Blood Bank Inventory Management Analysis

Elísabet Edda Guðbjörnsdóttir

Thesis of 30 ECTS credits
Master of Science in Engineering Management

June 2015

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Thesis of 30 ECTS credits submitted to the School of Science and Engineering
at Reykjavík University in partial fulfillment of
the requirements for the degree of
Master of Science in **Engineering Management**

June 2015

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Abstract

Improvement of a blood supply chain is a complex process. Blood is a perishable product with uncertainties in both supply and demand and blood stock management is therefore a judicius balance between shortage and wastage. Sufficient blood supply is critical to the healthcare industry and the general population. The challenge lies in the stochastic nature of donated and transfused blood units that have a short life span and follow extremely strict quality demands. This study was based on the Icelandic blood bank and its operations. It is a small blood bank on a global scale, with one centralised processing and distribution center. Discrete event simulation was used to determine which policy should be used in order to improve the blood supply chain and reduce shortage and wastage levels. For an improved understanding of the blood supply chain, multiple linear regression analysis was used to explore if and how blood supply could be affected. An understanding of the supply increases the probabiltiy of successfully designed experimental models in the simulation. Risk analysis was also used for the purpose of creating suitable experimental models by determining the most volatile variables. It can be quite costly to have excessive out-dated units in the system although it is clear that shortage of blood is not acceptable. It was therefore vital to locate the proper experimental models in order to improve the supply chain. Even though the base model was not properly validated due to insufficiency of data the results show that collecting blood units by seasonality could improve the inventory management of the Icelandic Blood Bank.

Keywords - Simulation, Multiple Linear Regression, Risk Analysis, Blood Stock Management, Inventory Management

Greining á birgðakerfi Blóðbankans

Elísabet Edda Guðbjörnsdóttir

Júní 2015

Útdráttur

Bæting ferla blóðbankans er flókið ferli. Blóð er viðkvæm vara með óvissu í bæði framboði og eftirspurn. Blóðbankastjórnun er því leit að jafnvægi milli skorts og sóunar vegna ofgnóttar. Það er nauðsynlegt fyrir heilbrigðiskerfið að til sé nóg af blóðeiningum til staðar í blóðbankanum. Áskorunin felst í því að fjöldi blóðgjafa og blóðþega eru strjálar breytur auk þess sem að blóð hefur takmarkaðan líftíma og gæðakröfur á hverja einingu strangar. Þessi rannsókn byggist á íslenska Blóðbankanum og starfssemi hans. Hann hefur sérstöðu á heimsvísu hvað varðar smæð, það er aðeins einn miðlægur lager og vinnslustöð þaðan sem allar einingar eru sendar frá. Til að rýna í birgðastýringu Blóðbankans og leita að bættri nýtingu kerfisins var strjált hermilíkan hannað. Til þess að bæta skilning á aðfangakeðjunni var aðhvarfsgreining notuð til að skoða hvort hægt væri að hafa áhrif á framboð blóðs og hversu breytilegt það væri. Með því að auka skilning á framboði blóðsins aukast líkur á því að hanna vel heppnuð tilrauna hermilíkön. Áhættugreining var einnig gerð til að auka líkur á viðeigandi tilraunalíkönum. Það getur reynst kostnaðarsamt að hafa óþarfar einingar í kerfinu en það er þó ljóst að mikilvægara er að verða ekki fyrir skorti. Það var því nauðsynlegt að hanna líkönin vel í leit að bætingu kerfisins. Þrátt fyrir að ná ekki að sannreyna grunnlíkanið sýndu niðurstöður að með því að stjórna framboði á blóði eftir breytilegri eftirspurn árstíða var hægt að bæta birgðakerfi Blóðbankans.

Lykilorð - hermun, margþætt línuleg aðhvarfsgreining, áhættugreining, blóðbankastjórnun, birgðastjórnun

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List of Abbreviations

IBB = Icelandic Blood bank
RCC = Red Cell Concentrate
LSH = Landspítali Háskólasjúkrahús, the Hospital in Reykjavík
FIFO = First in first out
LIFO = Last in first out
BAS test = Blood group and screening test
ICU Hr. = Intensive Care Unit on Hringbraut
Ob. & Gyn. = Obstetrics and gynaecology
Research Dept. Fv. = Research Department in Fossvogur

Chapter 1

Introduction

This chapter serves as a guideline for the thesis. The background of the project will be introduced along with the today operations of the Icelandic Blood Bank. The aim and objectives will be presented and limitations stated. The thesis outline will then be explained.

1.1 Background

The first documented evidence of blood transfusions can be traced to Oxford as far back as 1666 [1]. Since then there has been tremendous progress in the way blood is transfused, processed and stored. Surgeries today often require less blood transfusions than they previously did because many surgeries are becoming less invasive [2], [3]. On the other hand the population is increasing in industrialised countries and furthermore with increased longevity and declining fertility rates the age distribution is changing [4], [5], [6]. An ageing population requires more medical care and with that may follow an increased need for blood transfusions [6], [7]. Regular donations are needed for the supply chain to work. Today there are around 7,000 active blood donors in Iceland and around 2,800 blood transfusion receivers. The fact that only 2% of the eligible Icelandic population donated blood in 2012 is a concern and is low compared to UK and USA where 6% and 5% of the population, respectively, are active donors [8]. Importance of successful blood banking is therefore clear. The Icelandic Blood Bank (IBB) is sensitive towards shortage in supply and it is vital that they understand the flow of goods in the system. To seek knowledge and familiarise with a subject results in improvement. Maya Angelou once said: “I did then what I knew how to do. Now that I know better, I do better” [9]. Even if the process itself is already at its best, the improvement lies in the added understanding

behind the process and the willingness to explore. A simulation model that sets up the supply chain model induces critical thinking.

Supply Chain Management (SCM) can be defined as the system that effectively plans and manages all activities involved with sourcing and procurement, conversion and all logistics management activities within and between organisations [10], [11], [12]. With SCM there are value-enhancing, long-term benefits [12]. This applies especially to organisations with either large system inventories or organisations that supply perishable products of scarce resources, such as blood units. Whereas logistics is defined as the part of the supply chain that plans, implements and controls the efficient flow and storage of raw materials, in process inventory and finished goods. Logistics also includes service and information from point of origin to meet consumers requirements [10], [11].

The supply chain for blood and its components from donation to transfusion is in many ways similar to a traditional logistic chain. This is a planned process where the blood units are collected, processed and separated into components, stored, transported and transfused [13]. What is different from the traditional definition is that supply and demand are both stochastic and are difficult to control. Lead time is not as easy to forecast as it is for standardised products because of uncertainty connected with blood type, processing time and number of donations. Lean management principles or just in time techniques are not suitable for blood stock management as the system is sensitive towards shortage. For inventory systems with stochastic demand it is popular to use the s,Q model [13], [10]. Those models are organised in a way that when stock levels drop to a defined reorder point, s, an order of size Q is placed. With perishable products, such as blood, it is vital that the reorder point is not set too low so that the required demand levels cannot be met. The aim is to properly define the reorder point and try to keep donation levels at a certain level even though a specified lot size cannot be achieved. The literature on Blood Stock Management is limited even though it is an important subject as blood is a perishable, deteriorating product with uncertainty in both supply and demand. The challenge is to keep wastage at minimum but at the same time keep enough on stock to ensure maximum service levels. Traditional methods of SCM do not always apply to blood stock management where lead time is mostly unknown along with formerly mentioned stochastic supply and demand and the main focus is on maintaining the correct blood inventory levels where cost is usually the main focus for companies. Most blood banks use the first in first out (FIFO) policy where the oldest blood units are donated first. Research has been made on US hospitals using simulation where the possibility of using last in first out (LIFO) is tested using an age threshold of 14 days [14]. This requires sufficiency in blood supply but if the levels are high enough this leads to fresher blood being donated [14].

A successful standard supply chain has an accurate forecast for demand so that the supplier is able to produce and deliver the product in a timely and cost-effective manner [12]. In blood stock management this accurate demand forecast is not possible. An acceptable inventory policy in blood stock management seeks to meet demand requirements while minimising the number of expired units [13], [15]. By the use of historical data and simulation models it is possible to search for the best strategy in a risk free environment and estimate the needed stock levels for each period of time. A simulation model of the entire logistics chain in the blood bank is created to make it possible to seek for an inventory policy that creates the least conflicts between larger stock levels to meet unforeseen demand and smaller stock levels to reduce out-dating [16]. It can be difficult to control blood supply, which is dependent on donors showing up when needed. Regression methods can increase understanding on the effects the IBB can have on blood supply. For the sake of successful blood supply management, that understanding is important because it increases the likelihood of gaining control. A better understanding of the effects IBB can have on their blood stock management enables them to maintain better control of their stock levels. Where traditional SCM models seek to design the system to best mitigate the risk connected to disruption in supply and forecast demand, in blood stock management the aim is to find the optimal reorder point. This study uses simulation models that take in historical data to predict best practices. It is not a matter of optimisation but rather exploration on the effects of different practices and search of best practices by the use of simulation.

The ever-changing demand for blood transfusion creates an environment that constantly needs to be on alert. A simulation of that environment reduces risk in decision making. Blood banks are sensitive towards supply shortage because it can be a matter of life and death for the patient to get the blood transfusion on time and it is therefore vital to maintain best practices in blood stock management. A wasted unit has hidden costs involved, such as transportation costs, time spent by the donor as well as the healthcare staff, thus there are the monetary reasons further emphasising the importance of SCM. Additionally, there are moral reasons for not accepting a blood donation that will go to waste due to excess blood stock levels. Since donors in Iceland do not get paid for blood donations they are not only donating their blood but also their time. It is therefore desirable to keep wastage to a minimum. Testing and processing of each unit is also costly so it is important that the ratio of wasted blood units is not too high. The level of acceptable out-dating should be determined. The Icelandic population is so small that there is only one blood bank that processes all donated units and it has only centralised warehouse. The main issue is to ensure proper stock levels and a good code of practice with blood depots. This research is therefore different from the researches conducted in other industrialised countries where

one of the main issues is where to locate blood banks and whether to have a centralised warehouse or not [17], [18]. Due to the unique circumstances of the IBB there is limited literature on comparable research and the same applies to systems where both supply and demand are stochastic.

1.2 The Icelandic Blood Bank

The Icelandic Blood Bank has been operating since 1953. In 1994 a new production method was put into operation, improving the production of red blood cell concentrates greatly and extending the storage time to 42 days. In 2002 the Red Cross gave IBB a blood collection vehicle, making it possible to collect blood from donors around Iceland. Today IBB collects blood in Reykjavík, Akureyri and in the bus, everything is then processed in Reykjavík and sent from there to users.

During blood donation a sampling bag is first collected and those samples sent to be tested for infection, blood categorisation and general blood research. Then the donation bag is filled with 450 ml of the donors blood, which is about 10% of the total blood volume of an average person [19]. Each blood unit is then separated into red blood cell concentrates, plasma and platelets but blood can be processed into about 30 different sub-products [15]. Blood is composed of different components such as; plasma, red blood cells, white blood cells and platelets, see Fig. 1.1. Each component has a different function and can be used to treat various types of patients. Red blood cells are i.e. used for surgical, trauma and anemic patients. Platelets are i.e. used for cancer patients and plasma is among other things used for patients with liver diseases [15].

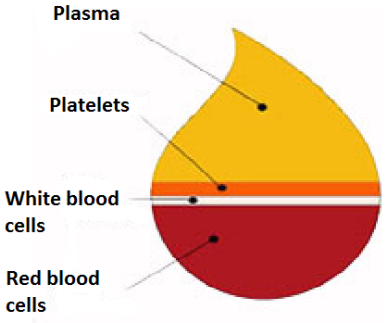

Figure 1.1: Blood divided into components [20]

When an unit of blood is ordered for a specific patient serological and compatibility cross-referencing tests are conducted before the unit is sent to the hospital [15]. Donations can take place during normal working hours Mondays to Thursdays but processing of units and dispatching of blood units can take place at any given time and the same applies to blood transfusions.

Blood Flow

The arrangement of the blood supply chain can be seen in Fig.1.2, where the flow of donated units of blood from the initial donation to the place of transfusion or wastage of units is shown. Proper storage of units is required at all stages in the supply chain. Blood is collected in three places; The Icelandic Blood Bank in Reykjavík, the blood collecting vehicle and in Akureyri. After donation all units go to the IBB in Reykjavík to go through processing and various tests are conducted, this can happen simultaneously as the test samples are only a small part of the donation. After processing the units go to a closed stock. If test results indicate that the unit is safe for use the blood units will be moved to open stock but if the test results have a bad outcome the units are thrown away and considered disposed units as opposed to other units that are thrown away and are regarded as outdated. From open stock the units are moved to various blood depots when demand calls for them.

The IBB sends blood units regularly to nine blood depots. They now all have a storage unit that can properly store the units so that they can be sent back to the IBB and put back into open stock where they wait to be again demanded by a blood depot. These depots are located at; Akranes, Akureyri, Ísafjörður, Neskaupsstaður, Sauðárkrókur, Vestmannaeyjar, LSH Fossvogur, one in the intensive care unit (ICU) at LSH Hringbraut and one in the obstetrics and gynecology at LSH Hringbraut. Units that are not booked on any of those depots are ordered directly from various departments of the hospital.

From blood donation there are four paths a blood unit can take. Most commonly the units travel to a depot and get transfused into a patient. Some units get outdated in the system, they get thrown away from the centralised stock at the IBB. Other units get disposed of because they did not meet quality demands for various reasons and finally there are units that are used for various researches.

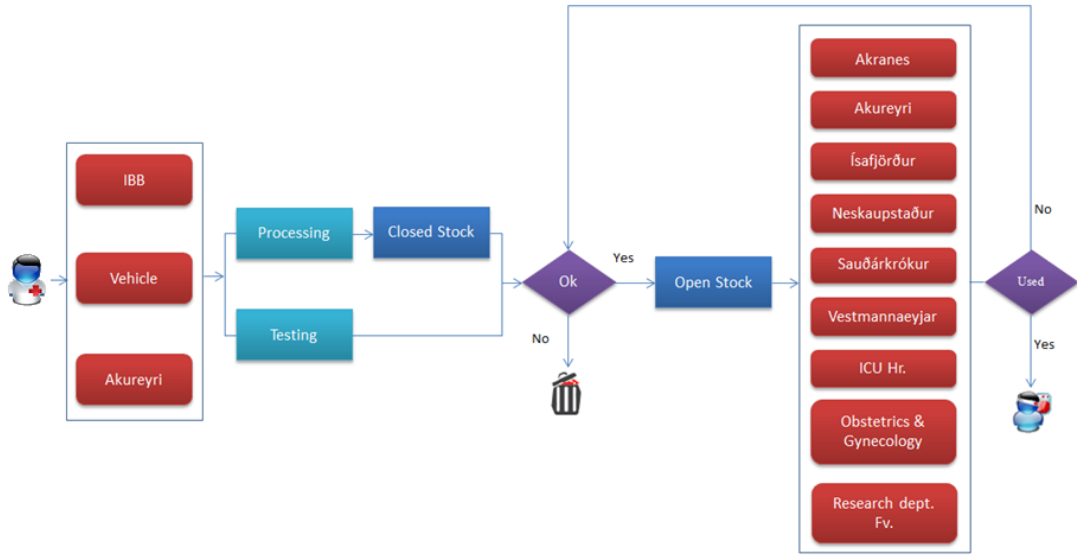

Figure 1.2: Current blood flow of the IBB, from donation to transfusion

The units that are ordered by blood type, cross-matched and assigned to a specific patient shall be sent back within two days if not transfused. There can be many reasons for a unit that is assigned to a specific patient not being used such as too many booked units or postponed surgery. The unused unit goes back to open stock when no longer reserved. If that unit is not logged as transfused and has not been resent within two weeks it atomatically gets registered as a transfused unit in the system. Other units are booked for emergency cases and a small stock kept at each depot, these stay there for 14 days before being sent back to open stock.

1.2.1 Supply and Demand

The difficulty to control the blood supply chain stems from the stochastic nature of both supply and demand. A spike in demand should be possible to meet with the benchmark stock levels. The IBB aims to keep 560 Red Blood Cell Concentrates (RCC) units on stock and considers stock levels below 450 units to be an emergency situation. Those stock levels are therefore assumed to be sufficient for both daily operations and unforeseen demand spikes.

The IBB has ways to reach out to donors in times of need both through emails, text messages and phone calls. In an emergency situation the IBB can reach out to donors through

the media, which has been proven an effective way to increase supply. In extreme cases where demand exceeds supply and normal procedures do not work, blood units can be ordered from Scandinavia but it will take 5 hours to get those units to the hospital.

1.2.2 Wastage and Service Level

Blood is an essential product used in modern medicine for surgical procedures and other medical purposes. It is vital that blood units are available whenever patients need them and so maximum service levels are required for the IBB.

Successful blood supply management seeks to supply blood without wasting it. This scarce product is valuable and it is important that as little of it is wasted as possible. Each unit is considered outdated at midnight 42 days after donation, regardless of the time of day the donation took place.

Wastage can be segregated into two types. Firstly there is wastage due to wrongly processed units of blood or test results that indicate that the unit is not safe to use. This can be the result of the unit bursting in a centrifuge, leakage in the bag, donor calling in sick after their donation or the unit does not meet the quality requirements of the IBB. Secondly there is wastage that stems from disposed units that were not used before outdating. Additionally there are units that do not get transfused because they are used for research purposes.

1.2.3 Stating the Problem

This study is based on the blood stock management of the Icelandic Blood Bank. Until now the IBB has not done any numerical research on their stock system but have rather based their stock levels on years of experience. It is vital to maintain adequate supply levels on stock, both because of the importance of not running out of blood units for patients and because it is preferred to try to limit wasted donated blood units that get out-dated in the system. Supply and demand of blood units change continuously. The challenge is to tune the reference stock levels in such a way that service level is maximised at the same time as waste is minimised. It is also interesting to see if other strategic or operational changes can improve the blood stock management of the IBB. The purpose of doing this research is therefore to search for ways of improvement in the blood supply chain at the Icelandic blood bank.

1.3 Research Aim and Objectives

The overall aim of this study is to eradicate guess work and minimise risk in the supply chain management of the Icelandic Blood Bank (IBB) by use of a discrete event simulation forecast model. To do so properly firstly Supply Chain Management (SCM) needs to be introduced and then blood stock management, a sub-subject of SCM, explained further. A proper insight into the theory will give a better understanding of the simulation model and its parameters. The model replicates the activities performed from initial blood donation to testing and transfusion. Models are a simplified representation of the real life system and they give no guarantees of validity, when properly structured they do however provide a good way to improve operational practices. This is important in the healthcare industry where trial and error methods are not an option and a simulation model offers ways to reconfigure and experiment without risk involvement.

The objectives are as follows:

- Analyse empirical data thoroughly
- Conduct a detailed research of related literature
- Identify the flow of blood units for an improved understanding
- Use appropriate statistical methods to analyse the data
- Create a simulation model
- Analyse the results and find a solution that yields improvement of the blood supply chain
- Conclude with recommendations for the Icelandic Blood Bank

The research question is designed with the aim and objectives of the research in mind to ensure the research focus stays intact. The question that has been set out to seek an answer for in this study is: Is it possible to meet demand with reduced stock levels?

Additionally, it is interesting to see if lower stock levels will engender in younger units of transfused blood as there are indications that this may serve well for some type of patients [14], [21].

1.4 Limitations

All studies were based on red blood cell concentrates, other types will not be included in this research but it should be easy to apply the methodology on i.e. plasma. Parameters for processing time and expiration rates would have to be modified for each case. Red blood cell concentrates will not be categorised into blood types and therefore the statistics assumed similar for all blood types. This is done for simplification reasons but later on it is possible to expand the model to include other factors in the operations of the IBB.

1.5 Thesis Outline

This thesis is organized into four chapters. In chapter one the day-to-day operations of the IBB are introduced and the importance of blood stock management is explained and emphasised. In chapter two empirical data is analysed and the and purpose of simulation models explained and justified for this dataset. Statistical analysis with multiple linear regression is used to analyse the supply in order to increase the likelihood of an appropriate selection of experimental models. Risk and uncertainty management is used to show the value of proper risk awareness and add validity to the selection of experimental models. Chapter three introduces findings and results of the study. In chapter four the findings and results from chapter three are discussed In chapter five the results are connected to the research objectives and aim. Proposed methods and possibilities for future work for the IBB are then introduced and discussed.

Chapter 2

Methods

This chapter gives full details of the methodology employed in the study and describes the data collection and processing. The main purpose of this chapter is to describe the experimental design and justify the appropriateness of the selected methods [22].

2.1 Data Collection and Processing

All data for the simulation model were collected from the IBB's database, ProSang-Interinfo, or based on those data. The data consists of information on the number of blood donations on a weekly basis as well as demand and number of transfusions for each blood depot. Additionally the out-dating and wastage levels are documented. Each unit is logged as out-dated at midnight on the 42nd day regardless of the time-stamp of the donation. The data is measured in the number of RCC units, one blood donation equals one RCC unit.

Data from 2013 and 2014 were collected for the simulation modelling. The simulation model only runs data from the year 2013 though because too much was missing from the data from 2014. The reason for not basing the simulation models on data created over a longer period of time is that before 2013 some of the blood depots did not have a proper cooling storage unit for the blood units. The blood units were sent to the blood depots but they had to dispose of unused units because all blood units need to be stored properly in a certified cooling unit. This means that using data from earlier years would have given the wrong image of blood usage and wastage levels. In this study all data was documented on a weekly basis so the model ran the data for each week of the year.

The data for the simulation were exported from ProSang into Excel. Discrepancies in the dataset were analysed thoroughly. To get all vectors in the dataset to match, a tenth depot was added after consultation with Sveinn Guðmundsson, the head physician at the IBB. That depot was named Direct to Unit and it was assumed that all units that were not connected to a specific depot in the data were assigned to that depot. Direct to unit refers to hospital units that ordered directly from the IBB and are not connected to the nine defined depots. The data data vectors from Akureyri had some errors, where the number of units sent from Akureyri was larger than number sent to Akureyri. This was fixed by switching the values and placing additional units in the direct to unit vector. SIMUL8 is a process simulation software that was used in this study. To be able to import the data into SIMUL8 all data needed to be organised in a specific way to make it possible for SIMUL8 to read through the dataset. Each depot's weekly demand and number of transfusions as well as the number of weekly donations were organized in separate columns. For the weeks that had no recorded demand a zero value was added to make sure that all weeks of each year were included. Wastage that stems from units that could not be processed properly and put through to open stock as well as units used for research purposes were subtracted from the initial donation number in the simulation model for simplification. That is, instead of having two representative activities in the simulation software subtracting units from the system that are not relevant for this study, they were subtracted directly from the input data. Doctors shall document blood transfusions for reserved blood units into ProSang. However, if a blood unit is ordered for a specific patient and never returns to the IBB the unit is assumed to have been transfused even though the responsible doctor has not documented the transfusion.

To explore the effects the IBB can have on supply levels, data consisting of the number of text messages sent out to donors were collected and compared with the number of donations from that same time period. This dataset consists of information from the years 2010, 2011 and 2013. The number of messages for the year 2012 was not available and therefore that year not explored further. This is the only data that comes from handwritten notes that were then manually added to an Excel spreadsheet.

Table 2.1 shows the desired number of blood units in stock as well as the, today defined, emergency levels kept in stock at the IBB and at the depot in Akureyri. When the blood units have two weeks left of their lifetime they get sent back from Akureyri to Reykjavík. Table 2.2 shows the desired number of O negative blood units that should be kept available for emergency situations at each depot. The abbreviations for their names is explained in the list of abbreviations. O negative units can be transfused to almost all patients regardless of their blood type. It is therefore convenient to keep O negative units on stock in places where demand is low and would be unreasonable to keep adequate levels of

all blood types available. These emergency units are kept at the depots until two weeks are left of their lifetime. They are then sent back to the centralised stock at the IBB to maximise the likelihood of the units being used. The employees of each depot are responsible for ordering new units of blood and when a depot has received new emergency units the older units get sent back to open stock. Each depot pays a fee for the units that are sent back so they do try to minimise the number of units required. The units that are ordered for a specific patient are kept at the hospital or depot for two days and if unused within that time-frame they get sent back to the centralised stock unit.

Depot	Desired No.of Units	Emergency Levels
IBB	561	450
Akureyri	118	70

Table 2.1: Stock levels of RCC units

Depot	No. of Emergency Units
Akranes	12
Ísafjörður	4
Neskaupstaður	4
Sauðárkrókur	4
Vestmannaeyjar	4
ICU Hr.	6
Ob.& Gyn.	4
Research Dept. Fv.	6

Table 2.2: Stock levels of O neg blood units at depots

All data provided by the IBB were anonymous and not connected to gender, age or blood type.

2.2 Risk Analysis & Risk Management

Risk analysis was conducted and the results used to place the appropriate focus in the simulation experimental models. It is important to carry out a proper analysis in risk management in order to realize which factors to take a closer look at. The cornerstone of risk management is risk awareness. That means being aware of and familiarise with the risks involved in the system. A risk analysis is a good tool to use because when properly

done it will increase the likelihood of a successful decision or project completion with regards to cost, time and performance [23]. It is important to understand that risk follows every decision but by analysing the risk a better control will be maintained and thus the risk reduced.

It is clear that there are high risks involved with wrong assumptions of blood unit stock levels and there can be serious implications, in worst case fatalities. It is therefore vital that the re-order point and desired stock levels are estimated correctly.

Risk analysis can be split into two stages; a qualitative analysis and a quantitative analysis [23]. A qualitative analysis focuses on identifying the risk factors where i.e. each risk factor and its impact are categorized subjectively [23]. A quantitative analysis often includes using computer software to do measurements of uncertainty in cost and time estimates and a probabilistic combination of individual uncertainties [23]. A quantitative analysis is not always carried out but the qualitative analysis should be done regardless. Risk management then follows risk analysis. In risk management the risks are evaluated and preventive measures identified and procedures designed to deal with risks if they should occur. Constant monitoring and review of risk factors is also important in risk management. The relations between risk analysis and risk management has been graphically represented in Fig. 2.1. Risk analysis and management is a continuous process that is valid at almost any stage of each project and can be continued until the cost of using it exceeds the potential benefits.

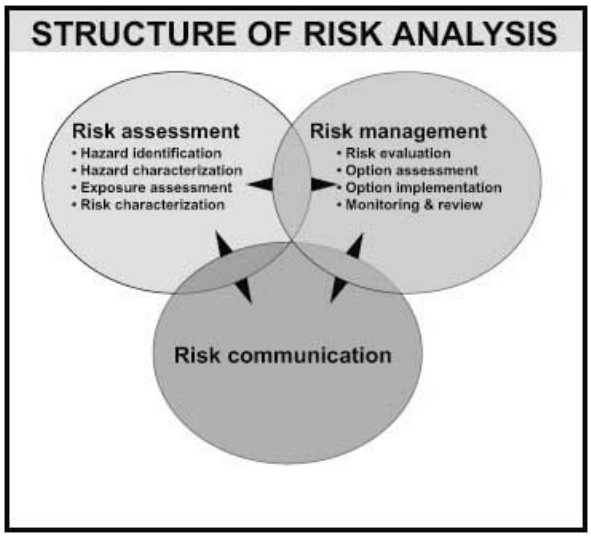

Figure 2.1: Risk Analysis and Management Diagram [24]

A qualitative risk analysis was made for the Icelandic Blood Bank where the main risk factors were identified, see table 3.1. Table 2.3 explains the colour codes for the probability and impact of the risk factors enumerated in table 3.1 [25]. The impact and probability for each risk factor are multiplied resulting in a risk number and action is then given for each factor [25]. It is important to notice the factors that have the highest risk numbers they are colour coded red and need to be monitored so that precautionary measures can be taken to minimize damage. The indices that resulted in a red risk scenario were then used as experimental models.

Table 2.3: Probability and impact table, explaining the colour codes for Table 3.1

			IMPACT ON PROJECT GOALS (TIME, COST, QUALITY, ETC.)				
			0,05	0,1	0,2	0,4	0,8
PROBABILITY	0,9	VERY HIGH	0,05	0,09	0,18	0,36	0,72
	0,7	HIGH	0,04	0,07	0,14	0,28	0,56
	0,5	AVERAGE	0,03	0,05	0,10	0,20	0,40
	0,3	LITTLE	0,02	0,03	0,06	0,12	0,24
	0,1	NONE	0,01	0,01	0,02	0,04	0,08

There are three categories for risk as can be seen from table 2.3; low marked with green, medium marked with yellow and high marked with red. The IBB can use simulation to improve risk control management in their daily operation. By simulating daily operations the entire logistic system is scrutinised and thus risk minimised. Each simulation case is designed using historical data and is created with the IBB's quality control management in mind. By careful data collection the IBB can use simulation as a control device for their operations. Proper risk factors need to be identified and descriptive attributes for each category defined. What the simulation of historical data will not show are so called Black Swan events, extreme events without precedence. A Black Swan is an abnormal event, an outlier [26]. They are called black swans because the norm are white swans and a black swan is something unexpected [26]. Black Swan events cannot be predicted due to their randomness and therefore the focus should be on what to learn from those events when they do occur to have the proper action plans in place. A severe case of an influenza epidemic or series of critical accidents are examples of Black Swan events. The simulation model can be used to show the effects of those dramatic events by using historical data and swap out a few data points with extreme cases.

2.3 Supply Analysis using Linear Regression

It can be difficult to control blood supply, which is dependent on donors showing up when needed. The impact of campaigns, aggressive campaigns in media and seasonality effects were explored by using regression on historical data in order to predict blood supply. Where sending text messages and/or emails to donors is referred to as campaigns. A better understanding of the effects IBB can have on their supply enables them to maintain better control of their blood stock management.

The first step was to go through the data and see if there is variety in the supply and if so analyse the controlling factors in order to minimise the risk connected with the supply. Until now IBB has not done any numerical research on the effects of their campaigns. The best way to see if there is variety is to look at fluctuations in the data graphically. Text messages and/or emails have been sent out almost every working day to ask for donations to keep the stock level they have felt they needed. Fig. 2.2 shows the stock level at the start of each week in the years 2011, 2012 and 2013 along with the purple line showing the benchmark level and the blue line showing the emergency stock level. The stock levels vary from week to week. A large portion of the year the stock levels are fluctuating well above benchmark levels but the weeks that hit below truly show the lack of control over the supply.

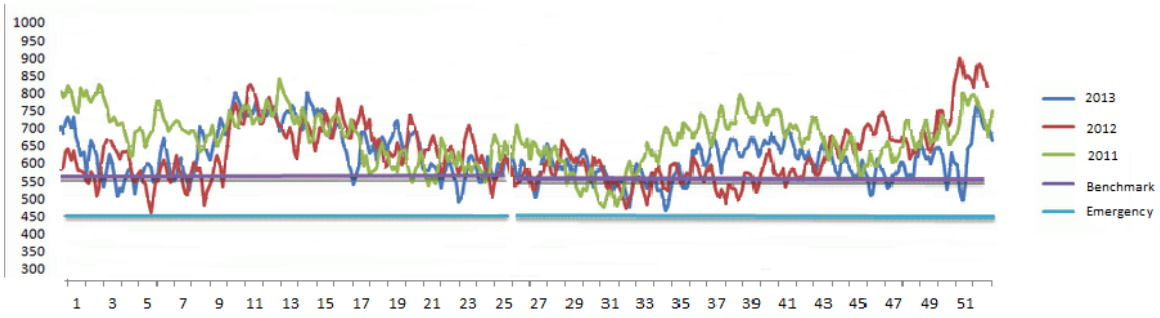

Figure 2.2: IBB's stock levels of red blood cell concentrates

Now that the supply variety had been established, the next step was to use regression methods to explore the effects IBB can have on their supply. Regression analysis is a statistical method that explores the relationships between a dependent variable, Y, and independent variables, x. Regression models have at least the following three goals [27]:

1. To understand the behaviour of Y, given x
2. Predict the value for future Y, given x
3. Causal interference

Where in the case of IBB, Y represents the number of donations given the chosen independent variables. The independent variables whose effects will be analysed are as aforementioned campaigns, aggressive campaigns and seasonality.

2.3.1 Simple Linear Regression

Simple linear regression can be used for building empirical models to scientific data [28]. The method of least squares is used to estimate the parameters in a linear regression model [28].

The first step in every regression analysis should be to make a scatter plot of the data to show graphical relations between the variables [29]. It can often make sense to transform the variables so that their relations will be close to linear it they are not already linear [27]. The control variables, in this case the number of text messages, shall be plotted on the x-axes and the response variable, here the number of blood donors, shall be plotted on the y-axes [29]. The scatter plot will display any outliers that can be vital in the analysis of data. Outliers shall be looked at carefully and their effects interpreted but removed if a mistake in data collection has been made. If the outliers are very influential it may be more reasonable to analyse the data both with and without them [28].

A regression line is a straight line that describes the relationship between the control and response variables. This line can for example be used to predict the number of blood donors given a specific number of messages sent out.

Equation 2.1 shows a simple linear regression model [28], it has only one independent variable or regressor. The slope, β_1, and the intercept of the line, β_0, are called regression coefficients. Correlation implies linear relations between variables. It is assumed that the expected value of the error factor, ϵ, is zero.

$$Y = \beta_0 + \beta_1 \cdot x_1 + \epsilon \tag{2.1}$$

In linear regression methods it is important to estimate σ^2 which is the variance of the error factor, ϵ [28]. The estimate of σ^2 represents the relative variation in Y that can be

explained by changes in values of the x variables [29]. The sum of squares of the residuals are used for the estimation of σ^2.

The method of least squares can be used to estimate the regression coefficients [28]. The solution to the normal equation results in the least squares estimators which give a fitted or estimated regression line. It is possible to use Microsoft Excel to find the regression coefficients for the simple linear regression model.

The vertical distance from the data points to the regression line are called residuals [29]. Points that are above the regression line have positive residuals but the ones below the line have negative residuals. Residuals are a good indication of how well the regression line describes the data. A residual plot is a good way to analyse the data. Residuals should be randomly distributed around zero and no order should be visible, nor should any correlation be found between residuals. If these conditions are not met, the regression model should be revised or discarded [28]. If the regression line captures the overall pattern of the data well the residuals should be relatively small in size in comparison to the values of the dependent variable.

Regression models are used to predict a value of Y, given x. When this is done for x in the same interval that can be found in the data used to evaluate the regressor coefficients it is called interpolation [29]. However when predicting Y for x that is beyond the original observation range it is called extrapolation. Extrapolation is in other words extending the regression line and it can be unreasonable in some cases. For example in the case of sending text messages there are limitations to how many text messages can be sent while expecting the same response as the coefficients in the regression model imply.

2.3.2 Multiple Linear Regression

Multiple linear regression analysis is a statistical process used to demonstrate and estimate the relationships between a single response variable and multiple predictors [30]. That will therefore show the effects various factors have on the number of donors and get a deeper understanding of the problem at hand. A regression model that contains more than one regressor variable is called a multiple linear regression model [29]. Multiple linear regression analysis attempts to increase the understanding of how a typical value of the criterion variable changes when a variable is varied while the others are held fixed [27]. This therefore estimates the conditional expectation of the number of donors given a criterion, whether that criterion is the number of text messages sent out, if aggressive campaigns have been staged or which quarter of the year it is.

The control variables that will be analysed in this multivariate regression model are the campaigns, aggressive campaigns in media and seasonality. Note that any regression model that has linear β parameters is a linear regression model, regardless of the generated surface [28].

As in the simple linear regression model the method of least squares can be used to estimate the regression coefficients in the multivariate regression model. MATLAB has built in functions for that. Matrices are used to express data in multiple linear regression models which can be put directly into MATLAB.

A regression model that has five regressor variables can be described with equation 2.2 [28].

$$Y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot Q_1 + \beta_4 \cdot Q_2 + \beta_5 \cdot Q_3 + \epsilon \tag{2.2}$$

Where in the case of the IBB, Y would represent the number of donors that donate each week, x_1 represents the number of campaigns held out and x_2 represents the aggressive campaigns and Q_i the number of each quarter of the year. This is therefore a multiple linear regression model with five regressors [28]. The regression model in equation 2.2 describes a linear function of the unknown parameters β_0, β_1, β_2, β_3, β_4 and β_5 [28]. It is again assumed that the expected value of the error factor, ϵ, is zero. Note that β_1 measures the expected change in Y per unit change in x_1 when x_2, Q_1, Q_2 and Q_3 are held constant and β_2 measures the expected change in Y per unit change in x_2 when x_1, Q_1, Q_2 and Q_3 are held constant [28].

Regressors Q_1, Q_2 and Q_3 are dummy variables created to include the yearly quarters Q_1, Q_2, Q_3 and Q_4 in the model. This is done in order to show seasonality for each quarter of the year. Regression analysis treats all independent variables, x, as numerical so dummy variables are created to trick the regression model into correctly analysing the attribute variables [31]. The dummy matrix is organised in a way that it has zero values everywhere except that it has the value one in the first column in the weeks in quarter one, for quarter two it has the value one for the weeks in the second quarter et cetera. The dummy variables then represent the binary independent variables and the number of qualitative variables in the model is always t-1 for a qualitative variable with t-levels. The fourth quarter is not needed in the model since these are binary variables and when none of the other three quarters apply the fourth one is a default.

When the β_0, β_1, β_2, β_4 and β_5 coefficients have been found the regression equation can be used to predict the number of donors given pre-defined conditions.

Residuals are also found for multiple linear regression models. As in the simple linear regression model it is important to estimate σ^2, the variance of the error factor ϵ [28].

Results from regression analysis were then used as a basis for selecting simulation scenarios. Doing a statistical analysis, such as regression, on the supply can greatly increase the likelihood of a proper choice of models for scenario testing in simulation modelling.

2.4 Simulation

The purpose of this research is to seek for improvements in the blood supply chain. Simulation is a numerical solution method used to draw conclusions about a specific system by the use of a model. A system is a collection of entities connected to reach a specific goal and a model is used to describe the system and its state and behaviour. Simulation is a good tool to use for scarce products such as blood because it allows for trial and error in a risk free environment. In general, whenever there is a need to analyse randomness and obtain overview of a system, simulation is a good tool to use. Simulation of various models allows for testing of scenarios that would otherwise be either impossible or too costly or, in the case of blood banking, too risky. It can be described as a virtual system that allows you to ask questions in a risk free manner and compare one scenario to another. It is therefore more of a "what if" analysis rather than optimisation because in the search for improvements in the system it is important that the correct questions be asked. The general purpose of simulating a supply chain is to see how small changes of parameters or minor adjustments in the system affect the entire system and the cost and time in system of the end product [32].

Simulation has been proven useful in the decision making of healthcare problems [33]. National Health Service (NHS) in the UK and Maasstad Hospital in the Netherlands have for example been using simulation for informed decision making and strategic changes in their operations [34]. Simulation has also been successfully applied to simulate complex systems in Iceland, for example Hafrannsóknarstofnun used it in fish farming of cod and Landsnet has used it for prediction of energy- and power balance [35], [36]. Additionally, the use of simulation models can improve understanding of complex systems. Simulation models are a somewhat simplified version of daily operations. They are an approximation of the real life system regardless of time and money spent on modelling. Simulation models should be a simplified representation and even though the credibility of the model increases with time and money it is not necessarily cost effective to spend unlimited time and money on increased validity. Increasing the validity beyond a certain

level can cost too much when the increased credibility is compared to the time and money put into the modelling [37]. No guarantee is provided with simulation although it does provide an important tool to optimise operations and improve understanding. Simulation, unlike integer or linear optimisation, does not focus on finding the optimal solution but rather is dependent on the scenarios set up by the modeller [38]. This often results in the near best solution but is dependent on the study done on the problem and the skills of the modeller [39]. Simulation only gives an estimate for specified criterion and it is difficult to generalise for other criteria. The modeller must be aware of the importance of a well defined goal. Excessive programming and data pre-processing can be a part of the simulation process and the modeller must therefore make sure not to get lost in details.

The process of the model work can be described by the use of a flow chart, see Fig. 2.3. What is important to understand is that simulation requires human intervention at all stages except for the actual running of the simulations. This calls for a skilled problem analysts and simulation modellers with a good grasp of statistical understanding [16], [39], [40]. If the problem is not properly defined in the beginning it is clear that the conclusion will not be optimal. Good research work of the problem at hand is therefore vital for successful simulation results. After formulation and data analysis with reconstruction of data the model is developed. Anyone can develop a model, what is important is that the model is a good representation of the real life events. Therefore, the model is verified and validated before running the simulation with the designed experimental models and a final conclusion achieved.

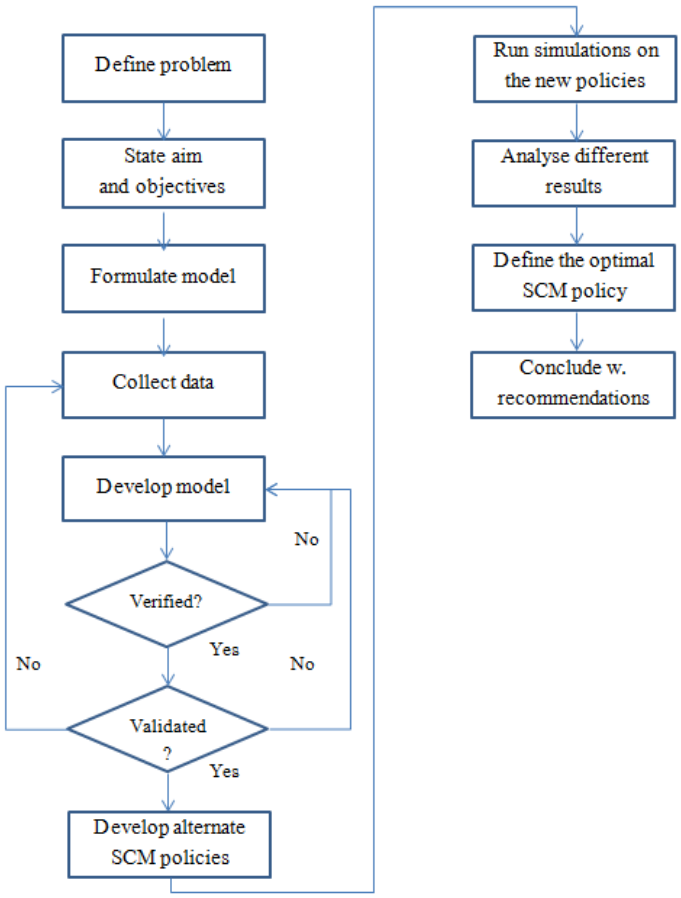

Figure 2.3: Flow chart for the modeling

The most important metrics of the blood supply chain are shortages and wastage levels. A successful blood supply chain responds to demand without unnecessary additional stock levels. The optimal blood supply chain management policy should be discovered with the use of the simulation model. Even if simulation results were to show that optimal practices are in operation it still increases the understanding of the blood supply chain and ensures that operations are not based on guess-work or intuition. Simulation enables the user to identify the variables that most affect the performance and identify bottlenecks [39].

A model is a simplified version of a system. It should be a good representation and therefore a judicious balance between accuracy and simplifications. Simplifications allow for increased understanding and make the model better to work with. It is important to be aware of which type of model is an appropriate representation of the problem and fits with the data. The behaviour of the data needs to be explored to see if it is deterministic or stochastic. The nature of the data and the problem should be explored with respect to time. If the model changes with time it is dynamic, otherwise static. It should also be explored

whether the system develops and changes continuously or in discrete times [41]. In the case of the IBB it is a discrete system and a stochastic and dynamic model used.

There are a few concepts that should be defined for an improved understanding of simulation. A blood unit is called an entity, something that is created, goes through the system and runs its course. Attributes are what defines each entity. Resources are what the entities use when going through the system. Each working centre then needs a queue so that the entities can stay in the queue either because they are not ready or demand has not called for them yet. Batching is when entities arrive in batches or when a entity goes through a working centre and splits in a few entities. Each working centre then needs to have routing in defined, that is how the entities arrive to the working centre and routing out, how the entities leave the centre. A label is a variable that follows an entity and can take either a numerical value or be set as a string.

Designing a successful simulation model of real life events requires more than implementing a flowchart into a simulation software [32]. Probability and statistics are a large part of every simulation study. A vast understanding of both subjects is needed in order to understand how to model a random system, how to validate the simulation model, how to generate random samples from distributions and how to perform analysis of the simulation output data [32]. A proper probability distribution needs to be determined for each action point in a simulation model. The distribution then allows for a random variate to be generated as an input to the model.

2.4.1 Base Model

The base model was designed to represent the operations shown in the flow diagram in chapter one, see Fig. 1.2. That is, the base model shall represent the current situation at the IBB. Both supply and demand are stochastic events. The base model for the IBB is discrete event simulation. This means that the system responds to the discrete events instantaneously [39] and the model runs in continuous time [18]. In other words, when a blood donation enters the system at the arrival point it affects the entire system. A blood bank system is actually a manufacturing line and manufacturing systems can in general be looked at as queuing systems that do not change continuously over time and are therefore categorised as discrete systems [32].

The base model was designed in iterative steps where each step got more complicated than the previous one. This is done to ensure that the model works correctly with each iterative addition and in order to make the model as accurate as possible. The purpose of

the base model is to make sure that the daily operations are properly represented in the simulation before various scenarios are tested.

The daily supply and demand fluctuations that stem from amongst other things varying opening hours are not included in the model because the data is given on a weekly basis. The simulation runs for 52 weeks at a time with a first in first out (FIFO) policy. When modelling the present situation there are a number of parameters that need to be included. The stock levels at the end of the year before the simulation period starts need to be set as the initial stock levels in the system at each location. Otherwise, the system would have no units to meet the initial demand and that would create deviations in the results. This was done by using a dummy start up to introduce the initial contents with the expiry information. The units then have to pass through the dummy to get the expiration value stamped onto them, otherwise those units would expire instantly. Another option would be to use a warm-up period in the system but that way the dataset would be reduced in size since some of the data-points would be used to initialise the model. The number of weekly donations then need to be implemented at the start point, excluding units used for research purposes and units that did not meet quality demands that were disposed before entering the centralised stock. Distributions for all activities were determined from historical data. A global variable representing the age of the units in the system needed to be implemented at the start point and updated continuously throughout the model to be able to implement the expiration time of 42 days. All units get outdated at midnight at the end of the 42nd day of their lifetime. An activity then collects the number of outdated units in the system so that they can be monitored. Demand varies from depot to depot and each depot sends a number of unused units back each week. This was implemented by two separate activities and the total usage of each depot recorded. The model was set up to run in minutes and working hours set as eight hours, five days a week. Units that have less than two weeks left of their lifetime cannot be sent to the nine official depots but can only be used when directly booked by various departments of the hospital.

Simplifications are needed in all simulations, in order to make the program simulate real life events properly and for a better overall understanding for the modeller. The simplifications needed in this model stem partially from limitations of the simulation software. The expiration time of units was modelled using labels in SIMUL8. However the unused units, both reserved and emergency units, that should be sent back within three and fourteen days, respectively, were in this model assumed to be sent back at the beginning of each week. This simplification to the model is done because the labels used for the 42 expiration days make it impossible to use labels for those two separate re-routing times. Having a global expiry can be difficult to implement, even more so in a complex simulation scenario like this one. A very large expiration time was set on all Depot R (see

Fig. 2.4) activities to represent the number of transfused units at each location. The global expiry in the system does not affect those units because then in the end they would all get pulled to the expiry bin even though they were used and should have left the system by that route.

The number of weekly donated units, the supply, were imported to the model by batching and data was retrieved every 2400 minutes. The value 2400 was retrieved by multiplying five days a week, by 8 hours a day, by 60 minutes, because the model runs in minutes. It then uses routing out to queue one. A dummy variable was set up as a dummy start up action to modify the system so that it initialises with end of last years stock levels. All queues update the expiration label, to represent the global expiry in the system, and the dummy variable seen in Fig. 2.4 is used for the purpose of the overall expiration time of blood units, 42 days. The processing working centre is modelled with triangular distribution for the processing time, it is a popular distribution to use when data is limited [32]. For the triangular distribution a mode of 24 hours is used, where mode is the most common value in a dataset, a upper level of 36 hours and a lower level of 12 hours of processing time for each unit, those data were estimated from a specialist within the IBB. The three collection points were united in the model into one action point so the parameters in the triangular distribution were designed to include all three factors. For simplifications this processing working centre is assumed to have 100% efficiency as those data were not present and believed redundant in this model. The Checking action point represents the cross-matching of blood units for specific patients. Routing out is used from the centralised warehouse to not only all the blood depots but also the bin that represents wastage from expired units.

The Depot R working centres, see Fig. 2.4, represent the units that get sent back to the central warehouse. These are activities used when unused units need to be sent back to Reykjavík to the centralised warehouse of the IBB from the depots. The number of resent units is retrieved from an internal Excel spreadsheet. They update the expiration time of each unit and send it back to the centralised warehouse where the blood unit goes to open stock and is again available to meet demand from the depots. The units that return to the central stock then take priority over other units as they will expire sooner. This is due to the fact that the global system is set to a FIFO policy and because each queue is set to use label prioritisation. Label priority makes sure that a unit with a lower lifetime value gets a higher priority in the system. The shelf life was increased to a very large number in the queue between each Depot and corresponding Depot R. This was done so that once the units are transfused at the depot, they will stay there and not be sent back to the centralised stock and in the end be documented as expired in the system. This enables SIMUL8 to follow how many units each depot actually used. The yellow and green boxes under each

activity in Fig. 2.4 show the current object status, where yellow means idle and green means working. This is used solely for verifying the behavior of the model.

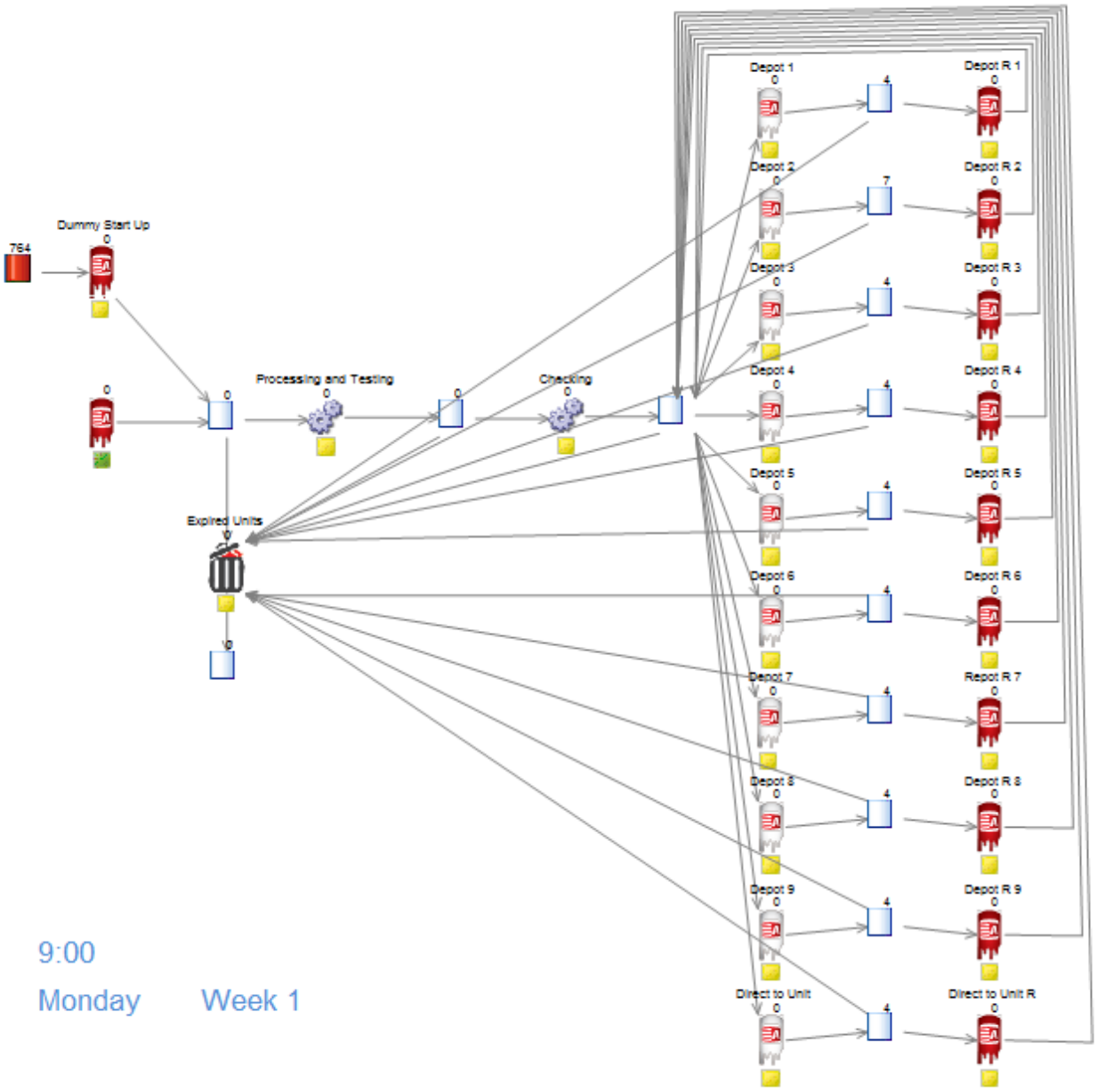

Figure 2.4: The model as it looks like in SIMUL8

Visual Logic is SIMUL8's internal Programming Language. It allows for a more detailed and complex modelling, by the use of written code, that cannot be achieved through the normal drag and drop actions of SIMUL8. That way the program allows the simulation to behave exactly as needed. It is only available with SIMUL8 Professional and therefore not included in the Educational version that the Reykjavík University uses for their students.

Visual logic was needed in order to allow each blood depot to have a separate weekly demand and actual number of required units, meaning that some units get sent back to the centralised warehouse. Each station may therefore require, and get sent, a number of units that is higher than the actual demand, or used units. Time check logic was used to make sure each station collects the required demand in a proper week. When each depot has received its required number of units, that route is blocked until the next week when the time check logic runs again. Each depot then uses Visual Logic to get the daily demand from imported Excel sheets. That way the arrivals get fixed to every 2400 minutes and are collected from an Excel spreadsheet by batching. SIMUL8 can have errors when collecting a value of zero, so instead of a zero value Visual Logic sets the value for that week to an impossibly high numerical value so that the activity will not collect any items for that week, here it was set to 10,000.

2.4.2 Verification and Validation

Validation is the process of evaluating whether the simulation model is an accurate representation of the system [37]. Once the base model has been constructed it has to be tested. It can be tested and verified iteratively with increased complexity in each step. It is only when the base model has been validated and verified that it is possible to try different scenarios in various experimental models.

Validation was done by simulating known conditions, first shorter periods of time and then throughout the entire period. Then comparing the results of the simulation with the performance of the actual system. This not only justifies the simplifications done to the model and ensures correct modelling but also gives the user faith in the model [16]. Note that a model is only valid if its logic is correct and appropriate data are used [37].

2.4.3 Design of Experimental Models

Experimental models as simulation scenarios are designed in a manner that meaningful changes are made to the input variables of the base model in order to see the effects [39]. In order to find the optimal policy that minimises both unsatisfied demand and wastage the results of different scenarios were then compared with regards to stock levels, unsatisfied demand and wastage due to expired units.

Three scenarios were tested. In the first experimental model the blood supply from the base model was decreased by 10%. That was done by changing the data in the internal Excel spreadsheet. Secondly the benchmark stock levels were changed according to

seasonality. Results from the multiple linear regression model were used as a frame of reference in order to find adequate levels. This means that the supply levels from the base models were not used but rather a flat number for each period. That was implemented by using a fixed distribution that was segregated into four separate distributions that each had their own entering rate. The entering rate was based on the average number of donations in each season. The third experimental model used LIFO policy instead of FIFO. This is a global setting in the simulation software. The LIFO policy was set for all units but an interesting option would be to set a FIFO policy for the system but LIFO for returned units. Limitations in the simulation software, SIMUL8, however do not allow for that modification. To set a LIFO policy on returned units would be done to ensure that the patients receive the freshest blood possible, this modification would not be done to minimise outdating levels.

Chapter 3

Findings and results

The objective of this chapter is to identify the optimal operational scenario of the IBB. First to show the results of the risk analysis and clarify the high risk scenarios from the risk analysis and the results from supply analysis using regression. Then to proceed to cover results from the base model and the experimental simulation models.

3.1 Risk & Uncertainty Management Results

Table 3.1 shows that the number of donations and extreme demand were the factors that resulted in the highest risk number. Those are factors that have high impact even though the probability is not very high. Distribution, processing and storage problems are issues with a yellow colour code, meaning that they should also be monitored but the impact of them is less significant. From table 3.1 the extreme demand risk factor can be categorised as a black swan event. The risk factors with a red colour code are related to the availability of blood units. Regression analysis showed that the IBB cannot easily affect the number of blood units donated without going through media channels and the effects of doing so are probably so strong because it is not used except for in the rare cases that the blood levels have fallen below emergency levels. It is therefore vital to not only predict the correct levels necessary but to have a appropriate action plan ready for each risk factor.

Table 3.1: Risk number retrieved from probability and impact

	Risk Factor	Impact (0,05-0,8)	Probability (0,1-0,9)	Risk number (AxL)	Action	Color
1	Extreme demand	0,8	0,3	0,24	Prepare procedures well, campaigns	
2	Too much out-dating	0,1	0,5	0,05	Make stock levels smaller	
3	Too much wastage from processing	0,1	0,3	0,03	Improve processing	
4	Too few donations	0,8	0,5	0,40	Hold aggressive campaigns	
5	Distribution problems	0,4	0,3	0,12	Different routing, different vehicles	
6	Processing problems	0,4	0,3	0,12	Use safety stock and fix machines	
7	Storage problems	0,2	0,3	0,06	Move units to a different location	

Extreme demand and lack of supply were risk factors used for the simulation analysis this time but it is important to maintain focus on risk management in order to be prepared. It is not necessarily so that the same risk factors will yield the same risk number at all times.

3.2 Regression Results

Fig.3.1 indicates correlation between the number of blood donors and number of campaigns carried out each week so this was analysed using regression models. From experience the staff at the IBB has felt it may be more difficult to get blood donors in during holiday seasons so after doing a simple linear regression analysis on the effects of campaigns the combined effects of different yearly quarters and aggressive campaigns were analysed, as well using multiple linear regression analysis.

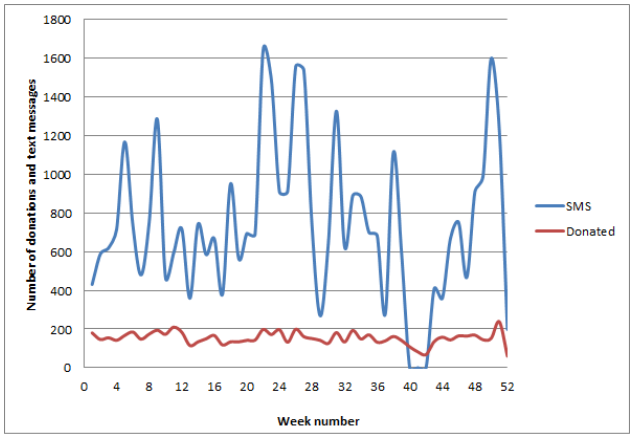

Figure 3.1: Number of messages sent to donors versus the number of donations, plotted for each week of the year 2013 to show correlation between the two factors

3.2.1 Linear Regression Analysis

All data for the linear regression analysis was recorded and processed in MS Excel. A graphical indication of the relationship between the number of campaigns and the number of blood donations in 2010 is shown in a scatter plot in Fig.3.2. Using the trendline function, the equation was displayed on the chart along with the R^2 value. Resulting in r=0.31 which indicates how close the data are to the regression line. Meaning that the correlation between the variables makes the model viable for use in linear regression analysis [29]. Analysis of data with regards to outliers showed two indices that were so influential that it was reasonable to analyse the data without them. The two weeks that aggressive campaigns had been held out by advertising in media were removed from the data set. The reason for that is not only that it would skew the results for the effect of campaigns but also because the effects of aggressive campaigns was analysed separately. From the equation for y on Fig.3.2 it can be seen that the effects of campaigns are concluded as weak but by sending 100 messages, 155 donors are predicted to show but only three of those because of the messages sent.

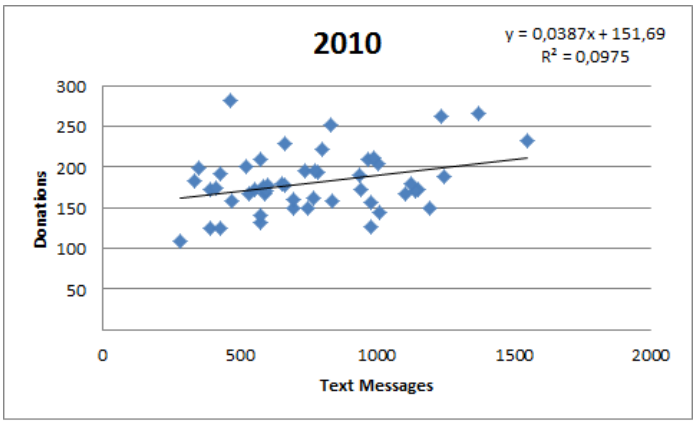

Figure 3.2: Number of donations vs. number of campaigns in 2010 plotted to show the linear relationship between the two factors

Residuals were calculated and plotted to show the validity of the model, see Fig. 3.3. The residuals are rather large but the regression line is nevertheless not an unrealistic measurement of the data because the residuals are distributed randomly around zero.

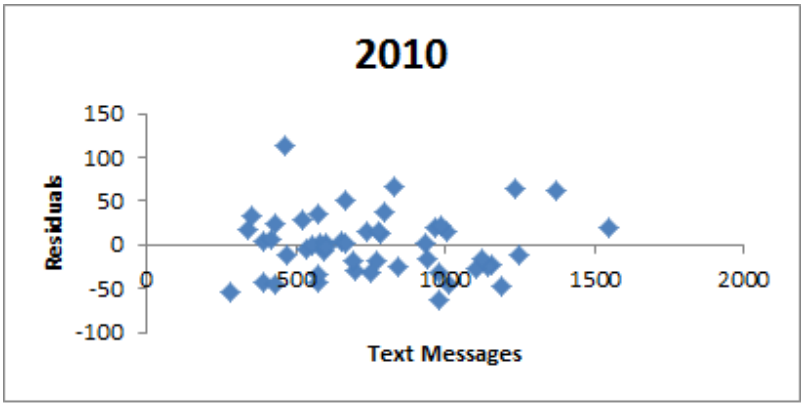

Figure 3.3: Residual plot for the data from 2010 to show the validity of the regression model

A scatter plot was also made of the number of campaigns versus the number of blood donors for the year 2011 as shown in Fig.3.4. Using the trendline function the equation was displayed on the chart along with the R^2 value. Resulting in r=0.21 which indicates that the correlation between the variables is not very strong. After analysing the data one outlier proved influential enough that it was reasonable to analyse the data without it. One week that aggressive campaigns had been held out by advertising in media was therefore removed from the data set. As shown on Fig.3.4 campaigns are even less effective than in 2010 which may be due to 6% decrease in the number of active donors between the years.

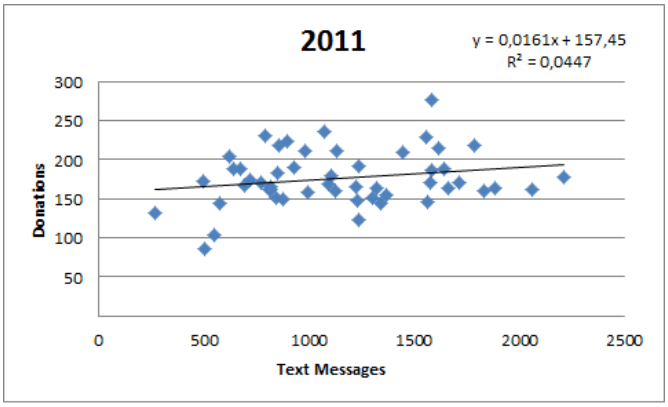

Figure 3.4: Number of donations vs. number of campaigns in 2011 plotted to show the linear relationship between the two factors

Residuals were calculated and plotted to prove the validity of the model, see Fig. 3.5. The residuals are smaller than in 2010 and the regression line describes the data in a reasonable way. The residuals are distributed randomly around zero.

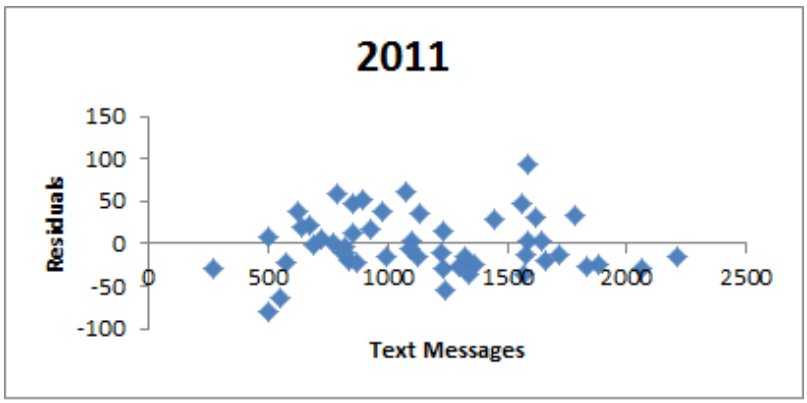

Figure 3.5: Residual plot for the data from 2011 to show the validity of the regression model

A scatter plot was made, see Fig.3.6, showing the graphical indication of the relationship between the number of campaigns and the number of blood donations in 2013. Using the trendline function the equation was displayed on the chart along with R^2. Resulting in r=0.62 indicating a reasonably strong correlation between the variables. Data analysis showed no major outliers and they were not so influential that it is reasonable to analyse the data without them. No aggressive campaigns had been held out by advertising in media so no weeks were removed from the data set. The regression factors are the highest for year 2013, indicating the strongest effect from campaigns. The stronger effects may be explained by the fact that in 2013 it happened three times that no messages were sent for a whole week which did not happen in 2010 or 2011. The β_0 coefficient immediately drops compared to previous values so again this shows that the results from the regression analysis would be much better if there were more zero indices.

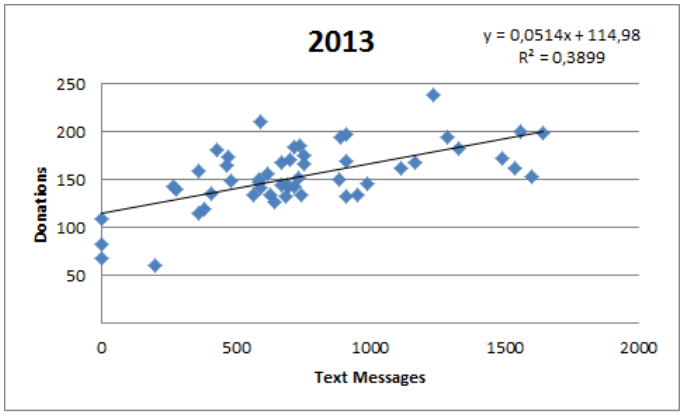

Figure 3.6: Number of donations vs. number of campaigns in 2013 plotted to show the linear relationship between the two factors

Residuals were calculated and plotted to verify the validity of the regression model, see Fig. 3.7. The residuals have the smallest values in 2013 indicating that the regression line describes the data in a good way. The residuals are distributed randomly around zero.

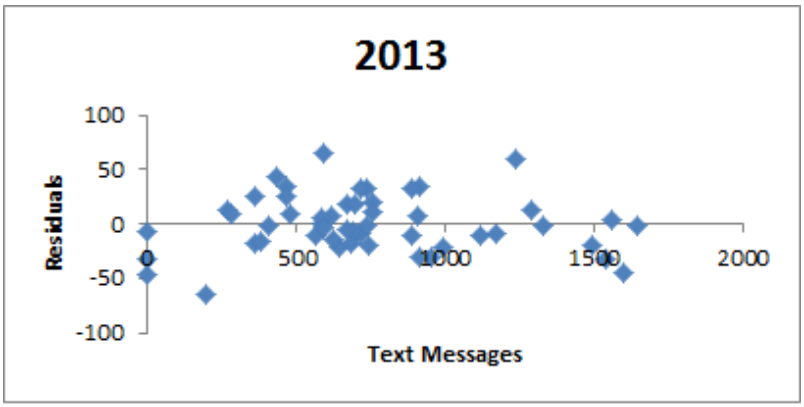

Figure 3.7: Residual plot for the data from 2013 to show the validity of the regression model

The strongest correlation between the number of campaigns held out and the number of blood donors was proven to be in year 2013 which is hopefully an indication of the future values of correlation.

Finally a scatter plot was made of the entire dataset from all the years, see Fig.3.8. As could be foreseen the value of r=0.37 is somewhere between the previously mentioned values. The weeks that had aggressive campaigns in the media were removed from the data set and no other outliers removed.

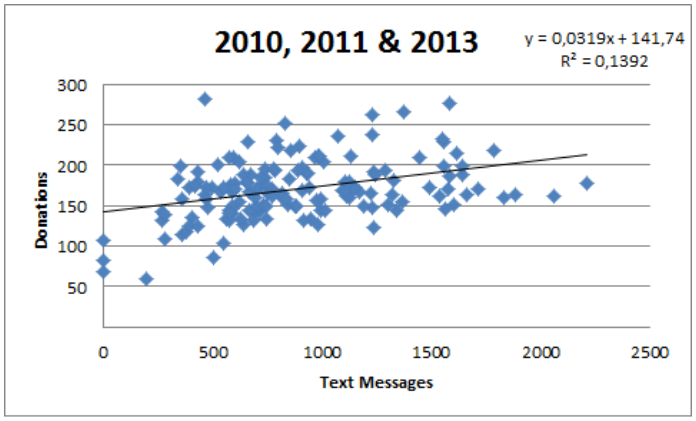

Figure 3.8: Scatter plot of the number of donations vs. the number of campaigns in the years 2010, 2011 and 2013 to show the linear relationship between the two factors

Residuals were calculated and plotted, see Fig. 3.9. The residuals indicate that the regression line describes the data in a reasonable way. The residuals are distributed randomly around zero.

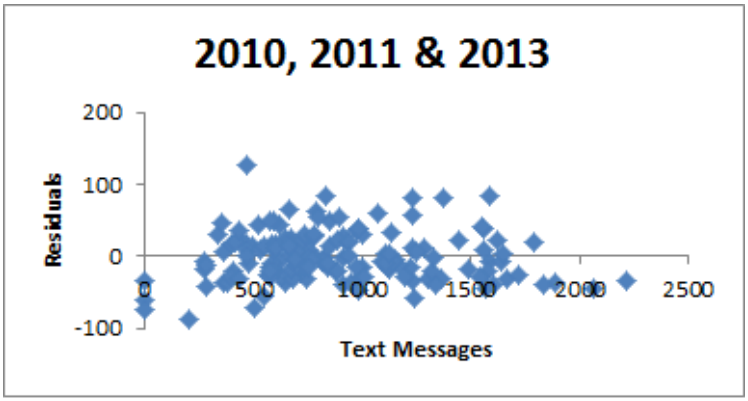

Figure 3.9: Residual plot for the data from the years 2010, 2011 and 2013 to show the validity of the regression model

The fact that 2013 showed stronger effects of campaigns compared to the other years is only partially explained by the weeks that had zero text messages sent out because when those weeks were removed from the data set the correlation was still stronger than in previous years and the β_0 value lower.

3.2.2 Multiple Linear Regression Analysis

The multiple linear regression analysis was done in MATLAB. Before starting on the multiple linear regression analysis the dependency between the dependent variable, in this case the number of blood donors, and the independent variables were reviewed separately. Dependency between the number of blood donors and the number of campaigns held out was shown in section 3.2.1. Strong dependency is obvious between the aggressive campaigns and the number of blood donations because when looking at the data the number of donations is significantly higher in those weeks Blóðbankinn advertised their needs in the media. Fig. 3.10 indicates seasonality for the number of blood donations by showing the moving average trendline. There seems to be quite a difference between the years when looking at the moving average for each year.

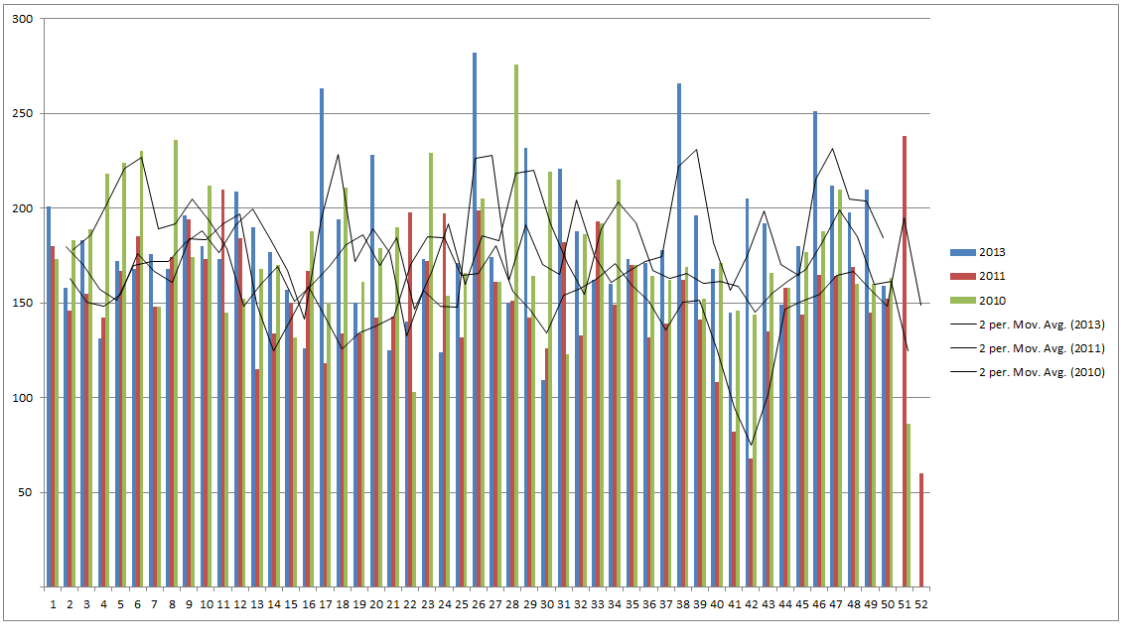

Figure 3.10: The number of donors each week from the years 2010, 2011 and 2013, the moving average lines show the seasonality fluctuations

After reaching the conclusion that each of the independent variables show dependency to the dependent variable separately the next step was to create the multiple regression

model. For that purpose the data matrices, including data from the years 2010, 2011 and 2013, were inserted into MATLAB.

By using the regression function in MATLAB the program gives the regressor coefficients or the β values along with the confidence intervals for the coefficients.

The multiple linear regression model can be seen in equation 3.1, where the β coefficients have been inserted into equation 2.2.

$$Y = 125.1398 + 0.0375 \cdot x_1 + 193.3291 \cdot x_2 + 27.7068 \cdot Q_1 + 11.2055 \cdot Q_2 + 8.1518 \cdot Q_3 + 0.4 \tag{3.1}$$

Results show that forecasted number of donors should not go below 125 in quarter four when no campaigns are held out. The model shows that the effects of aggressive campaigns by advertising the need in media has great effects on the number of donors but that should return 193 extra donations to that week. The model shows similar results as the simple linear regression model showed in regards to effects of campaigns but as previously mentioned this would most likely show stronger effects if the data had included more cases where there were no messages sent out.

A residual plot was made for the multiple linear regression model, see Fig. 3.11. It shows randomly distributed values around zero which shows that the model is valid.

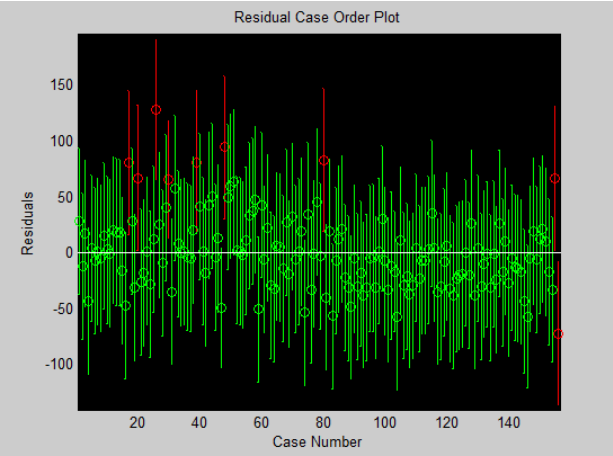

Figure 3.11: Residual plot for the data from the years 2010, 2011 and 2013 to show the validity of the multiple linear regression model

3.3 Simulation Results

This section lists the results from SIMUL8, both the results from the base model and from the scenarios designed. The 764 units that represent the RCC stock levels at the end of the year before the simulation starts skew the stock levels and the out-dating levels because they all enter the system at the same time and last for 42 days after start-up. It is clearly a simplification to assume that these units all have their full lifetime of 42 days left in the system but due to limitations of the simulation software they all entered at the same time. Using a warm up period would not change the fact that they all enter the system at the same time and therefore all expire at the same time.

3.3.1 Results from the Base Model

The base model was set up to replicate the today operations of the Icelandic Blood Bank. The donation levels were set by data retrieved from an Excel spreadsheet. For the simulated year of 2013, 11,667 units entered the system and none were lost. The 764 units that were added through the dummy start up, combined with the 11,667 units that were donated in 2013 make 12,431 blood units that flow through the system in that year. That number fits with the total number of units flowing through the system, that is the combined number of units in all queues. That total number of units in the system can be seen in Appendix B as the total number for the top row marked Checking, which is the working station in the model that checks the units before going to the centralised stock, and that corresponds with the number of completed jobs.

	Number Entered	Number Lost	Net Number Entered
Start Point 1	11667	0	11667

Figure 3.12: The number of units arriving through the start point

In Appendix B the results from 500 trial runs can be seen with a 95% confidence interval. The reason for the stability between the average results and the 95% range is that in the

base model there are almost no stochastic variables. That is, the today operations were modelled from historical data, not a derived distribution. Table 3.2 shows the stock levels for each week of the year 2013, in both the centralised stock at the IBB and results from the base model in SIMUL8. Note that the zero stock value in week one stems from the fact that even though there are 764 units at the start up, they arrive through a separate dummy start up and are not added directly to the centralised stock because of the global expiry label. Fig. 3.13 plots the stock levels shown in table 3.2. It is clear from the figure that the model does not capture the stock levels at the IBB adequately but it does follow fluctuations in the actual stock levels. The input data does not explain the large drop that happens around week 19. Neither the results from the model nor the actual data show shortage of blood. This base model can therefore be used for experimentation purposes and be set as a base for scenario testing in SIMUL8.

Table 3.2: Stock levels of RCC units at IBB and in base model

Week	Stock levels in 2013	Stock levels in Simul8
1	820	0
2	808	227
3	789	414
4	714	590
5	702	690
6	788	754
7	723	794
8	692	766
9	710	762
10	751	808
11	764	903
12	781	940
13	800	891
14	757	875
15	743	711
16	729	542
17	692	508
18	580	450
19	634	290
20	639	273
21	619	252
22	673	218
23	632	260
24	600	204
25	682	259
26	718	269
27	726	285
28	670	297
29	662	284
30	582	269
31	591	169
32	530	190
33	614	159
34	673	211
35	719	249
36	736	239
37	749	193
38	783	101
39	815	69
40	790	29
41	771	197
42	725	85
43	750	182
44	688	135
45	695	21
46	646	167
47	677	111
48	751	67
49	746	224
50	735	93
51	821	268
52	764	340

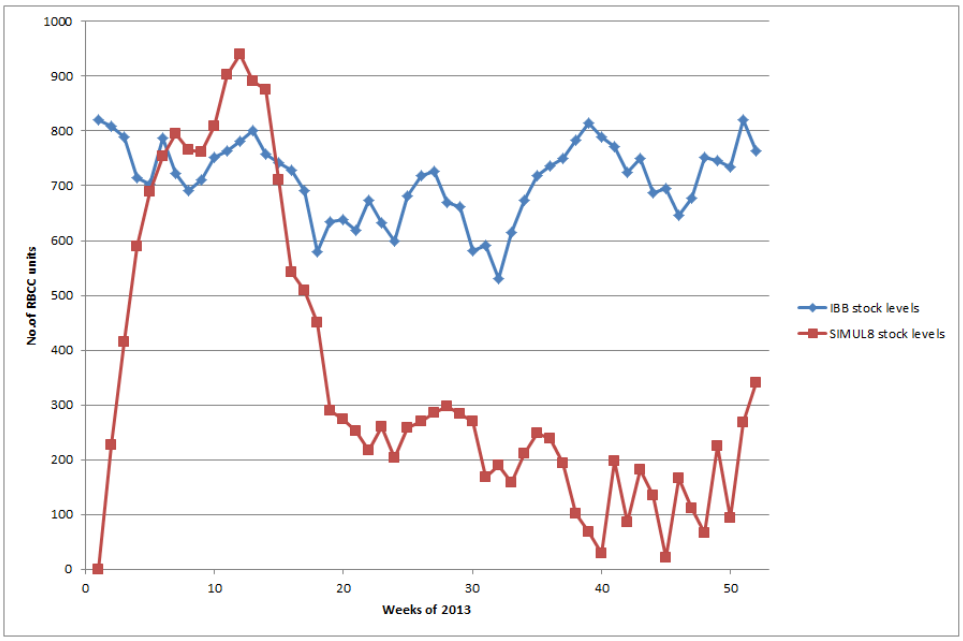

Figure 3.13: RCC stock levels plotted on a weekly basis in 2013, data was retrieved from SIMUL8 and IBB

The proportional number of expired units in the system is one of the main criteria for successful blood stock management. The model in SIMUL8 was set up to collect all expired units into one bin. In the base model, 1,809 RCC units are counted as expired for the year 2013. As can be seen in Appendix A the actual number of expired units in the year 2013 was counted as 602. That means that out of the 11,667 donated units 5,2% actually expired in 2013 at the IBB, whereas the model counts 15,5% of the units as outdated. It was to be expected that there would be some difference between the actual data and the data retrieved from the model because of inconsistencies in the dataset. The data for Akureyri had to be corrected and the data for the tenth depot were generated from an educated guess. Fig. 3.14 shows the cumulative number of expired units collected over the 53 weeks that the model runs for. SIMUL8 was set to run in minutes so that is the reason for the high numerical values on the x-axis. The figure shows almost a linear relation of expired units with time, meaning that the number of blood units that expires each week is similar.

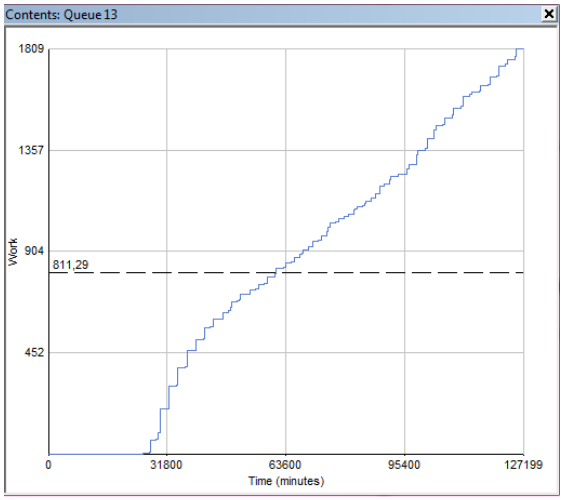

Figure 3.14: Cumulative number of expired RCC units in the year 2013, counted in minutes because the model runs in that unit

Fig. 3.15 and table 3.3 show the total number of transfused units at each depot for the year 2013. An explanation for the abbreviated names of the depots can be seen in the list of abbreviations. The combined number of transfused units from all depots is 10,438 from the base model in SIMUL8. The actual combined number of transfused units for the year 2013 is 10,616. The difference lies in number of units in the centralised stock queue. Even though the model is set to run for 54 weeks the results remain the same.

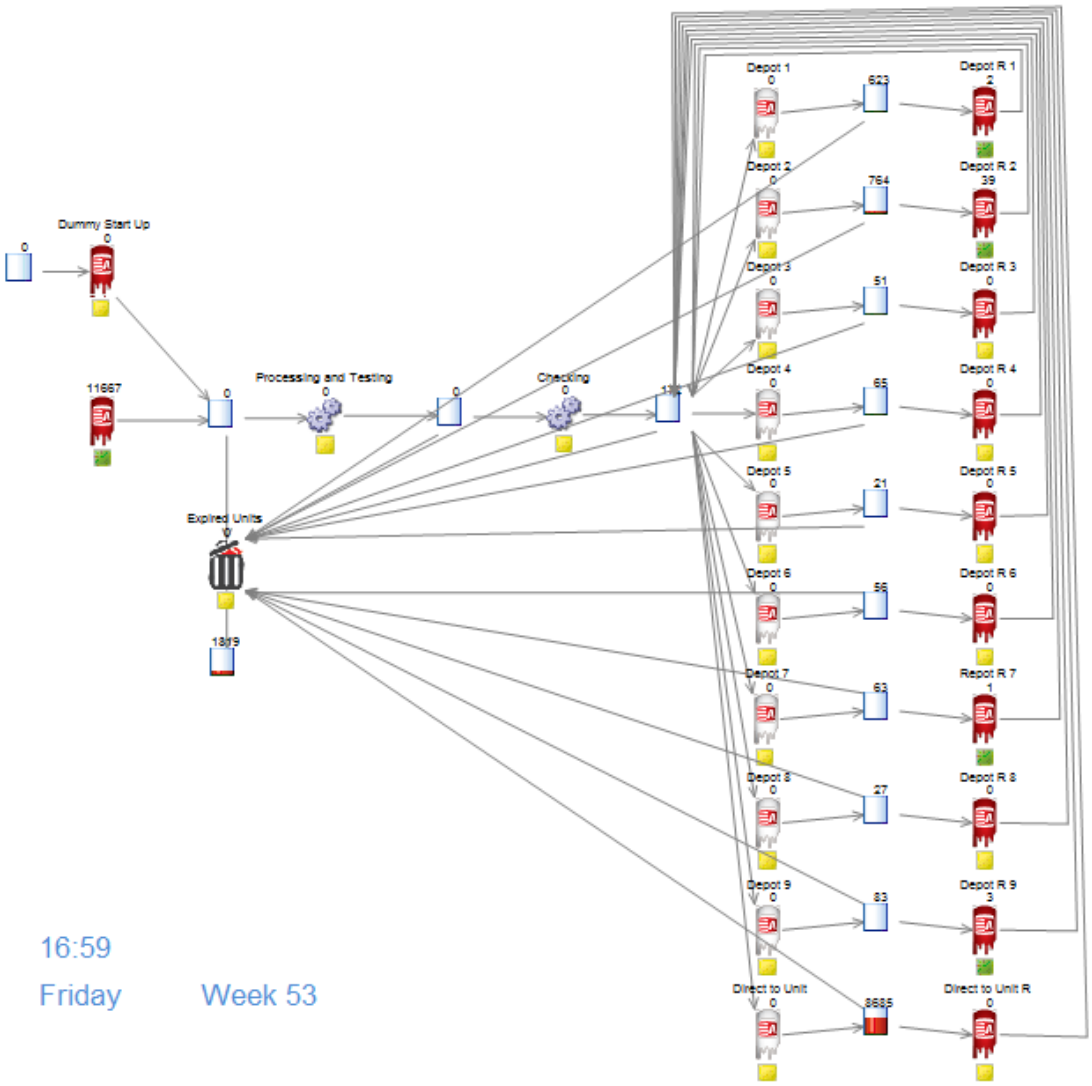

Figure 3.15: The Base Model after running through the model, total usage per depot shown at the top of the queues for each depot

Depot	No. of units
Akranes	623
Akureyri	764
Ísafjörður	51
Neskaupstaður	65
Sauðárkrókur	21
Vestmannaeyjar	56
ICU Hr.	63
Ob.& Gyn.	27
Research Dept. Fv.	83
Direct to unit	8,685
Total	10,438

Table 3.3: The number of used RCC units at each depot

3.3.2 Results from Experimental Models

Model 1

When the input data was decreased down to 90% of the number of donations for 2013 the stock levels from the base model clearly just shift slightly down, as can be seen in Fig. 3.16. Due to the fact that the model was not validated properly because of unreliable data it is difficult to interpret the results from the simulation model. However, looking at raw data (see Appendix A) it can be concluded that the donations could have been decreased in 2013 by the 10% that the model was supposed to test for. Even though the stock levels are significantly lower than real data implies, the stock levels never go down to a zero value. Week 30 has the lowest stock level with a value of three RCC units.

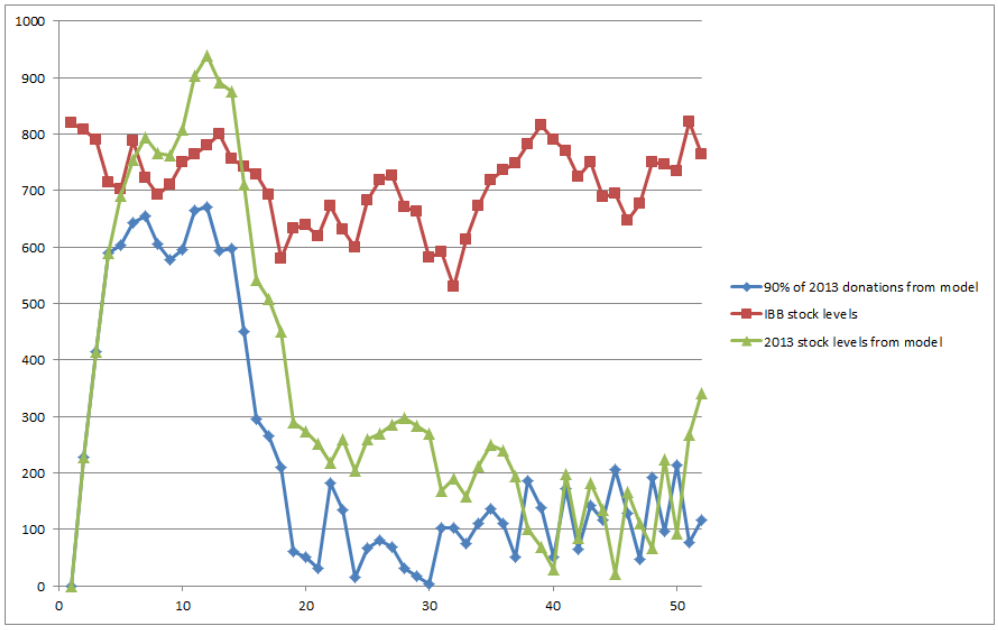

Figure 3.16: RCC stock levels at the IBB in 2013, from base model and from model 1

The model in SIMUL8 does take in the proper amount of donated units, all working stations are active and collect both demanded and transfused units. See Appendix for comparison of input and output data. No units were lost in the system. The number of RCC units sent to the depot named Direct to unit decreases from 8,685 in the base model to 7,856. Since those data were generated from an educated guess based on the data available it is impossible to say which number is closer to reality. Table 3.4 shows the number of transfused units at each depot. The number of expired RCC units goes down from 1,809 to 1,543 which is around 15% decrease. This shows that the decrease in expiration levels is not necessarily proportional to the decrease in the number of donations.

Depot	No. of units
Akranes	623
Akureyri	764
Ísafjörður	51
Neskaupstaður	65
Sauðárkrókur	21
Vestmannaeyjar	56
ICU Hr.	63
Ob.& Gyn.	27
Research Dept. Fv.	83
Direct to unit	7,856
Total	9,609

Table 3.4: The number of used RCC units at each depot

Model 2

For the second experimental model of the simulation, seasonality was used as a basis for the input data. Results from the multiple linear regression showed that there was significant difference between each quarter of the year. The average number of donations for each quarter was then calculated and these four averages used for each week of the corresponding quarter. In this model the number of expired units was decreased down to 1,002 units and the total number of transfused units counted as 10,192. All depots except for the generated Direct to unit depot, which was missing around 200 units, had the required number of transfused units. The simulation model again shows that it works as the proper amount of donated units enter the system and all working stations collect and transfuse units. Fig. 3.17 shows the stock levels that this model generated as well as the stock levels from the base model and from the real data from the IBB. Table 3.5 shows the number of transfused units at each depot.

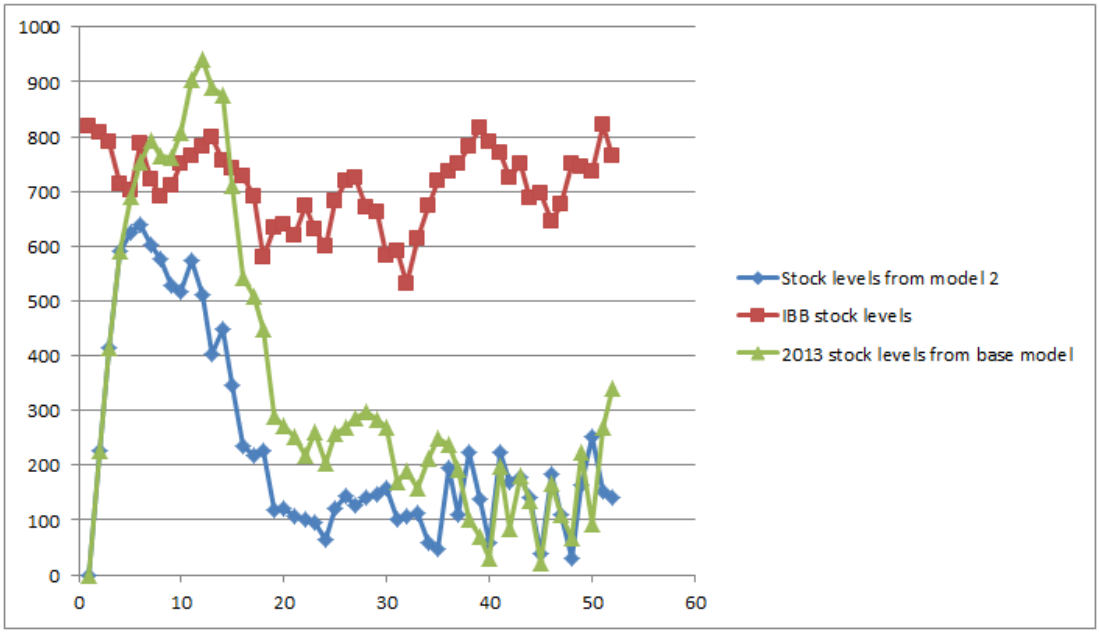

Figure 3.17: RCC stock levels at the IBB in 2013, from base model and from model 2

Depot	No. of units
Akranes	623
Akureyri	764
Ísafjörður	51
Neskaupstaður	65
Sauðárkrókur	21
Vestmannaeyjar	56
ICU Hr.	63
Ob.& Gyn.	27
Research Dept. Fv.	83
Direct to unit	8,439
Total	10,192

Table 3.5: The number of used RCC units at each depot

Model 3

The third experimental model was set up in every way almost the same as the base model. The exception was that each queue was set on LIFO policy instead of FIFO policy and the returned units from each depot were also set on reverse priority on the expiry label. This model returned 3,515 expired units and the total number of transfused units decreased

down to 8,808. All depots received their required number of units except for the generated Direct to unit depot. The simulation model took in the correct amount of input units and no units were lost in the system. All depots collected and transfused units and Table 3.6 shows the number of transfused units at each depot. Fig. 3.18 shows the stock levels for this model compared with the base model and the real data from the IBB.

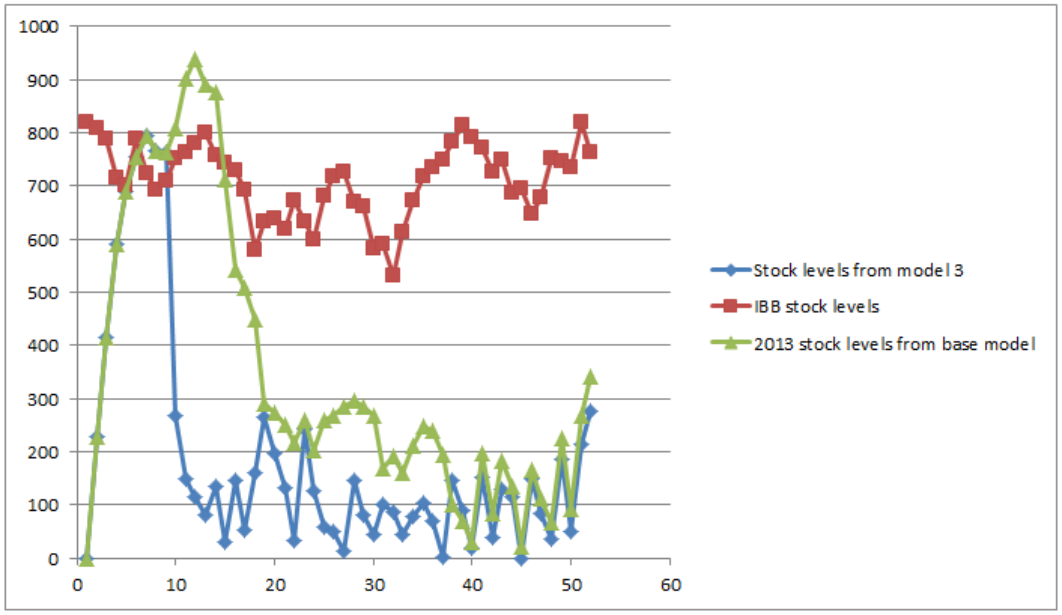

Figure 3.18: RCC stock levels at the IBB in 2013, from base model and from model 3

Depot	No. of units
Akranes	623
Akureyri	764
Ísafjörður	51
Neskaupstaður	65
Sauðárkrókur	21
Vestmannaeyjar	56
ICU Hr.	63
Ob.& Gyn.	27
Research Dept. Fv.	83
Direct to unit	7,055
Total	8,808

Table 3.6: The number of used RCC units at each depot

Chapter 4

Discussion

The importance of successful blood stock management is clear. Shortage of blood has severe consequences and in worst cases it can lead to casualties. Even though the monetary value connected to each unit of blood is difficult to calculate it is known that the costs behind each wasted unit are high. Additionally, it can be argued that it is ethically wrong to allow for excessive amounts of blood units to go to waste as people have donated their blood and time. The goal is therefore to limit both shortages and wastage caused by outdating. These are clearly contradicting goals and so it is a delicate and judicious balance. Benchmark stock levels should therefore be evaluated and estimated carefully. A study such as this one shows the importance of a proper data collection system. The optimal thing would have been to have those data spanning several years. With a longer time span the simulation and regression models get a better grasp of seasonal and monthly trends as well as an added likelihood of extreme events. During the middle of summer time and during other vacation periods the demand for blood units is significantly lower because most blood units are used for surgeries. During those vacation periods surgeries are usually not done except in emergency situations. Provisional conclusions could therefore be drawn on varying benchmark stock levels without simulation analysis but it is too risky without proper analysis. It should however be mentioned, that blood donors are more difficult to reach during summer time and thus the control over the supply less.

It may prove difficult to completely conclude the effects campaigns have on donations due to high frequency of campaigns. Messages are sent out almost every working day so there are only a few instances that show days where no campaigns were held out. Another factor is that the long term affects are not known for the messages sent out to donors. A message sent out does not necessarily mean an instant show up by the donor, it might have a delayed factor. The strong effect of aggressive campaigns in media would most

likely not be so strong if IBB was more often in the news and similar can be said about text messages, they might be more effective if they were less frequent.

It would be interesting to see if control over the supply would increase if the IBB would send out fewer messages but instead increase the positive publicity and educational information regarding the importance of blood donations. The IBB has a function on their web-page where users can follow the in-stock status of each blood type by looking at a drop of blood. It is a drop that graphically shows the status of each blood type by presenting how full the drop is each time. By raising awareness on their Facebook page they could get donors more involved by following the drop status on their web-page. They hope that after some time they could get people to schedule their donations to have a more foreseeable supply. This is a process that has already started as some donors now schedule their appointments but as can be seen in Oslo the supply there is still rather stochastic as only 59% of scheduled donors arrive on average and the day-to-day variations are large [42]. The regression analysis focused only on blood supply. Results from multiple linear regression show that it may be interesting to vary benchmark and emergency stock levels for different months of the year due to seasonal and regional trends.

Differing results between the years that were analysed in the multiple regression analysis indicate that some changes have been made between the years 2011 and 2013. In the fall of 2012 Jórunn Ósk Frímannsdóttir took over as the new department manager for blood collection and in early 2013 the IBB started a new campaign with emphasis on good publicity and educating people on the importance of blood donations. Their blood collecting vehicle was painted and renovated and the IBB celebrated their 60th birthday which was used as an opportunity to educate people about blood donations. This new marketing strategy the IBB implemented seems to have worked since in 2013 all indications point to the effect of campaigns being more effective than they were in previous years.

A study such as this one is not a small scale project and in order to do it properly, vast amount of data and information need to be analysed and the system understood before the modelling can begin. This is therefore a tool to increase understanding and induce critical thinking rather than something used for daily trial and error testing. Using simulation software is a good way to increase understanding of a system and its problems and possible improvements. It allows for a unique overview of situations where it can be difficult to see the forest for the trees. The staff at the IBB are very open towards constant improvements of their systems. What would be interesting to see after the strike affecting the IBB is over, is if the data for the simulation model is available to be able to properly use the generated simulation model. If the data is not available it allows for an improvement in their documentation systems.

Chapter 5

Conclusions and Discussions

The objective of this study was to eradicate guess work connected with the blood bank inventory mangement of the IBB and see if it would be possible to meet demand with reduced stock levels. Additionally, it was speculated if a smaller stock would engender in younger units of transfused blood units. By conducting a risk analysis and using regression methods to analyse the supply the operations of the IBB were reviewed. Results from the risk analysis show that the IBB is sensitive towards shortage, whether it stems from unexpectedly high demand or unusually low supply. Regression analysis revealed that using information about seasonality in the data could improve the blood inventory management of the IBB.

A simulation model was developed with input from the regression- and risk analysis results. The model itself worked properly, however the data was unreliable. When the data for the Akureyri depot for example was scrutinised it turned out that more units were going out that arriving in, which in fact is impossible. Akureyri are the only depot that uses ProSang, the data system of the IBB, and that should give them an advantage when it comes to data collection but something was wrong there. Due to a strike at the IBB, there was unfortunately nobody to correct those data. For the model to work at all, the data was therefore altered in a way that more units were going in than out of the Akureyri depot. Removing Akureyri from the dataset was not an option because it would skew the results for the number of expired units severely because Akureyri is the largest depot and in comparison the other depots are so small that the model would be redundant without Akureyri. Out of the 11,667 units that were donated in 2013, only a small amount was accounted for in the available data. What was done to fix that was that a tenth depot was generated in consultation with Sveinn Guðmundsson, the head physician at the IBB. With out the proper data it is however impossible to say whether that simplification is justifi-

able. Even though the difference between the base model and reality was significant the model is functional and gave the opportunity for some testing. The stock levels derived from the model do not give a realistic idea but altering settings or input data does show that there is a possibility for improvement. It is clear that the known difference in work load between seasons can be used to the IBB's advantage. Most blood units are used for planned ahead surgeries and the blood usage can therefore be roughly estimated and thus the supply controlled in order to minimise shortage and wastage. The stock levels were, except for only a few instances during summer time, well above benchmark levels. The stock levels could therefore not only reduced but the benchmark stock levels and emergency levels could possibly be redefined. Changing from FIFO policy to LIFO increases wastage significantly but if the IBB decides to place higher emphasis on younger transfused units an interesting way would be to use FIFO on all units except for returned units that would have LIFO.

5.1 Future Work

Even though simulation models never give 100% certainty that the experimental changes will work the same in the actual system, validity and verification are crucial factors in trusting the model. Due to unreliable data it was not possible to validate the base model. A long strike, that the staff off the IBB participated in, made it impossible to conclude whether those data exist or not. If not, the proper data should be collected so that they can be used as an input in the model. The model itself is finalised and only needs proper data for the flow to work correctly. It would also be interesting to update the model if changes occur in the system in the future as well as gather more data in following years to improve the model. Additionally, categorisation into blood types could be added to explore the difference in out-dating rates for rare blood types versus the more common ones. The simplification of assuming the same statistics for all blood types might somewhat skew the results. The model could therefore be improved with reliable data and further scenario testing continued. A scenario that could be tested would be to change the age of units that are re-sent to the centralised stock. The strike at the IBB is also an example of an interesting scenario that could be added both to the risk analysis matrix and to the simulation model. Another option would be to do a further statistical analysis on the supply using Time Series Analysis and inspecting the differences between not only the four quarters but between months or even weekdays.

Adding a LIFO policy only on the returned units is unfortunately not possible to add to this simulation model. If the IBB decide later on to place higher emphasis on fresher units

of transfused blood they could try using FIFO for transfused units and LIFO for returned units. This policy has been proven to result in younger units being transfused to patients. For this combined policy to work a sufficiency of blood units is required as this might lead to a higher level of outdated units. The IBB was in most cases with stock levels well above benchmark levels so this is a policy that they should be able to successfully implement.

Each year, over 4000 units of blood travel unnecessarily between the IBB and the depots. The stock kept at the hospitals is not showing good results in terms of efficiency in blood usage. Even though there has been progress in recent years when it comes to using fewer units of blood there is still deficiency with regards to reservation of blood units and shipment of blood units. It seems as the demanded number in each shipment has not followed these improvements with time. Blood group and screening test (BAS test) is a test performed in a laboratory that identifies blood group antigens to ensure that the patient in need of a blood transfusion will receive a compatible blood unit. In other words, they cross-match the donated unit to the needs of the patient. If these tests are performed they create the opportunity for a short lead time of reserved blood units and thus reduce the stock levels at the hospitals. By reducing those stock levels the efficiency of the safety stock for other patients is increased, wastage is limited and it induces a supply flow of younger units. Those additional units that are sent back and forth create unneeded work for the employees of the IBB and entail shipment costs. Despite a comprehensive introduction on the subject, the hospitals are still quite far from making improvements. That most likely stems from the fact that it is not a big issue for the hospital to have excessive blood units sent back and forth through their stock, their main focus is on blood sufficiency. This is however, an important issue for the IBB as this is wastage and an opportunity for improvement. In 2008, they did introduce BAS tests and it resulted in improvements but the usage was only for a limited time and since then there have been no improvements. The IBB is now looking into making this a priority again and are constantly looking for ways of improvement. It should be mentioned that compared with other countries the IBB is doing well even though it is difficult to maintain control over a blood bank inventory with only one centralised stock that processes everything and a number of small depots that all require frequent shipments of fresh units. The positive demeanour of the staff at the IBB and their willingness to explore and improve likely plays a major role in that success.

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Appendix A

Sample data from the IBB

2013 Red Blood Cell Concentrates			
Week	Transfused	Resent	Disposed
2013-01	126	57	27
2013-02	196	81	26
2013-03	256	86	29
2013-04	226	58	25
2013-05	181	91	44
2013-06	194	100	1
2013-07	231	87	0
2013-08	240	112	15
2013-09	204	94	9
2013-10	163	94	6
2013-11	241	115	29
2013-12	239	110	8
2013-13	132	52	22
2013-14	241	141	5
2013-15	236	112	10
2013-16	247	90	6
2013-17	201	90	4
2013-18	284	111	14
2013-19	179	116	4
2013-20	205	134	7
2013-21	215	92	9
2013-22	194	150	2
2013-23	233	97	8
2013-24	209	92	5
2013-25	191	93	0
2013-26	231	81	4
2013-27	196	57	8
2013-28	170	74	6
2013-29	145	61	10
2013-30	222	70	15
2013-31	174	54	30
2013-32	150	45	25
2013-33	172	82	2
2013-34	160	58	0
2013-35	199	82	5
2013-36	211	81	3
2013-37	224	101	6
2013-38	204	100	0
2013-39	155	137	9

2013-40	239	94	9
2013-41	222	61	9
2013-42	181	87	10
2013-43	175	89	15
2013-44	239	90	20
2013-45	206	85	46
2013-46	236	89	9
2013-47	181	107	8
2013-48	195	94	6
2013-49	226	169	4
2013-50	244	110	9
2013-51	206	68	3
2013-52	148	88	12
Total	10616	4779	602

Units sent to depots in 2013									
Akranes	Akureyri	Isafjordur	Neskaups.	Saudarkr.	Vestm.	ICU	Ob.Gyn.	Fv.	Direct
35	24	0	0	0	2	3	1	3	115
17	46	6	0	0	8	0	0	5	195
23	86	0	0	4	6	3	3	4	213
44	28	4	0	0	2	3	2	1	200
21	86	0	0	0	0	1	0	3	161
15	54	0	0	4	3	2	0	2	214
19	44	0	0	0	0	0	5	6	244
24	60	4	0	0	0	4	2	0	258
32	42	0	0	0	0	2	0	1	221
23	79	0	0	4	5	0	0	11	135
28	90	4	0	8	2	0	4	12	208
23	36	8	0	0	6	4	0	4	268
8	29	0	0	0	0	2	0	2	143
33	54	0	0	0	5	0	5	9	276
27	56	4	2	4	0	10	2	10	233
10	68	0	0	0	2	2	2	0	253
31	42	0	0	0	2	2	6	0	208
8	70	4	0	4	0	0	0	1	308
28	24	8	0	0	2	5	2	8	218
31	42	4	4	0	3	1	0	11	243
10	37	0	4	4	0	3	4	0	245
35	31	0	0	4	0	2	0	3	269
11	30	0	4	0	3	4	2	3	273

26	60	0	0	0	4	0	6	1	204
26	31	4	8	4	4	0	0	1	206
2	42	6	6	0	4	4	1	0	247
13	28	8	4	0	0	4	2	5	189
34	46	0	2	0	0	0	1	1	160
7	37	6	8	4	4	4	1	0	135
28	41	10	4	4	3	2	2	6	192
6	35	0	0	0	6	0	1	8	172
7	24	0	0	4	0	0	0	8	152
19	48	0	2	0	3	4	1	8	169
11	38	6	8	0	0	0	0	4	151
19	32	0	0	0	8	2	3	3	216
33	24	0	4	4	3	0	0	1	227
31	49	0	2	0	4	4	1	3	231
27	41	6	4	0	0	2	4	2	223
31	26	0	4	0	0	2	2	1	226
26	32	0	0	4	5	2	0	15	249
1	57	0	4	0	4	0	2	0	215
26	30	6	4	0	0	6	2	6	188
44	30	0	0	0	0	0	0	0	200
44	34	0	0	6	3	0	0	17	225
33	47	0	0	0	0	6	4	2	199
26	40	6	8	0	0	6	0	6	233
41	29	0	0	0	0	0	2	2	214
16	42	0	4	4	0	2	4	9	228

52	48	4	0	0	3	3	6	4	275
18	26	6	4	0	0	1	8	3	288
12	56	2	8	4	0	0	0	4	188
16	42	0	0	0	0	5	0	11	162
1211	**2273**	**116**	**102**	**74**	**109**	**112**	**93**	**230**	**11065**

Units sent from depots in 2013									
Akranes	Akureyri	Isafjordur	Neskaups.	Saudarkr.	Vestm.	ICU	Ob.Gyn.	Fv.	Direct
6	17	0	0	0	0	3	1	3	27
8	28	3	0	0	4	0	0	3	35
15	43	0	0	4	6	3	3	3	9
28	14	4	0	0	1	3	2	0	6
12	43	0	0	0	0	1	0	3	32
6	32	0	0	4	2	2	0	2	52
14	22	0	0	0	0	0	5	6	40
8	30	4	0	0	0	3	1	0	66
25	22	0	0	0	0	2	0	0	45
12	45	0	0	0	0	0	0	6	31
14	52	0	0	4	1	0	4	6	34
21	21	4	0	0	3	4	0	4	53
7	16	0	0	0	0	2	0	2	25
15	32	0	0	0	4	0	4	5	81
17	32	4	2	4	0	9	1	7	36
10	42	0	0	0	0	1	2	0	35
16	21	0	0	0	2	1	2	0	48
5	42	0	0	4	0	0	0	1	59
22	13	4	0	0	2	5	2	6	62
15	25	4	0	0	2	0	0	2	86
3	23	0	0	2	0	0	4	0	60
22	17	0	0	2	0	2	0	3	104

4	19	0	4	0	1	4	0	3	62
17	43	0	0	0	4	0	4	0	24
15	21	0	0	4	2	0	0	1	50
0	38	4	3	0	2	4	1	0	29
11	22	4	2	0	0	4	2	5	7
21	35	0	0	0	0	0	1	1	16
3	28	0	4	0	3	4	1	0	18
15	39	5	0	4	0	2	2	3	0
6	25	0	0	0	3	0	1	3	16
0	21	0	0	4	0	0	0	6	14
14	35	0	0	0	0	4	1	6	22
0	32	5	3	0	0	0	0	3	15
16	18	0		0	4	2	3	2	37
33	23	0	4	4	0	0	0	1	16
16	42	0	0	0	2	4	1	3	33
12	26	4	2	0	0	2	4	2	48
15	21	0	4	0	0	2	2	1	92
24	23	0	0	4	3	2	0	15	23
1	42	0	2	0	2	0	2	0	12
25	20	6	0	0	0	6	2	6	22
4	29	0	0	0	0	0	0	0	56
7	32	0	0	5	1	0	0	9	36
4	44	0	0	0	0	6	4	2	25
9	9	6	0	0	0	5	0	1	59
6	26	0	0	0	0	0	0	1	74
0	35	0	3	4	0	2	2	5	43
4	45	2	0	0	3	3	2	4	106
3	18	6	4	0	0	1	4	1	73
4	34	0	4	4	0	0	0	2	20
2	39	0	0	0	0	5	0	3	39
592	1516	69	41	57	57	103	70	151	2113

Stock levels at weeks end		
Weeks	2013	2014
1	820	728
2	808	779
3	789	784
4	714	775
5	702	736
6	788	725
7	723	746
8	692	728
9	710	713
10	751	712
11	764	743
12	781	674
13	800	633
14	757	640
15	743	612
16	729	593
17	692	517
18	580	474
19	634	669
20	639	726
21	619	679
22	673	629
23	632	642
24	600	590
25	682	595
26	718	568
27	726	603
28	670	569
29	662	561
30	582	526
31	591	520
32	530	535
33	614	572
34	673	578
35	719	619
36	736	659
37	749	708
38	783	654
39	815	585
40	790	590
41	771	576

42	725	612
43	750	641
44	688	705
45	695	635
46	646	616
47	677	607
48	751	552
49	746	569
50	735	571
51	821	674
52	764	677

Total weekly blood donations		
Weeks	2013	2014
1	224	191
2	228	283
3	236	255
4	185	222
5	252	218
6	278	205
7	199	216
8	249	169
9	256	214
10	243	286
11	302	229
12	265	192
13	191	191
14	214	251
15	208	233
16	238	236
17	180	124
18	197	200
19	227	315
20	237	260
21	207	195
22	282	194
23	201	253
24	233	187
25	233	189
26	274	240
27	195	294
28	178	195

29	168	182
30	159	193
31	214	213
32	151	172
33	289	237
34	243	215
35	248	248
36	231	259
37	224	236
38	253	207
39	223	213
40	210	253
41	170	234
42	170	215
43	228	208
44	215	219
45	238	99
46	257	209
47	241	191
48	230	206
49	262	267
50	229	232
51	335	273
52	67	168
Total	11667	11386

Appendix B

Results from Results Manager in SIMUL8

Base Model Results retrieved from SIMUL8, based on data from the year 2013

	Queue for Checking	Minimum Queue Size	Average Queue Size	Maximum Queue Size	Minimum Queuing Time	Minimum (Non-zero) Queuing Time	Average Queuing Time	Average (Non-zero) Queuing Time	Maximum Queuing Time	Number of Non-zero Queuing Times	% Queued Less Than Time Limit	"Queued Less Than" Time	St Dev of Queuing Time	Current Contents	Items Entered
Central Stock	0	0	351,149	1078	0	0,028	2712,023	3529,92	19799,06	12325	24,511	10	5173,107	182	16224
Depot 1 Q	4	0	264,653	623	0	2400	26363,586	26453,564	64254,857	586	0,34	10	14950,032	623	1211
Depot 2 Q	7	0	474,998	764	0	2400	27928,429	28591,588	50400	1474	2,319	10	15363,147	764	2273
Depot 3 Q	1	0	29,49	51	4800	4800	31495,385	31495,385	55200	65	0	10	14924,858	51	116
Depot 4 Q	2	0	26,434	65	14400	14400	33016,216	33016,216	55200	37	0	10	14820,585	65	102
Depot 5 Q	0	0	14,774	21	7200	7200	26535,849	26535,849	45600	53	0	10	11388,238	21	74
Depot 6 Q	2	0	33,038	56	2001,447	2001,447	31562,756	31562,756	62400	53	0	10	16111,62	56	109
Depot 7 Q	2	0	32,047	63	6789,18	6789,18	37640,154	37640,154	72000	49	0	10	19536,123	63	112
Depot 8 Q	1	0	12,186	27	0	2400	17812,612	18086,853	33600	65	1,515	10	9085,438	27	93
Depot 9 Q	1	0	38,352	83	1969,807	1969,807	22770,581	22770,581	40800	147	0	10	12320,501	83	230
Queue 13	0	0	811,294	1809	0	0	0	0	0	0	0	10	0	1809	1809
Queue for Dummy Start Up	0	0	0	764	0	0	0	0	0	0	0	10	0	0	0
Depot 9 Q 2	4	0	4387,249	8685	0	2400	27857,98	28389,71	52800	1205	1,873	10	12685,332	8685	9913
Queue for Processing and Testing	0	0	58,016	888	0	109,081	592,462	973,677	4881,343	7564	39,152	10	847,172	0	12431

	Waiting %	Working %	Blocked %	Stopped %	Number Completed Jobs	Minimum Use	Average Use	Maximum Use	Current Contents	Change Over %	Off Shift %	Resource Starved %
Checking	0	0	0	0	12431	0	0	1	0	0	0	0
Depot 1	1,886	98,114	0	0	52	0	22,849	52	0	0	0	0
Depot 2	1,886	98,114	0	0	52	0	42,887	90	0	0	0	0
Depot 3	60,377	39,623	0	0	21	0	2,189	10	0	0	0	0
Depot 4	58,49	41,51	0	0	22	0	1,925	8	0	0	0	0
Depot 5	67,924	32,076	0	0	17	0	1,396	8	0	0	0	0
Depot 6	47,17	52,83	0	0	28	0	2,057	8	0	0	0	0
Depot 7	35,849	64,151	0	0	34	0	2,113	10	0	0	0	0
Depot 8	39,622	60,378	0	0	32	0	1,755	8	0	0	0	0
Depot 9	16,981	83,019	0	0	44	0	4,34	17	0	0	0	0
Depot R 1	9,434	90,566	0	0	47	0	11,17	33	2	0	0	0
Depot R 2	2,271	97,729	0	0	51	0	28,453	52	39	0	0	0
Depot R 3	69,811	30,189	0	0	16	0	1,302	6	0	0	0	0
Depot R 4	75,472	24,528	0	0	13	0	0,774	4	0	0	0	0
Depot R 5	71,698	28,302	0	0	15	0	1,075	5	0	0	0	0
Depot R 6	58,49	41,51	0	0	22	0	1,075	6	0	0	0	0
Repot R 7	0	100	0	0	52	0	1	1	1	0	0	0
Depot R 8	43,396	56,604	0	0	30	0	1,321	5	0	0	0	0
Depot R 9	22,642	77,358	0	0	40	0	2,849	15	3	0	0	0
Processing and Testing	0	0	0	0	12431	0	50,917	100	0	0	0	0
Expired Units	100	0	0	0	1809	0	0,002	1	0	0	0	0
Dummy Start Up	0	0	0	0	764	0	0,03	764	0	0	0	0
Direct to Unit	11,32	88,68	0	0	47	0	187,038	308	0	0	0	0
Direct to Unit R	45,283	54,717	0	0	29	0	23,245	104	0	0	0	0

		Low 95% Range	Average Result	High 95% Range
Expired Units	Waiting %	100.00	100.00	100.00
	Working %	0.00	0.00	0.00
	Blocked %	0.00	0.00	0.00
	Stopped %	0.00	0.00	0.00
	Number Completed Jobs	1753.10	1759.34	1765.58
	Minimum Use	0.00	0.00	0.00
	Average Use	0.00	0.00	0.00
	Maximum Use	1.00	1.00	1.00
	Current Contents	0.00	0.00	0.00
	Change Over %	0.00	0.00	0.00
	Off Shift %	0.00	0.00	0.00
	Resource Starved %	0.00	0.00	0.00
Processing and Testing	Waiting %	0.00	0.00	0.00
	Working %	0.00	0.00	0.00
	Blocked %	0.00	0.00	0.00
	Stopped %	0.00	0.00	0.00
	Number Completed Jobs	12431.00	12431.00	12431.00
	Minimum Use	0.00	0.00	0.00
	Average Use	50.91	50.91	50.92
	Maximum Use	100.00	100.00	100.00
	Current Contents	0.00	0.00	0.00
	Change Over %	0.00	0.00	0.00
	Off Shift %	0.00	0.00	0.00
	Resource Starved %	0.00	0.00	0.00
Start Point 1	Number Entered	11667.00	11667.00	11667.00
	Number Lost	0.00	0.00	0.00
	Net Number Entered	11667.00	11667.00	11667.00
Central Stock	Minimum Queue Size	0.00	0.00	0.00
	Average Queue Size	342.70	343.02	343.34
	Maximum Queue Size	1064.92	1065.66	1066.39
	Minimum Queuing Time	0.00	0.00	0.00
	Minimum (Non-zero) Queuing Time	0.04	0.04	0.05
	Average Queuing Time	2659.88	2661.48	2663.08
	Average (Non-zero) Queuing Time	3458.96	3461.18	3463.39
	Maximum Queuing Time	19796.24	19796.40	19796.57
	Number of Non-zero Queuing Time:	12369.73	12374.27	12378.81
	% Queued Less Than Time Limit	24.41	24.42	24.43
	"Queued Less Than" Time	10.00	10.00	10.00
	St Dev of Queuing Time	5100.81	5102.61	5104.41
	Current Contents	127.19	131.72	136.25
	Items Entered	16224.00	16224.00	16224.00

		Low 95% Range	Average Result	High 95% Range
Expired Units	Waiting %	100.00	100.00	100.00
	Working %	0.00	0.00	0.00
	Blocked %	0.00	0.00	0.00
	Stopped %	0.00	0.00	0.00
	Number Completed Jobs	1742.65	1762.70	1782.75
	Minimum Use	0.00	0.00	0.00
	Average Use	0.00	0.00	0.00
	Maximum Use	1.00	1.00	1.00
	Current Contents	0.00	0.00	0.00
	Change Over %	0.00	0.00	0.00
	Off Shift %	0.00	0.00	0.00
	Resource Starved %	0.00	0.00	0.00
Processing and Testing	Waiting %	0.00	0.00	0.00
	Working %	0.00	0.00	0.00
	Blocked %	0.00	0.00	0.00
	Stopped %	0.00	0.00	0.00
	Number Completed Jobs	12431.00	12431.00	12431.00
	Minimum Use	0.00	0.00	0.00
	Average Use	50.89	50.91	50.93
	Maximum Use	100.00	100.00	100.00
	Current Contents	0.00	0.00	0.00
	Change Over %	0.00	0.00	0.00
	Off Shift %	0.00	0.00	0.00
	Resource Starved %	0.00	0.00	0.00
Start Point 1	Number Entered	11667.00	11667.00	11667.00
	Number Lost	0.00	0.00	0.00
	Net Number Entered	11667.00	11667.00	11667.00
Central Stock	Minimum Queue Size	0.00	0.00	0.00
	Average Queue Size	343.06	344.01	344.97
	Maximum Queue Size	1062.96	1065.00	1067.04
	Minimum Queuing Time	0.00	0.00	0.00
	Minimum (Non-zero) Queuing Time	0.03	0.05	0.06
	Average Queuing Time	2661.52	2666.30	2671.07
	Average (Non-zero) Queuing Time	3461.48	3468.11	3474.74
	Maximum Queuing Time	19795.94	19796.49	19797.05
	Number of Non-zero Queuing Times	12351.14	12363.46	12375.78
	% Queued Less Than Time Limit	24.40	24.43	24.45
	"Queued Less Than" Time	10.00	10.00	10.00
	St Dev of Queuing Time	5103.09	5108.41	5113.73
	Current Contents	130.63	142.68	154.73
	Items Entered	16224.00	16224.00	16224.00

Experimental Model 1 Results retrieved from SIMUL8

	Queue for Checking	Minimum Queue Size	Average Queue Size	Maximum Queue Size	Minimum Queueing Time	Minimum (Non-zero) Queueing Time	Average Queueing Time	Average (Non-zero) Queueing Time	Maximum Queueing Time	Number of Non-zero Queueing Times	% Queued Less Than Time Limit	"Queued Less Than" Time	St Dev of Queueing Time	Current Contents	Items Entered
Central Stock	0	0	232	843	0	0,024	1936,537	2579,576	19794,158	11221	26,494	10	3871,498	113	15060
Depot 1 Q	4	264,426	623	0	2400	26363,586	26453,564	64254,857	586	0,34	10	14950,032	623	1211	
Depot 2 Q	7	474,309	764	0	2400	27928,429	28591,588	50400	1474	2,319	10	15363,147	764	2273	
Depot 3 Q	1	29,49	51	4800	4800	31495,385	31495,385	55200	65	0	10	14924,858	51	116	
Depot 4 Q	2	26,421	65	14400	14400	33016,216	33016,216	55200	37	0	10	14820,585	65	102	
Depot 5 Q	0	14,774	21	7200	7200	26535,849	26535,849	45600	53	0	10	11388,238	21	74	
Depot 6 Q	2	33,038	56	2001,447	2001,447	31562,756	31562,756	62400	53	0	10	16111,62	56	109	
Depot 7 Q	2	32,047	63	6789,18	6789,18	37640,154	37640,154	72000	49	0	10	19536,123	63	112	
Depot 8 Q	1	12,176	27	0	2400	17794,742	18068,508	33600	65	1,515	10	9067,046	27	93	
Depot 9 Q	1	38,352	83	1969,807	1969,807	22770,581	22770,581	40800	147	0	10	12320,501	83	230	
Queue for Processing and Testing	0	47,359	866	0	6,127	533,614	946,063	4760,298	6355	43,605	10	834,123	0	11267	
Queue 13	0	659,986	1543	0	0	0	0	0	0	0	10	0	1543	1543	
Queue for Dummy Start Up	0	0	764	0	0	0	0	0	0	0	10	0	0	0	
Depot 9 Q 2	4	4079,062	7856	0	2400	27857,98	28389,71	52800	1205	1,873	10	12685,332	7856	9084	

	Waiting %	Working %	Blocked %	Stopped %	Number Completed Jobs	Minimum Use	Average Use	Maximum Use	Current Contents	Change Over %	Off Shift %	Resource Starved %
Checking	0	0	0	0	11267	0	0	1	0	0	0	0
Depot 1	1,886	98,114	0	0	52	0	22,849	52	0	0	0	0
Depot 2	1,886	98,114	0	0	52	0	42,887	90	0	0	0	0
Depot 3	60,377	39,623	0	0	21	0	2,189	10	0	0	0	0
Depot 4	58,49	41,51	0	0	22	0	1,925	8	0	0	0	0
Depot 5	67,924	32,076	0	0	17	0	1,396	8	0	0	0	0
Depot 6	47,17	52,83	0	0	28	0	2,057	8	0	0	0	0
Depot 7	35,849	64,151	0	0	34	0	2,113	10	0	0	0	0
Depot 8	39,622	60,378	0	0	32	0	1,755	8	0	0	0	0
Depot 9	16,981	83,019	0	0	44	0	4,34	17	0	0	0	0
Depot R 1	9,434	90,566	0	0	47	0	11,17	33	2	0	0	0
Depot R 2	2,271	97,729	0	0	51	0	28,453	52	39	0	0	0
Depot R 3	69,811	30,189	0	0	16	0	1,302	6	0	0	0	0
Depot R 4	75,472	24,528	0	0	13	0	0,774	4	0	0	0	0
Depot R 5	71,698	28,302	0	0	15	0	1,075	5	0	0	0	0
Depot R 6	58,49	41,51	0	0	22	0	1,075	6	0	0	0	0
Repot R 7	0	100	0	0	52	0	1	1	1	0	0	0
Depot R 8	43,396	56,604	0	0	30	0	1,321	5	0	0	0	0
Depot R 9	22,642	77,358	0	0	40	0	2,849	15	3	0	0	0
Processing and Testing	0	0	0	0	11267	0	46,16	100	0	0	0	0
Expired Units	100	0	0	0	1543	0	0,002	1	0	0	0	0
Dummy Start Up	0	0	0	0	764	0	0,03	764	0	0	0	0
Direct to Unit	18,868	81,132	0	0	43	0	171,397	308	0	0	0	0
Direct to Unit R	45,283	54,717	0	0	29	0	23,245	104	0	0	0	0

	Number Entered	Number Lost	Net Number Entered
Start Point 1	10503	0	10503

Experimental Model 2 Results retrieved from SIMUL8

	Minimum Queue Size	Average Queue Size	Maximum Queue Size	Minimum Queuing Time	Minimum (Non-zero) Queuing Time	Average Queuing Time	Average (Non-zero) Queuing Time	Maximum Queuing Time	Number of Non-zero Queuing Times	% Queued Less Than Time Limit	"Queued Less Than" Time	St Dev of Queuing Time	Current Contents	Items Entered
Queue for Checking	0	0	1	0	0	0	0	0	0	100	10	0	0	11320
Central Stock	0	230,901	804	0	0,014	1925,42	2560,11	19796,091	11273	26,666	10	3980,588	124	15113
Depot 1 Q	4	264,653	623	0	2400	26363,586	26453,564	64254,857	586	0,34	10	14950,032	623	1211
Depot 2 Q	7	475,097	764	0	2400	27928,429	28591,588	50400	1474	2,319	10	15363,147	764	2273
Depot 3 Q	1	29,49	51	4800	4800	31495,385	31495,385	55200	65	0	10	14924,858	51	116
Depot 4 Q	2	26,434	65	14400	14400	33016,216	33016,216	55200	37	0	10	14820,585	65	102
Depot 5 Q	0	14,774	21	7200	7200	26535,849	26535,849	45600	53	0	10	11388,238	21	74
Depot 6 Q	2	33,038	56	2001,447	2001,447	31562,756	31562,756	62400	53	0	10	16111,62	56	109
Depot 7 Q	2	32,047	63	6789,18	6789,18	37640,154	37640,154	72000	49	0	10	19536,123	63	112
Depot 8 Q	1	12,186	27	0	2400	17812,612	18086,653	33600	65	1,515	10	9085,438	27	93
Depot 9 Q	1	38,352	83	1969,807	1969,807	22770,581	22770,581	40800	147	0	10	12320,501	83	230
Queue 13	0	445,478	1002	0	0	0	0	0	0	0	10	0	1002	1002
Queue for Dummy Start Up	0	0	764	0	0	0	0	0	0	0	10	0	0	0
Depot 9 Q 2	4	4288,405	8439	0	2400	27857,98	28389,71	52800	1205	1,873	10	12685,332	8439	9667
Queue for Processing and Testing	0	45,785	866	0	6,127	513,437	914,571	4760,298	6355	43,869	10	824,88	0	11320

	Waiting %	Working %	Blocked %	Stopped %	Number Completed Jobs	Minimum Use	Average Use	Maximum Use	Current Contents	Change Over %	Off Shift %	Resource Starved %
Checking	0	0	0	0	11320	0	0	1	0	0	0	0
Depot 1	1,886	98,114	0	0	52	0	22,849	52	0	0	0	0
Depot 2	1,886	98,114	0	0	52	0	42,887	90	0	0	0	0
Depot 3	60,377	39,623	0	0	21	0	2,189	10	0	0	0	0
Depot 4	58,49	41,51	0	0	22	0	1,925	8	0	0	0	0
Depot 5	67,924	32,076	0	0	17	0	1,396	8	0	0	0	0
Depot 6	47,17	52,83	0	0	28	0	2,057	8	0	0	0	0
Depot 7	35,849	64,151	0	0	34	0	2,113	10	0	0	0	0
Depot 8	39,622	60,378	0	0	32	0	1,755	8	0	0	0	0
Depot 9	16,981	83,019	0	0	44	0	4,34	17	0	0	0	0
Depot R 1	9,434	90,566	0	0	47	0	11,17	33	2	0	0	0
Depot R 2	2,271	97,729	0	0	51	0	28,453	52	39	0	0	0
Depot R 3	69,811	30,189	0	0	16	0	1,302	6	0	0	0	0
Depot R 4	75,472	24,528	0	0	13	0	0,774	4	0	0	0	0
Depot R 5	71,698	28,302	0	0	15	0	1,075	5	0	0	0	0
Depot R 6	58,49	41,51	0	0	22	0	1,075	6	0	0	0	0
Repot R 7	0	100	0	0	52	0	1	1	1	0	0	0
Depot R 8	43,396	56,604	0	0	30	0	1,321	5	0	0	0	0
Depot R 9	22,642	77,358	0	0	40	0	2,849	15	3	0	0	0
Processing and Testing	0	0	0	0	11320	0	46,375	100	0	0	0	0
Expired Units	100	0	0	0	1002	0	0,002	1	0	0	0	0
Dummy Start Up	0	0	0	0	764	0	0,03	764	0	0	0	0
Direct to Unit	13,207	86,793	0	0	46	0	182,397	308	0	0	0	0
Direct to Unit R	45,283	54,717	0	0	29	0	23,245	104	0	0	0	0

	Number Entered	Number Lost	Net Number Entered
Start Point 1	10556	0	10556

Experimental Model 3 Results retrieved from SIMUL8

	Minimum Queue Size	Average Queue Size	Maximum Queue Size	Minimum Queuing Time	Minimum (Non-zero) Queuing Time	Average Queuing Time	Average (Non-zero) Queuing Time	Maximum Queuing Time	Number of Non-zero Queuing Times	% Queued Less Than Time Limit	"Queued Less Than" Time	St Dev of Queuing Time	Current Contents	Items Entered
Queue for Checking	0	0	1	0	0	0	0	0	0	100	10	0	0	12431
Central Stock	0	182,998	997	0	0,087	1407,181	1712,415	14871,141	13245	19,258	10	2634,753	106	16224
Depot 1 Q	4	264,514	623	0	2400	26359,299	26449,263	64244,485	586	0,34	10	14845,586	623	1211
Depot 2 Q	7	469,938	764	0	2400	27788,775	28448,617	49920,813	1474	2,319	10	15211,941	764	2273
Depot 3 Q	1	29,464	51	4800	4800	31443,919	31443,919	54781,846	65	0	10	14848,592	51	116
Depot 4 Q	2	26,434	65	14400	14400	33016,216	33016,216	55200	37	0	10	14820,585	65	102
Depot 5 Q	0	14,774	21	7200	7200	26535,849	26535,849	45600	53	0	10	11388,238	21	74
Depot 6 Q	2	33,038	56	2001,447	2001,447	31562,756	31562,756	62400	53	0	10	16111,62	56	109
Depot 7 Q	2	32,008	63	6789,18	6789,18	37640,154	37640,154	72000	49	0	10	19536,123	63	112
Depot 8 Q	1	12,186	27	0	2400	17812,612	18086,653	33600	65	1,515	10	9085,438	27	93
Depot 9 Q	1	38,229	83	1969,807	1969,807	22770,581	22770,581	40800	147	0	10	12320,501	83	230
Queue 13	0	1911,307	3515	0	0	0	0	0	0	0	10	0	3515	3515
Queue for Dummy Start Up	0	0	764	0	0	0	0	0	0	0	10	0	0	0
Depot 9 Q 2	4	3491,53	7055	0	2400	27857,98	28389,71	52800	1205	1,873	10	12685,332	7055	8283
Queue for Processing and Testing	0	58,016	888	0	5,165	592,462	973,677	8276,32	7564	39,192	10	1090,594	0	12431

	Waiting %	Working %	Blocked %	Stopped %	Number Completed Jobs	Minimum Use	Average Use	Maximum Use	Current Contents	Change Over %	Off Shift %	Resource Starved %
Checking	0	0	0	0	12431	0	0	1	0	0	0	0
Depot 1	1,886	98,114	0	0	52	0	22,849	52	0	0	0	0
Depot 2	1,886	98,114	0	0	52	0	42,887	90	0	0	0	0
Depot 3	60,377	39,623	0	0	21	0	2,189	10	0	0	0	0
Depot 4	58,49	41,51	0	0	22	0	1,925	8	0	0	0	0
Depot 5	67,924	32,076	0	0	17	0	1,396	8	0	0	0	0
Depot 6	47,17	52,83	0	0	28	0	2,057	8	0	0	0	0
Depot 7	35,849	64,151	0	0	34	0	2,113	10	0	0	0	0
Depot 8	39,622	60,378	0	0	32	0	1,755	8	0	0	0	0
Depot 9	16,981	83,019	0	0	44	0	4,34	17	0	0	0	0
Depot R 1	9,434	90,566	0	0	47	0	11,17	33	2	0	0	0
Depot R 2	2,271	97,729	0	0	51	0	28,453	52	39	0	0	0
Depot R 3	69,811	30,189	0	0	16	0	1,302	6	0	0	0	0
Depot R 4	75,472	24,528	0	0	13	0	0,774	4	0	0	0	0
Depot R 5	71,698	28,302	0	0	15	0	1,075	5	0	0	0	0
Depot R 6	58,49	41,51	0	0	22	0	1,075	6	0	0	0	0
Repot R 7	0	100	0	0	52	0	1	1	1	0	0	0
Depot R 8	43,396	56,604	0	0	30	0	1,321	5	0	0	0	0
Depot R 9	22,642	77,358	0	0	40	0	2,849	15	3	0	0	0
Processing and Testing	0	0	0	0	12431	0	50,917	100	0	0	0	0
Expired Units	100	0	0	0	3515	0	0,001	1	0	0	0	0
Dummy Start Up	0	0	0	0	764	0	0,03	764	0	0	0	0
Direct to Unit	24,528	75,472	0	0	40	0	156,284	276	0	0	0	0
Direct to Unit R	45,283	54,717	0	0	29	0	23,245	104	0	0	0	0

	Number Entered	Number Lost	Net Number Entered
Start Point 1	11667	0	11667

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