 69.3, percent of the optimum.

The one way analysis of variance *(ANOVA) F test* was used on each of the 16 combinations (LP with rolling horizon and forecast window length, N = 1, 3, 5, 7, or 9; FIFO=0/LIFO=100, 10/90, 20/80, 30/70, 40/60, 50/50, 60/40, 70/30, 80/20, 90/10, and 100/0).

Figure 5.7 shows the comparison of the heuristic and the LP with rolling horizon methods using the ANOVA test.

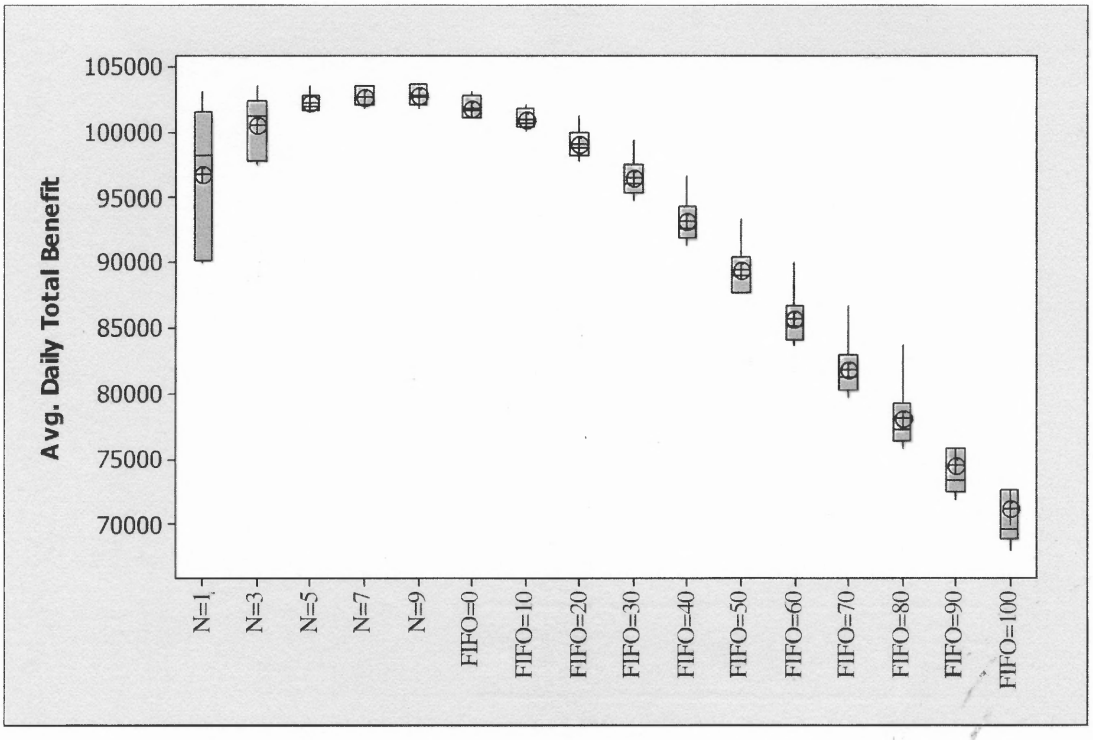

Figure 5.7 Comparison of heuristic and LP-rolling horizon methods.

The null hypothesis was H_0: the average daily total benefit for the 16 combinations was identical for ***all*** methods, and the alternative hypothesis was H_1: the average total benefit values for the 16 combinations are ***not all*** identical. The *ANOVA F test* was statistically significant with a *p*-value less than 0.0005 indicating that there was sufficient evidence that ***not all*** the average daily total benefits were equal when the confidence level was set at 95 percent. Hence the null hypothesis was rejected and concluded that there was strong statistical evidence that the average daily total benefits are not equal.

A similar analysis was conducted for Group B and C revenue schedules as indicated in

Table 5.5 and 5.6. In both cases the LP with rolling horizon schedule and a forecast window length, N = 9 produced the maximum average daily total benefit.

Table 5.5 Average Daily Total and Standard Deviation (Group B)

Method	Average Daily Total Benefit	Std. Dev	Percent
N=1	$88,398	1470	97.1%
N=3	$89,679	698	98.5%
N=5	$89,936	863	98.8%
N=7	$90,546	593	99.4%
N=9	**$91,048**	**820**	
FIFO=0/LIFO=100	$89,263	716	98.0%
FIFO=10/LIFO=90	**$89,721**	**645**	**98.5%**
FIFO=20/LIFO=80	$89,550	896	98.4%
FIFO=30/LIFO=70	$88,934	1120	97.7%
FIFO=40/LIFO=60	$87,970	1267	96.6%
FIFO=50/LIFO=50	$86,800	1335	95.3%
FIFO=60/LIFO=40	$85,591	1423	94.0%
FIFO=70/LIFO=30	$84,339	1526	92.6%
FIFO=80/LIFO=20	$83,105	1678	91.3%
FIFO=90/LIFO=10	$81,942	1995	90.0%
FIFO=100/LIFO=0	$80,833	2309	88.8%

Table 5.6 Average Daily Total and Standard Deviation (Group C)

Method	Average Daily Total Benefit	Std. Dev	Percent
N=1	$83,858	2497	95.0%
N=3	$83,965	2452	95.1%
N=5	$86,462	1380	97.9%
N=7	$87,211	1300	98.8%
N=9	**$88,273**	**1223**	
FIFO=0/LIFO=100	$86,042	702	97.5%
FIFO=10/LIFO=90	$86,928	715	98.5%
FIFO=20/LIFO=80	**$87,245**	**1187**	**98.8%**
FIFO=30/LIFO=70	$87,145	1472	98.7%
FIFO=40/LIFO=60	$86,803	1673	98.3%
FIFO=50/LIFO=50	$86,301	1755	97.8%
FIFO=60/LIFO=40	$85,771	1841	97.2%
FIFO=70/LIFO=30	$85,196	1953	96.5%
FIFO=80/LIFO=20	$84,643	2102	95.9%
FIFO=90/LIFO=10	$84,161	2364	95.3%
FIFO=100/LIFO=0	$83,686	2588	94.8%

For the heuristic model it was observed that for Group A, the maximum average total benefit was recorded when FIFO=0/LIFO=100 or pure LIFO. The maximum average total benefit for Group

B was recorded when FIFO=10/LIFO=90, and for Group C when FIFO=20/LIFO=80. It was observed that the near optimal for the heuristic model with Group A revenue schedule was at FIFO=0/LIFO=100 or pure LIFO, Group B revenue schedule was at FIFO=10/LIFO=90, and Group C revenue schedule was at FIFO=20/LIFO=80. For the heuristic model, the revenue schedule influenced the near optimal 'mixed' FIFO/LIFO policy.

5.7 Case Study II

A blood center has to determine the way to fulfill daily demand of blood products. Historical data for 78 weeks were used for both the daily released quantity ***R*** and demand ***D***. (Tetteh and Baldwin, 2006)

The blood center used to produce Single Donor Platelets (SDPs) that expire on the fifth day (5 Day) after collection. However, the blood center in collaboration with Gambro BCT has been licensed by the Food and Drug Administration (FDA) to produce SDPs that expire on the seventh day (7 Day) of collection.

The revenue for filling one unit of a 5 - Day or a 7 - Day platelet is presented in Table 5.7.

Table 5.7 Revenue Schedule for 5 - Day and 7 - Day Platelets

	Age 3	Age 4	Age 5	Age 6	Age 7
5 Day Platelet - Group A	$600	$500	$400		
7 Day Platelet - Group A	$600	$550	$500	$450	$400
5 Day Platelet - Group C	$500	$500	$500		
7 Day Platelet - Group C	$500	$500	$500	$500	$500

The lost sales attract a penalty $100 per unit due to unrealized revenue and loss of goodwill from customers, holding one unit in inventory will cost $10 per day, and a unit that has expired costs $50.

The objective is to develop a simulation model comparing the 5 - Day and 7 - Day SDPs in terms of inventory management to:

(1) Determine how the blood center can maximize daily welfare or total benefit (revenue less lost sale, outdate, and holding cost) by fulfilling SDP demand using the released quantity $\boldsymbol{R}$ and demand $\boldsymbol{D}$.

(2) Calculate the outdate rate, and the average age of SDPs shipped to hospital blood banks.

5.7.1 Stochastic Approach

Based on the given historical data, random variables for $(\boldsymbol{R}, \boldsymbol{D})_t$ were generated and identical distributions were used with the 5 - Day and the 7 - Day LP with rolling horizon method.

In section 5.6 it was shown that an LP model with rolling horizon forecast window length, $N = 9$ would achieve a near optimal issuing policy for the inventory problem. Hence this method was used for both the 5 - Day and 7 - Day models in the simulation. Using the parameters given in the case study the performance measures of interest namely, average daily total benefit, average outdate rate, and the average age of products shipped to the hospital blood bank was obtained.

5.7.2 Simulation Results

Table 5.8 displays the simulated result of the 7 - Day and the 5 - Day models for the average daily total benefit and their standard deviations, the average outdate rate and the average age of products shipped to the hospitals for the Group A and C revenue schedules.

Table 5.8 Comparison of the 5 Day and 7 Day Models

Variable	Average Daily Total Benefit	Stdev	Average Outdate	Average Age
7-Day Group A	$102,750	$661	7.00%	3.31
5-Day Group A	$100,421	$687	7.54%	3.26
7-Day Group C	$87,726	$670	7.00%	3.31
5-Day Group C	$88,340	$727	6.59%	3.41

5.7.3 Average Daily Total Benefit

To compare the statistical significance of the average daily total benefit of the 7 - Day and the 5 - Day models a two sample T-Test was employed. Figures 5.9 and 5.10 show the graph for the daily benefit for the 7 - Day and the 5 - Day models.

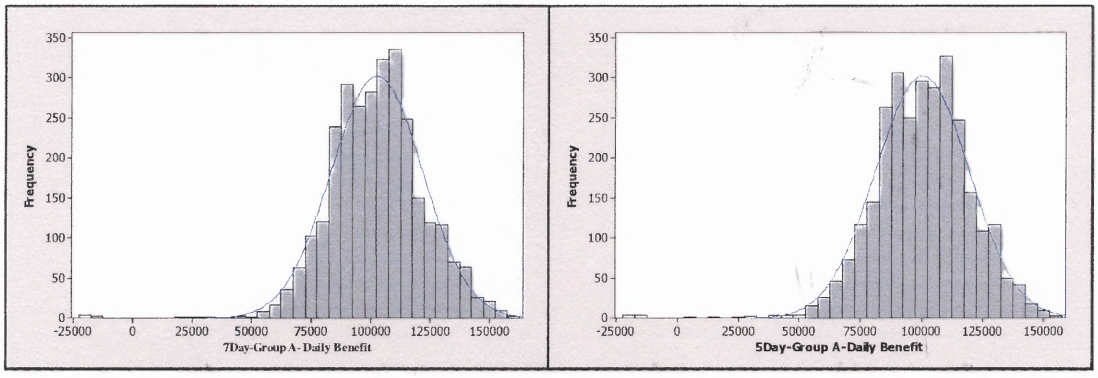

Figure 5.9 Average daily total benefit – 7 - Day vs. 5 - Day Group A.

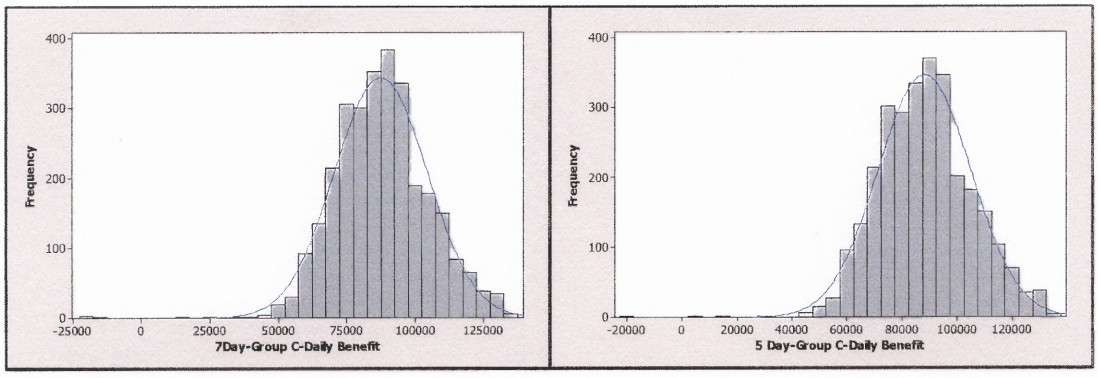

Figure 5.10 Average daily total benefit – 7 - Day vs. 5 - Day Group C.

The hypotheses in terms of the average daily total benefit for the 7 - Day model, μ_7, and the average daily total benefit for the 5 - Day model, μ_5 were:

$$H_0: \mu_7 = \mu_5$$

$$H_a: \mu_7 \neq \mu_5$$

For the revenue schedule of Group A, a p-value of 0.0005 from the two-sample T-Test with a 95 percent confidence level suggested the null hypothesis could be rejected. Thus, the mean average daily total benefit for the 7 - Day model, $102,750, was not equivalent to the 5 Day model of $100,421. The 7 - Day model will achieve a noticeably greater average daily total benefit.

For the revenue schedule of Group C, a p-value of 0.165 from the two-sample T-Test with a 95 percent confidence level suggested the null hypothesis could not be rejected. Thus, the mean average daily total benefit for the 7 - Day model, $87,726 was equivalent to the 5 - Day model of $88,340. The holding and outdate costs could be the reason the average daily total benefit for the 7 - Day model with revenue schedule Group C was slightly lower than the 5 - Day model. The results indicate that the significance of the average daily total benefit for 7 - Day and 5 - Day platelet models depend on the revenue schedule.

5.7.4 Average Outdate Rate

Figure 5.11 shows the 7 –Day average outdate rate. For the Group A revenue schedule, the average outdate rates were 7.00 and 7.50 percent for the 7 - Day and 5 - Day models respectively, and were not statistically significant.

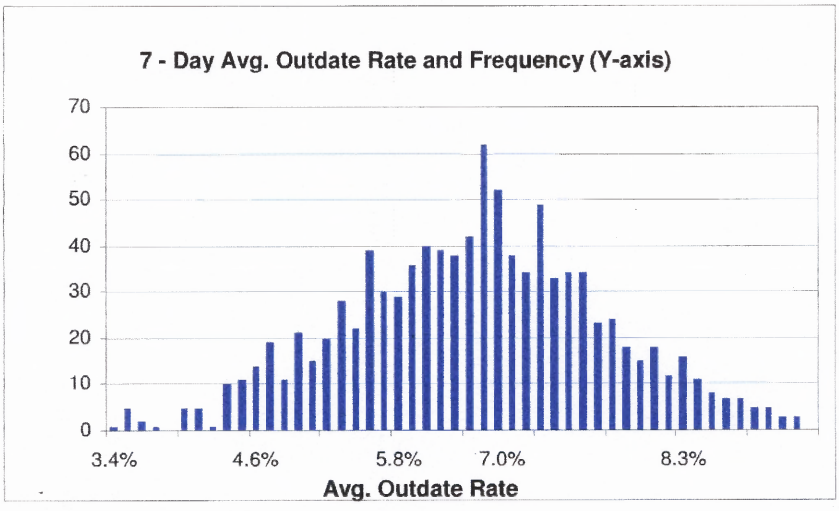

Figure 5.11 7 Day average outdate rate.

Also for the Group C revenue schedule, the average outdate rates were 7.00 and 6.59 percent for the 7 Day and 5 Day model respectively, and were not statistically significant.

5.7.5 Average Age of Products Shipped

The average age of products shipped to hospital blood banks for both the 7 Day and 5 Day models for Groups A and C were around 3.30 days, and were equivalent. However, for the 7 - Day model an average age of 3.31 days indicates 88.56 hours remaining for the product to expire. Similarly, for the 5 - Day model an average age of 3.26 days indicates 41.76 hours remaining for the product to expire. Thus, the 7 - Day model would allow a blood center to

distribute more 'fresher' SDP products.

5.7.6 Discussion

Prior to the introduction of the 7 - Day platelets to the hospital blood banks, a marketing survey indicated the following:

(1) While hospitals "value" the reduced outdating and better inventory management associated with 7-Day platelets, they demonstrated no willingness to pay extra for increased shelf life.

(2) Reduced outdating may benefit smaller hospitals rather than larger ones as smaller hospitals generally have higher outdating.

(3) The general practice within hospitals is to release the oldest (i.e., closest to expiration date) product first with exceptions for special cases (e.g., pediatric needs)

When a blood center distributed only 5 - Day platelets, 50 percent of the products had a shelf-life of 45 hours remaining. With the introduction of the 7 - Day platelets, 50 percent of the products had over 75 hours remaining.

The simulation results indicate that the blood center could distribute 'fresher' platelets and not significantly affect their outdate rate or ability to cover shortages. The 7 - Day platelet introduction by Gambro BCT would reduce hospital banks' outdates by having 'fresher' products distributed to them by the blood center.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER STUDIES

6.1 Conclusions

Forecasting Blood Supply and Demand

A linear regression model was used as a forecasting method for the blood supply prediction and a moving average for the blood demand. The *ImR* computer plots used to verify that the forecasting method results in are appropriate in Chapter 3 indicated no out-of-control or unpredictable conditions for the forecasted released products and sales. Thus, there are no special causes. One could conclude that the methodology was appropriately predicting the quantity of SDP products to be released and sales (demand) for each period.

Blood Inventory Management

A heuristic and an LP with rolling horizon schedule methods were used to solve the blood inventory problem. The heuristic method implemented on a Microsoft Excel spreadsheet formulation (Appendix F) with data provided for the released quantities $\mathbf{R_t}$ and demand $\mathbf{D_t}$, considered that the issuing policy was FIFO from 0% to 100%. The empirical study in Chapter 5 suggested that an LP with rolling horizon forecast windows within the ranges of 5 to 9 days could achieve a near optimal solution to the inventory problem. It was observed that the near optimal for the heuristic model with a Group A revenue schedule was at FIFO=0/LIFO=100 or pure LIFO. The Group B revenue schedule near optimum was at FIFO=10/LIFO=90, and the Group C revenue schedule near optimum was at FIFO=20/LIFO=80. For the heuristic model, the revenue schedule influenced the near optimal 'mixed' FIFO/LIFO policy.

6.2 Further Studies

Further studies on the forecasting and optimal allocation of blood products (with special reference to Single Donor Platelets) could focus on the following: (1) blood supply (collection and production) and demand (2) pricing of blood products.

Blood Supply and Demand

Based on the historical data analysis, it was assumed that blood supply (collection and production) was stable and similar throughout the year. A similar analysis of blood demand from historical data exhibited the same characteristics, hence demand was assumed to be constant throughout the year. Future studies could investigate how the limited control strategies of the inventory manager affect blood supply (collection) and demand. Other prediction models could be used if blood supply and demand were not constant.

Pricing of Blood Products

For the heuristic model, it was observed that the revenue schedule influenced the near optimal 'mixed' FIFO/LIFO policy. Even though pricing of blood products is not highly regulated, blood centers need to recover processing and replacement costs.

It has been the philosophy of the American Red Cross (ARC) that the blood supply is a "community" responsibility, and patients' should not pay a replacement fee (Johnson 1977). Just as most firms face competition for customers, most nonprofit blood suppliers face competition for the resources and support they need. As with any business, a nonprofit organization must take in as much money as it spends or it will not survive. However, a nonprofit institution may not

measure "profit" in the same terms as a firm. It is difficult to evaluate the benefits of blood supply to the society relative to what it costs.

Blood centers operate as non-profit organizations, and will charge a service fee to recover costs for processing blood after collection, laboratory testing, storage and distribution. Quantitative cost measurements of the inventory system of a blood center are difficult, since the estimation of the benefits (or costs) resulting from the availability or lack of platelets just-in-time for an emergency transfusion is very subjective. It will not be an easy task to place a value on a life saved through a needed platelet transfusion. The pricing of blood products remains an open research question.

APPENDIX A

FORECAST OUTPUT OF QUANTITY RELEASE (R) AND DEMAND/SALES (D) FOR JULY 2006

Actual and forecasted released products and the deviations are depicted in Table A.1.

Table A.1 Actual and Forecasted Released Products/Sales

Date	Actual Rel	Forecast Rel	Deviation	Actual Sales	Fore. Sales	Deviation
7/1/2006	237	247	-10	147	165	-18
7/2/2006	248	269	-21	146	132	14
7/3/2006	200	222	-22	183	220	-37
7/4/2006	126	122	4	184	174	10
7/5/2006	270	299	-29	152	181	-29
7/6/2006	0	0	0	184	207	-23
7/7/2006	202	239	-37	180	185	-5
7/8/2006	260	290	-30	190	158	32
7/9/2006	274	271	3	185	141	44
7/10/2006	195	229	-34	176	217	-41
7/11/2006	52	63	-11	234	208	26
7/12/2006	258	266	-8	154	182	-28
7/13/2006	219	205	14	229	197	32
7/14/2006	173	129	44	156	181	-25
7/15/2006	208	219	-11	142	171	-29
7/16/2006	222	220	2	168	158	10
7/17/2006	207	166	41	183	203	-20
7/18/2006	55	45	10	162	193	-31
7/19/2006	167	159	8	214	197	17
7/20/2006	220	184	36	188	223	-35
7/21/2006	202	165	37	190	179	11
7/22/2006	182	188	-6	148	166	-18
7/23/2006	170	159	11	167	165	2
7/24/2006	236	240	-4	222	184	38
7/25/2006	79	45	34	154	192	-38
7/26/2006	237	190	47	208	167	41
7/27/2006	205	184	21	183	216	-33
7/28/2006	213	195	18	182	183	-1
7/29/2006	193	200	-7	168	166	2
7/30/2006	226	194	32	144	168	-24
7/31/2006	239	205	34	193	193	0

APPENDIX B

CONSTANTS FOR CONTROL CHARTS

Table B.1 Constants for Control Charts.

Subgroup Size										A^2 for Median Charts			
N	A_2	d_2	D_3	D_4	A_3	c_4	B_3	B_4	E_2		A_4	D_5	D_6
2	1.880	1.128	-	3.267	2.659	0.798	-	3.267	2.660	1.880	2.224	-	3.865
3	1.023	1.693	-	2.574	1.954	0.866	-	2.568	1.772	1.187	1.091	-	2.745
4	0.729	2.059	-	2.282	1.628	0.921	-	2.266	1.457	0.796	0.758	-	2.375
5	0.577	2.326	-	2.114	1.427	0.940	-	2.089	1.290	0.691	0.594	-	2.179
6	0.483	2.534	-	2.004	1.287	0.952	0.030	1.970	1.184	0.548	0.495	-	2.055
7	0.419	2.704	0.076	1.924	1.182	0.959	0.118	1.882	1.109	0.508	0.429	0.078	1.967
8	0.373	2.847	0.136	1.864	1.099	0.965	0.185	1.815	1.054	0.433	0.380	0.139	1.901
9	0.337	2.970	0.184	1.816	1.032	0.969	0.239	1.761	1.010	0.412	0.343	0.187	1.850
10	0.308	3.078	0.223	1.777	0.975	0.973	0.284	1.716	0.975	0.362	0.314	0.227	1.809

Source: Benhow, D.W., Kubiak, T.M., "The Certified Six Sigma Black Belt," ASQ Quality Press, Milwaukee, Wisconsin, 2005.

APPENDIX C

92 DAY FORECAST AND ACTUAL QUANTITY RELEASE (R) AND DEMAND/SALES (D)

Table E.1 92 Day Forecast and Actual Quantity Release (R) and Demand/Sales (D)

Day	ForeRel	ActRel	RError	ForeDem	ActDem	DError	Day	ForeRel	ActRel	RError	ForeDem	ActDem	DError
1	230	259	29	165	174	9	47	197	187	-10	196	169	-27
2	244	267	23	188	217	29	48	241	228	-13	168	151	-17
3	55	54	-1	223	194	-29	49	218	214	-4	164	145	-19
4	213	205	-8	188	142	-46	50	228	214	-14	239	216	-23
5	182	247	65	204	244	40	51	46	71	25	195	203	8
6	207	214	7	207	186	-21	52	179	172	-7	224	219	-5
7	214	234	20	156	151	-5	53	190	220	30	203	165	-38
8	183	246	63	166	137	-29	54	202	187	-15	188	164	-24
9	209	246	37	209	238	29	55	206	160	-46	162	149	-13
10	48	86	38	207	196	-11	56	240	251	11	155	174	19
11	211	181	-30	180	185	5	57	223	203	-20	239	218	-21
12	186	168	-18	207	182	-25	58	61	112	51	203	209	6
13	164	191	27	208	158	-50	59	150	183	33	208	208	0
14	240	234	-6	154	149	-5	60	194	208	14	196	174	-22
15	228	233	5	160	153	-7	61	202	188	-14	185	166	-19
16	202	210	8	226	238	12	62	184	186	2	162	164	2
17	44	50	6	202	230	28	63	187	183	-4	159	158	-1
18	207	232	25	180	178	-2	64	218	261	43	228	235	7
19	173	194	21	216	189	-27	65	52	84	32	207	179	-28
20	214	234	20	194	184	-10	66	191	233	42	238	193	-45
21	222	226	4	157	164	7	67	181	203	22	185	164	-21
22	213	238	25	161	162	1	68	190	182	-8	180	123	-57
23	256	253	-3	241	209	-32	69	256	306	50	161	136	-25
24	57	68	11	215	170	-45	70	320	362	42	158	123	-35
25	194	162	-32	195	184	-11	71	261	293	32	233	184	-49
26	201	214	13	211	196	-15	72	65	94	29	182	167	-15
27	195	193	-2	198	163	-35	73	179	172	-7	197	228	31
28	228	216	-12	163	185	22	74	229	236	7	167	147	-20
29	219	259	40	170	158	-12	75	255	223	-32	186	226	40
30	223	234	11	235	263	28	76	244	226	-18	165	177	12
31	54	70	16	204	191	-13	77	332	307	-25	154	175	21
32	200	214	14	187	188	1	78	230	232	2	216	201	-15
33	206	222	16	212	217	5	79	68	69	1	195	196	1
34	182	214	32	190	176	-14	80	213	205	-8	188	142	-46
35	220	190	-30	169	145	-24	81	160	180	20	177	209	32
36	218	209	-9	163	162	-1	82	150	164	14	188	175	-13
37	220	219	-1	245	202	-43	83	234	258	24	165	152	-13
38	53	84	31	204	180	-24	84	226	285	59	163	162	-1
39	231	238	7	197	228	31	85	210	237	27	214	266	52
40	226	246	20	203	145	-58	86	48	78	30	198	232	34
41	262	314	52	188	183	-5	87	227	220	-7	209	176	-33
42	313	344	31	168	155	-13	88	194	196	2	184	197	13
43	242	238	-4	234	252	18	89	183	218	35	190	179	-11
44	72	75	3	199	198	-1	90	193	197	4	164	176	12
45	258	254	-4	209	247	38	91	186	243	57	160	172	12
46	232	230	-2	195	228	33	92	235	273	38	231	250	19

APPENDIX D

LINGO MODEL

Figure D.1 Contains the objects or sets that define the problem are Days, Time, Release, Demand, Quantity moved to fill demand (x3, x4, x5, x6, x7), Products Remaining in Inventory (y3, y4, y5, y6, y7), Outdate, Total in Inventory, and Lost sale.

```
MODEL:
SETS:
DAYS/D1..D30/:TIME,REL,DEM,X3,X4,X5,X6,X7,Y3,Y4,Y5,Y6,Y7,O,L;
ENDSETS
MAX=@SUM(DAYS:
550*(X3+X4+X5+X6+X7)-10*(Y3+Y4+Y5+Y6+Y7)-550*L -50*O );
@FOR(DAYS(I)|TIME(I)#GT#1:
Y3(I)+X3(I)=REL(I);
Y4(I)+X4(I)=Y3(I-1);
Y5(I)+X5(I)=Y4(I-1);
Y6(I)+X6(I)=Y5(I-1);
Y7(I)+X7(I)=Y6(I-1);
O(I)=Y7(I-1);
X3(I)+X4(I)+X5(I)+X6(I)+X7(I)+L(I)=DEM(I););
Y3(1)+X3(1)=REL(1);
Y4(1)+X4(1)=106;
Y5(1)+X5(1)=106;
Y6(1)+X6(1)=106;
Y7(1)+X7(1)=106;
O(1)=0;
X3(1)+X4(1)+X5(1)+X6(1)+X7(1)+L(1)=DEM(1);
DATA:
REL=193     149   151   169   115   23    174   164   132   155   189   133
      41    169   179   143   169   201   147   67    197   190   135   169
      198   146   71    184   171   176;
DEM=143     94    104   123   125   170   116   211   186   96    116   166
      138   191   171   120   121   115   185   145   179   146   150   116
      112   170   132   187   188   140;
TIME=1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,
28,29,30;
ENDDATA
 END
```

Figure D.1 Lingo Model for solving the Inventory Problem.

APPENDIX E

LINGO OUTPUT

Table E.1 LINGO Output for the Inventory Problem.

Global optimal solution found.
Objective value: 2334590
Total solver iterations: 115

Time	Rel	Dem	X_3	X_4	X_5	X_6	X_7	Y_3	Y_4	Y_5	Y_6	Y_7	O	L
1	193	143	143	0	0	0	0	50	106	106	106	106	0	0
2	149	94	94	0	0	0	0	55	50	106	106	106	106	0
3	151	104	82	0	0	22	0	69	55	50	84	106	106	0
4	169	123	83	0	0	40	0	86	69	55	10	84	106	0
5	115	125	115	0	0	0	10	0	86	69	55	0	84	0
6	23	170	23	0	39	53	55	0	0	47	16	0	0	0
7	174	116	100	0	0	0	16	74	0	0	47	0	0	0
8	164	211	164	0	0	0	47	0	74	0	0	0	0	0
9	132	186	132	0	54	0	0	0	0	20	0	0	0	0
10	155	96	96	0	0	0	0	59	0	0	20	0	0	0
11	189	116	59	37	0	0	20	130	22	0	0	0	0	0
12	133	166	133	33	0	0	0	0	97	22	0	0	0	0
13	41	138	41	0	97	0	0	0	0	0	22	0	0	0
14	169	191	169	0	0	0	22	0	0	0	0	0	0	0
15	179	171	171	0	0	0	0	8	0	0	0	0	0	0
16	143	120	120	0	0	0	0	23	8	0	0	0	0	0
17	169	121	121	0	0	0	0	48	23	8	0	0	0	0
18	201	115	115	0	0	0	0	86	48	23	8	0	0	0
19	147	185	147	38	0	0	0	0	48	48	23	8	0	0
20	67	145	67	0	48	30	0	0	0	0	18	23	8	0
21	197	179	179	0	0	0	0	18	0	0	0	18	23	0
22	190	146	141	5	0	0	0	49	13	0	0	0	18	0
23	135	150	101	49	0	0	0	34	0	13	0	0	0	0
24	169	116	82	34	0	0	0	87	0	0	13	0	0	0
25	198	112	28	84	0	0	0	170	3	0	0	13	0	0
26	146	170	0	170	0	0	0	146	0	3	0	0	13	0
27	71	132	3	129	0	0	0	68	17	0	3	0	0	0
28	184	187	184	0	0	0	3	0	68	17	0	0	0	0
29	171	188	171	0	0	17	0	0	0	68	0	0	0	0
30	176	140	140	0	0	0	0	36	0	0	68	0	0	0
Total	**4500**	**4356**	**3204**	**579**	**238**	**162**	**173**	**1296**	**787**	**655**	**599**	**464**	**464**	**0**

APPENDIX F

HEURISTIC METHOD USING MICROSOFT EXCEL

Figure F.1 Heuristic Method using Microsoft Excel.

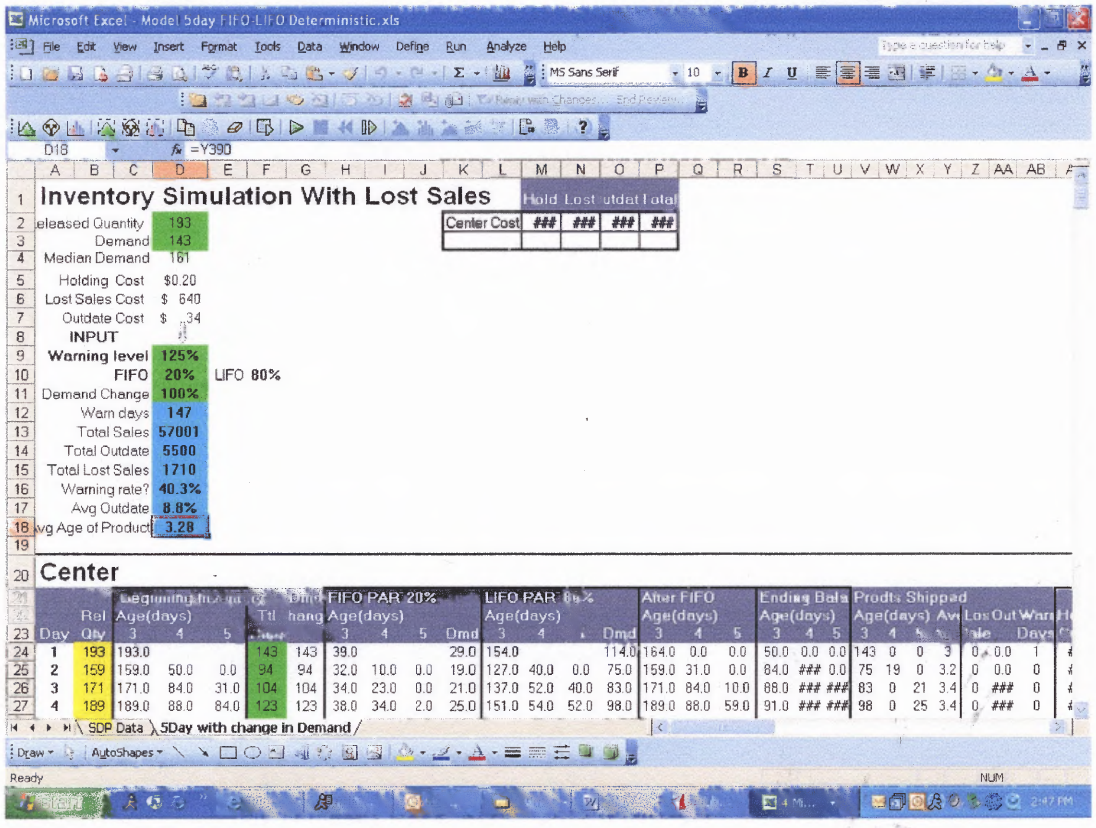

Figure F.1 Heuristic Method using Microsoft Excel.

To critically examine the issuing policy for the 5-day platelet model, set the following headings in a spreadsheet as depicted in Figure 4.07: Day (cell A23), Released Quantity (cell B23), Beginning Inventory with Ages 3, 4, 5 (cells D23-F23), Demand (cell G23), FIFO % (cells I23-K23), LIFO% (cells M23-O23), After FIFO (cells Q23-S23), After LIFO (cells T23-V23), Proportions (W23-Z23), Ending Balance (cells AA23-AC23), Age of Products Shipped (cells AE23-AG23), Average Age (cell AH23), Lost Sale (cell AI23), Outdate (cell AJ23), Warning

Days (cell AK 23). The Day heading column was filled through out the period (365 days). To illustrate the movement of platelets into the system, the Released Quantity represents the aggregate platelets released every morning after collection and laboratory testing for two days; this enters the Beginning Inventory as Age 3. Age 4 in cell E25 was obtained from cell AA24- the Ending Balance on the previous day. The Demand was the aggregate demand from the data given. The FIFO policy indicates that Age 5 platelets would leave the system first, then Age 4, and Age 3 in that order. The LIFO policy was the reverse.

For FIFO Part % in cell J25 type the formula **=MAX (0, IF (J24 +K24>=L24, I24, IF(J24+K24< L24, I24 + J24 +K24-24, I24)))**; for LIFO Part % in cell N25 enter **=MAX(0,IF(M24>=P24,M24-P24, IF (M24 < P24, 0, M24)))**; for After FIFO Age 3 in cell Q25 "**=IF(SUM(R25:S25)>0,D25, IF(D25 >$L25-E25-F25,D25+E25+F25-$L25,0))**"; for After LIFO Age 3 in cell T25 "**=IF(Q25>$P25,Q25-$P25,0)**"; for Proportions (Remaining) in cell W25 "**=H25-(SUM(D25:F25)-SUM(T25:V25))**";for Ending Balance in cell AA25 "**=MAX(0,ROUND(T25-(W25*X25),0))**"; for Products Shipped Age 3 in cell AE25 "**=D25-AA25**";for Average Age in cell AH25 "**=IF (SUM(AE25:AG25) =0, 0, SUMPRODUCT ($AE$23:$AG$23, AE25:AG25) /SUM(AE25:AG25))**"; for Lost Sales in cell AI25 "**=IF(SUM(D25:F25)<H25,H25-SUM(D25:F25),0)**"; for Outdate in cell AJ25 "**=AC25**", the same as the Ending Balance for Age 5; for Warning Days in cell AK25 "**=IF(SUM(D25:F25)<$D$9*$E$4,1,0)**".

The Lost Sale occurs when the total platelets in the Beginning Inventory are less than the aggregate Demand for the day; The Outdate occurs when a product at Age 5 was not shipped the same day; The Warning Level was triggered when the total platelets in the Beginning Inventory was less than 125 percent of the annual average demand. FIFO, LIFO policies were varied from

0 to 100 percent and the impact on Lost Sale, Outdate, and Warning Levels were monitored. FIFO and LIFO policies were held at 50 percent and the Demand was varied to measure the impact.

APPENDIX G

FACTORS WITH LEVELS FOR DOE ON OBJECTIVE FUNCTION

Table G.1 Factors with Levels for DOE on Objective Function

Pattern	Benefit	Hold	Lost	Outdate	T. Benefit
2232	L2	L2	L3	L2	1038794
3231	L3	L2	L3	L1	1139770
2223	L2	L2	L2	L3	1437795
3333	L3	L3	L3	L3	1130165
2333	L2	L3	L3	L3	1029190
1333	L1	L3	L3	L3	625290
3111	L3	L1	L1	L1	1865654
2132	L2	L1	L3	L2	1046479
1232	L1	L2	L3	L2	634895
1231	L1	L2	L3	L1	634895
1131	L1	L1	L3	L1	642579
2121	L2	L1	L2	L1	1445479
3113	L3	L1	L1	L3	1865654
1132	L1	L1	L3	L2	642579
3121	L3	L1	L2	L1	1546454
3123	L3	L1	L2	L3	1546454
3112	L3	L1	L1	L2	1865654
1322	L1	L3	L2	L2	1024290
2311	L2	L3	L1	L1	1747390
1221	L1	L2	L2	L1	1033895
2222	L2	L2	L2	L2	1437795
2231	L2	L2	L3	L1	1038795
2131	L2	L1	L3	L1	1046479
3133	L3	L1	L3	L3	1147454
3321	L3	L3	L2	L1	1529165
3132	L3	L1	L3	L2	1147454
2133	L2	L1	L3	L3	1046479
1211	L1	L2	L1	L1	1353095
1331	L1	L3	L3	L1	625290
2233	L2	L2	L3	L3	1038795
2321	L2	L3	L2	L1	1428190
3311	L3	L3	L1	L1	1747390
1222	L1	L2	L2	L2	1033895
2221	L2	L2	L2	L1	1437795
1311	L1	L3	L1	L1	1343490
3213	L3	L2	L1	L3	1857970
3322	L3	L3	L2	L2	1529165
1212	L1	L2	L1	L2	1353095
1313	L1	L3	L1	L3	1343490
2122	L2	L1	L2	L2	1445479
2312	L2	L3	L1	L2	1747390
3332	L3	L3	L3	L2	1130165
3232	L3	L2	L3	L2	1139770
1121	L1	L1	L2	L1	1041579
3313	L3	L3	L1	L3	1848365
1133	L1	L1	L3	L3	642579
2322	L2	L3	L2	L2	1428190
2112	L2	L1	L1	L2	1764679
1122	L1	L1	L2	L2	1041579
2323	L2	L3	L2	L3	1428190
1223	L1	L2	L2	L3	1033895
2212	L2	L2	L1	L2	1756995
1321	L1	L3	L2	L1	1024290
2332	L2	L3	L3	L2	1029190
3223	L3	L2	L2	L3	1538770
2213	L2	L2	L1	L3	1756995
3312	L3	L3	L1	L2	1848365
3212	L3	L2	L1	L2	1857970
3122	L3	L1	L2	L2	1546454
1113	L1	L1	L1	L3	1360779
1213	L1	L2	L1	L3	1353095
1123	L1	L1	L2	L3	1041579
3222	L3	L2	L2	L2	1538770
3331	L3	L3	L3	L1	1130165
2313	L2	L3	L1	L3	1848365
3211	L3	L2	L1	L1	1857970
1332	L1	L3	L3	L2	625290
1111	L1	L1	L1	L1	1360779
2211	L2	L2	L1	L1	1756995
1233	L1	L2	L3	L3	634895
1312	L1	L3	L1	L2	1343490
2113	L2	L1	L1	L3	1764679
2331	L2	L3	L3	L1	1029190
3323	L3	L3	L2	L3	1529165
2123	L2	L1	L2	L3	1445479
3233	L3	L2	L3	L3	1139770
3221	L3	L2	L2	L1	1538770
1112	L1	L1	L1	L2	1360779
1323	L1	L3	L2	L3	1024290
3131	L3	L1	L3	L1	1147454
2111	L2	L1	L1	L1	1764679

REFERENCES

1. Baker, K.R., Peterson, D. W., "An Analytic Framework for Evaluating Rolling Schedules," *Management Science*, Vol. 25, No. 4, April 1979, pp. 341-351.

2. Benhow, D.W., Kubiak, T.M., "The Certified Six Sigma Black Belt," ASQ Quality Press, Milwaukee, Wisconsin, 2005.

3. Breyfogle III, F.W., "Implementing Six Sigma- Smarter Solutions using Statistical Methods", John Wiley & Sons, Inc., Hoboken, New Jersey, 2nd Ed. 2003.

4. Brodheim, E., Derman, C., Prastacos, G., "On the Evaluation of a Class of Inventory Policies for Perishable Products such as Blood", *Management Science*, Vol. 21, Iss. 11, July 1975, pp. 1320-1325.

5. Chand, S., Ning H., Vernon, S., "Forecast, Solution, and Rolling Horizons in Operations Management Problems" *Manufacturing & Service Operations Management*, Vol. 4 Iss. 1, Winter 2002, p. 25.

6. Chazan, D., Gal, S., "A Markovian Model for a Perishable Product Inventory," *Management Science*. Vol. 23, 1977, pp. 512-521.

7. Clark, Alistair R., "Rolling Horizon Heuristics for Production Planning and Set-up Scheduling with Backlogs and Error-Prone Demand Forecasts," *Production Planning & Control*, Vol. 16 Iss. 1, January 2005, pp. 81-97.

8. Code of Federal Regulations, Title 42 CFR part 493.801, Washington, DC: US Government.

9. Cohen, M.A., "Analysis of single Critical Number Ordering Policies for Perishable Inventories," *Operations Research*, 24, 1976, pp. 726-741.

10. Cohen, M.A., Pekelman, D., "LIFO Inventory Systems," *Management Science*, Vol. 24, No.11, July 1978.

11. Cohen, M.A., Pierskalia, W.P., "Target Inventory Levels for a Hospital Blood Bank or a Decentralized Regional Blood Banking System," *TRANA*, 19, 4, 1979, pp. 444-453.

12. Croston, J.D., "Forecasting and Stock Control for Intermittent Demands," *Oper. Res. Quart.*, 23, 1972, pp. 283-303.

13. Crystal Ball ® Software by Decisioneering, Inc. Version 7.1. 2005.

14. Dantzig, George B., "Linear Programming under Uncertainty" *Management Science*, Vol. 1 Iss. 3/4, April-July 1955, pp. 197-206.

15. Derman, C., Klein, M., "Inventory Depletion Management," *Management Science*, Vol. 4 No. 4, July 1958.

16. Derman, C., Klein, M., "Inventory Depletion Management," Management Science, Vol. 5 No. 2, January 1959, pp. 210-213.

17. Elston, R.C., and Pickrel, J.C., "A Statistical Approach to Ordering and Usage Policies for Hospital Blood Bank," *Transfusion,* 3, 1963, pp. 41-47.

18. Entrup, M. L., Günther, H.-O., Van Beek, P., Grunow, M., Seiler, T., "Mixed-Integer Linear Programming Approaches to Shelf-Life-Integrated Planning and Scheduling in Yoghurt Production" *International Journal of Production Research*, Vol. 43 Iss. 23, December 2005, pp. 5071-5100.

19. Frankfurter, G. M., Kendall, K.E., Pegels, C. C., "Management Control of Blood through Short-Term Supply-Demand Forecast System," *Management Science*, Vol. 21 Iss. 4, December 1974, pp. 444-452.

20. Fries, B., "Optimal Ordering Policy for a Perishable Commodity with Fixed Lifetime," *Operations Research*, 23, 1, 1975, pp. 46-61.

21. Gardner, Jr., E. S., "Box-Jenkins vs. Multiple Regression: Some Adventures in Forecasting the Demand for Blood Tests," *Interfaces*, Vol. 9 No. 4, August 1979, pp. 49-54.

22. Gardner, Jr., E. S., "Evaluating Forecast Performance in an Inventory Control System," *Management Science*, Vol. 36 No. 4, April 1990, pp. 490-499.

23. Gardner Jr., E. S., McKenzie, Ed., "Forecasting Trends in Time Series," *Management Science*, Vol. 31 Iss. 10, October 1985, pp. 1237-1246.

24. Goh, C. H., Greenberg, B.S., Matsuo, H., "Two-Stage Perishable Inventory Models," *Management Science*, Vol. 39 No. 5, May 1993.

25. Graves, S.C., "The Application of Queuing Theory to Continuous Perishable Inventory Systems," *Management Science*, Vol. 28 Iss. 4, 1982.

26. Haijema, R., Van Der Wal, J., Van Dijk, N.M., "Blood Platelet Production: Optimization by Dynamic Programming and Simulation," *Computers & Operations Research*, 34, 2007 pp. 760-779.

27. Hoover, S.V., Perry, R.F., "Simulation-A Problem Solving Approach," Addison Wesley Publishing Company, Reading, May 1989.

28. Jennings, J.B., "An Analysis of Hospital Blood Bank Whole Blood Inventory Control Policies," *Transfusion*, 8, 6, 1968, pp. 335-342.

29. Jennings, J.B., "Blood Inventory Control," *Management Science*, 19, 1973, pp.637-645.

30. Johnson, J.B., "Blood Policy: Issues and Alternatives," American Enterprise Institute, Washington, D.C.,1977.

31. JMP® Statistical Software from SAS Version 5 2005.

32. Kendall, K., Lee, S.M., "Formulating Blood Rotation Policies with Multiple Objectives," *Management Science*, Vol. 26 No. 11, November 1980.

33. Kuang, Harvey H.S., "Allocation of Random Supply of Tomatoes of Varied Quality Produced in Different Areas Among Plants Producing Multiple Product Lines," *American Journal of Agricultural Economics*, Vol. 54 Iss. 5, December 1972, p. 790.

34. Law, M.A., and Kelton, D.W., "Simulation Modeling and Analysis," McGraw-Hill, New York, 1982.

35. Lee, T.S., Adam Jr., Everett E., "Forecasting Error Evaluation in Material Requirements Planning (MRP) Production-Inventory Systems," *Management Science*, Vol. 32 Iss. 9, September 1986, pp. 1186-1205.

36. Leung, S. C. H., Ng, Wan-Lung, "A Stochastic Programming model for production planning of perishable products with postponement" *Production Planning & Control*, Vol. 18 Iss. 3, April 2007, pp. 190-202.

37. McLeod, B.C., Price, T.H., Weinstein, R., "Apheresis: Principles and Practice," AABB Press, Bethesda, MD. 2003, p. 195.

38. Minitab Software by Minitab 2006.

39. Modigliani F., Hohn, F.E., "Production Planning over Time and the Nature of the Expectation and Planning Horizon," *Econometrica*, Vol. 23 No.1, January 1955, pp. 46-66.

40. McBride, Richard D., "Advances in Solving the Multicommodity-Flow Problem" *Interfaces*, Vol. 28 Iss. 2, March/April 1998, pp. 32-41.

41. Nahamias, S., "A Comparison of Alternative Approximations for Ordering Perishable Inventory," *INFOR*, 13, 1975, pp. 175-184.

42. Nahamias, S., "Perishable Inventory Theory: A Review," *Operations Research*, Vol. 30 No 4, July-August 1982.

43. Nelson, B.L., "Stochastic Modeling-Analysis & Simulation," McGraw-Hill, New York, 1995.

44. NYBC pamphlet "Donate Blood now. People can't live without it" 2004.

45. Omosigho, S.E., "Determination of Outdate and Shortage Quantities in the Inventory Problem with Fixed Lifetime", *International Journal of Computer Mathematics*, Vol. 79 Iss. 11, 2002, pp. 1169-1177.

46. Pegels, C.C., and Jelmert, A.E, "An Evaluation of Blood Inventory Policies: A Markov Chain Application," *Operations Research*, Vol. 18, 1970, pp. 1087-1098.

47. Pereira, A., "Performance of Time-Series Methods in Forecasting the Demand for Red Blood Cell Transfusion," *Transfusion*, Vol. 44, May 2004, pp. 739.

48. Pierskalla, W.P., "Optimal Issuing Policies in Inventory Management," Technical Report, No. 7, National Science Foundation, Program in Operation Research, Stanford University, August 1965.

49. Pierskalla, W.P., Roach, C.D., "Optimal Issuing Policies for Perishable Inventory," *Management Science*, Vol. 18 No. 11, July 1972, pp. 603.

50. Prastacos, G.P., "Allocation of a Perishable Product Inventory," *Operations Research*, 20 1, 1981, pp. 95-107.

51. Prastacos, G.P. "Blood Inventory Management: An Overview of Theory and Practice," *Management Science*, Vol. 30 Iss. 7, July 1984, pp. 777-801.

52. Prastacos, G.P., Brodheim, E., "PBDS: A Decision Support System for Regional Blood Management," *Management Science*, Vol. 26 Iss. 5, May 1980.

53. Shewhart, W.A., Statistical Method from Viewpoint of Quality Control, Dover, New York, 1939.

54. Schulze, M.A., (1998). Linear Programming for Optimization [Document posted on Web site Mark Schulze]. Retrieved August 24, 2006 from the World Wide Web: http://www.markschulze.net/LinearProgramming.pdf.

55. Sirelson, V., Brodheim, E., "A Computer Planning Model for Blood Platelet Production and Distribution", *Computer Methods and Programs in Biomedicine*, Vol. 35 Iss. 4, August 1991, pp. 279-291.

56. Spitter, J.M., de Kok, A.G., Dellaert, N.P. "Timing Production in LP models in a Rolling Schedule," *International Journal of Production Economics*, Vol. 93-94, January 2005, pp. 319-329.

57. Tetteh, G.A., Baldwin, C.A., "Inventory Management with 7 Day Apheresis Platelet" Abstract A19-020D Selected for Oral Presentation at AABB 2006 Annual Meeting Miami (Florida) *Transfusion*, Vol. 46 No. 9S, September 2006, p. 172A.

58. Tetteh, G., Baldwin, C., Blomquist, A., "Forecasting Single Donor Platelets and Inventory Practice" Abstract AP98 Selected for Poster Presentation at AABB 2007 Annual Meeting Anaheim (California) *Transfusion*, Vol. 47 No. 3S, September 2007, p. 258A.

59. Wagner, Harvey M., Whitin, Thomson M., "Dynamic Version of the Economic Lot Size Model," *Management Science*, Vol. 5 Iss. 1, October 1958, pp. 89-96.

60. Watson, R.B., "The Effects of Demand-Forecast Fluctuations on Customer Service and Inventory Cost When Demand is Lumpy," *Oper. Res. Soc.*, 38, January 1987, pp. 75-82.

61. Winston, W.L., "Operations Research Applications and Algorithms," Thomson Learning. Belmont, CA. 2004.

62. Whybark, D.C., "A Comparison of Adaptive Forecasting Techniques," *Log. Transportation Rev.*, 8, 1973, pp. 13-36.

63. Zipkin, P., "Foundations of Inventory Management," McGraw-Hill, New York. 2000.