

**JUST IN TIME PROCUREMENT AND
INVENTORY MANAGEMENT FOR A
HOSPITAL**

JUST IN TIME PROCUREMENT AND INVENTORY MANAGEMENT FOR A HOSPITAL

By

MOSTAFA ABDI, B.Sc., M.Sc.

A Thesis

Submitted to the School of Graduate Studies

in Partial Fulfilment of the Requirements

for the Degree

Master of Science

McMaster University

© Copyright by Mostafa Abdi, August 2014

MASTER OF SCIENCE (2014)

DeGroote School of Business

eHealth Program

McMaster University

Hamilton, Ontario

TITLE: Just in Time Procurement and Inventory Management for a
Hospital

AUTHOR: Mostafa Abdi, B.SC (Yazd University), M.Sc. (McMaster
University)

SUPERVISOR: Dr. Elkafi Hassini

NUMBER OF PAGES: ix, 86

Table of Contents

Abstract	vi
Acknowledgments	vii
List of Figures	viii
List of Tables	ix
Chapter 1 Introduction	1
1.1 Motivations	1
1.2 Hospital Supply Chain Systems	4
Chapter 2 Literature Review	8
2.1 Optimization Models.....	8
2.2 Heuristic Models	14
Chapter 3 Current State Review	19
3.1 Background on Hospital	19
3.2 Logistics and Purchasing Current State	20
3.3 Logistics and Purchasing Performance Measurement	24
3.4 Logistics and Purchasing Practice Under Just in Time	29
Chapter 4 Model and Analysis	33
4.1 Dialysis Clinic – Pre-analysis	33

4.1.1 Demand Analysis	34
4.1.2 Ordering Cost	38
4.1.3 Transportation Cost	39
4.1.4 Grouping	39
4.1.5 Size Categories	39
4.1.6 Future Store Rooms	40
4.1.7 Safety Stock	41
4.2 Optimization Model	43
4.3 Optimization Results and Analysis	47
4.4 A Heuristic Solution Approach	54
4.5 Implementation and Testing	61
4.6 Further Implementation	65
Chapter 5 Conclusion and Future Work	67
5.1 Thesis Summary	67
5.2 Future Work	68
References	69
Appendix A	73
Appendix B	77

Appendix C82

Abstract

In this thesis we review a hospital supply chain management system and propose a purchasing optimization model to improve efficiency. We provide a background on the hospital being studied and evaluate current hospital practice by mapping out all the supply chain related processes and identifying appropriate key performance indicators (KPIs) to assess the current hospital operations. A mixed integer programming (MIP) model to optimize procurement and inventory management is then proposed. Utilizing CPLEX solver in GAMS, we obtain the exact solution to the problem using real data from the hospital. To overcome the complexity of implementing a MIP model in a hospital setting, we develop a heuristic algorithm and present numerical computations to test its performance. A visual basic application is developed in Excel to automate the steps of heuristic model and facilitate the implementation. Finally, the performance of the heuristic model is tested against the exact solution. We find that the heuristic solutions are on average 97% close to the exact solution.

Acknowledgement

I would like to acknowledge my supervisor Dr. Elkafi Hassini for all his aid, scientific support and inspiration during the course of my study over the last two years. Without his guidance as a great mentor, this work would not have been possible and I am always grateful for that.

I would also like to thank my supervisory committee, Dr. Norm Arhcer and Dr. Prakash Abad for their valuable comments and recommendations which helped to improve the quality of this thesis.

I would like to express my gratitude to Dr. Ann McKibbon the director of eHealth program for her kindness and continued support. I am very grateful to Iris Kehler at the eHealth office for her friendship during the last two years.

My friends and family have always been kind and supportive of my work and I can't thank them enough.

This work would not have been completed without the patience and support of my beautiful wife and very special friend, Shahrzad.

List of Figures

Figure 1-1: The share of supply chain practice in hospital annual expenses (based on data from Nachtmann and Pohl [14])

Figure 1-2: Conventional hospital supply chain network – Adopted from [16].

Figure 1-3: Modern hospital supply chain network

Figure 3-1: Inventory turnover for two sites

Figure 4-1: Curve fitting for patient's arrival

Figure 4-2: Excel data input interface.

Figure 4-3: Percentage of items ordered on each day.

Figure 4-4: Annual saving associate with decreasing service level.

Figure 4-5: Percentage of the storerooms' space that should be assigned to each group

Figure 4-6: Daily available space at the storeroom based on the schedule.

Figure 4-7: Flowchart of the heuristics

Appendix A- Figure 1: The map for the process of issuing items to the department through a requisition

Appendix A- Figure 2: The map for the process of dealing with backordered items

Appendix A- Figure 3: The map for the process of dealing with new item requests

Appendix A- Figure 4: The map for the process of ordering items

Appendix A- Figure 5: The map for the shipping and receiving process

Appendix A- Figure 6: The map for the process of dealing with returned items

List of Tables

Table 3-1: Percentage of stocked and non-stocked items purchased in one year period.

Table 3-2: Percentage of items under contract.

Table 3-3: Number of purchase orders in each month.

Table 3-4: Number of lines on each purchase order

Table 4-1: Size categories.

Table 4-2: Supply Equipment.

Table 4-3: Current and future practice storeroom comparison

Table 4-4: The exact solution of the Dialysis unit optimization problem

Table 4-5: Ordering schedule for the first 20 items

Table 4-6: Initial condition set-up

Table 4-7: Rules to generate random sample values

Table 4-8: Rules to generate random sample volume

Table 4-9: Comparison between the performances of exact solution vs. heuristic solution.

Table 4-10: Summary of performance results.

Table B-1: The list of all the items with their Package size, Volume category, Daily usage, Value and Safety Stock

Table B-2: The list of all the items with their optimal deliveries obtained by solving the optimization problem using GAMS.

Table B-3 Comparison between the performances of exact solution vs. heuristic solution for a two month time horizon.

Chapter 1

Introduction

1.1 Motivation

The term eHealth has gained growing popularity over the past two decades. There has been several attempts to understand what people generally imply when they use this term [1, 2]. Eysenbach defines eHealth as *“an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. ... [It] characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide....”*[1]. Oh et al. [2] suggest that eHealth mainly refers to the services and the systems in the healthcare industry rather than to the peoples’ health. They also discovered that in one quarter of the studies that they reviewed, improving the cost-effectiveness of health care in addition to making processes more efficient are some of the most expected outcomes of eHealth.

Although there are several important players in the healthcare sector, hospitals remain vital and play a central role as primary care providers in all around the globe. Different studies have shown that hospitals account for as much as 30 to 50 percent of the total healthcare budget in different countries [3, 4]. Although hospitals are responsible for such large budgets, they still do not necessarily operate as efficiently as other industries [5]. Landry and Beaulieu reported on a number of different factors that would result in such inefficiency in hospital supply chain systems. Difficulty of integration of internal and external supply chains, involvement of different staff with almost no supply chain training in the supply chain processes, diversity of the products and finally ignoring the purchasing

and logistic function of the hospital by senior management are some of the main reasons that a hospital may not always be able to deliver the best supply chain practice [6]. Some have estimated that a more efficient supply chain system could result in a potential saving as high as \$19 billion per year in the United State healthcare system [7].

It hence becomes evident that the unique role of hospitals combined with the notable effect that they have on the healthcare budget would drive eHealth professionals to make special efforts to improve the efficiency and productivity in hospitals. These efforts would lead to save money by improving the clinical and non-clinical practices as well as enhancing the quality of care which is the ultimate goal of any healthcare system.

The healthcare budget has always been a subject of discussions in Canada. In 2007 healthcare spending was around 10% of the Canadian GDP and is expected to be as high as 20% by 2050 [8]. Recent trends in demographic changes in Canada, such as the aging population (Canadian life expectancy has increased from 71 in 1960 to 80 in 2011 [9]), will drastically increase the costs of managing elderly and chronically ill patients. In addition the increasing rate of immigration (since 2001, Canada has hosted around 250,000 immigrants per year [10]) implies that the growth in the healthcare budget will be inevitable.

Given that the resources to cover healthcare costs are limited it is not surprising that hospitals are experiencing excessive expenditures and consequently facing deficits. To avoid a deficit, hospitals decision makers are forced to cut budgets accordingly. Quoting Dr. Robert Ting, president of the Scarborough Hospital's medical staff association, [11]: "These are going to be very, very hard cuts to the hospital but we have to do them to balance our books." Improving efficiency and productivity as well as optimizing the current healthcare operations can help hospitals maintain a quality patient care and prepare for more tight budgets in the future.

The use of new technology has been shown to improve different aspects of quality of care by improving communication, standardizing processes, and enhancing workflows

[12]. New technologies can also allow the providers to fully dedicate their time to patient care without being distracted by administrative activities.

The concept of a “digital hospital” that can utilize the most current technologies to enhance all aspects of quality care delivery by improving efficiency, accuracy, reliability and safety has been recently introduced in North America [13]. Digital hospitals are trying to properly integrate different clinical and non-clinical processes in a way that the right information and resources can be delivered to the point of care in a timely fashion [4].

Although hospitals are clinically focused environments and most of the spending occurs on the clinical side, their associated logistics and supply chain cost should not be underestimated [6]. A survey conducted by Nachtmann and Pohl [14] found that on average 31% of annual operating expenses in a hospital setting is used to support the supply chain cost with around 9% on inventory management, 10% on ordering management, 4% on shipping and receiving and 3% on transportation management (see Figure 1-1). Improvement in any of the above supply chain costs, especially inventory and ordering costs, can result in considerable operating costs savings.

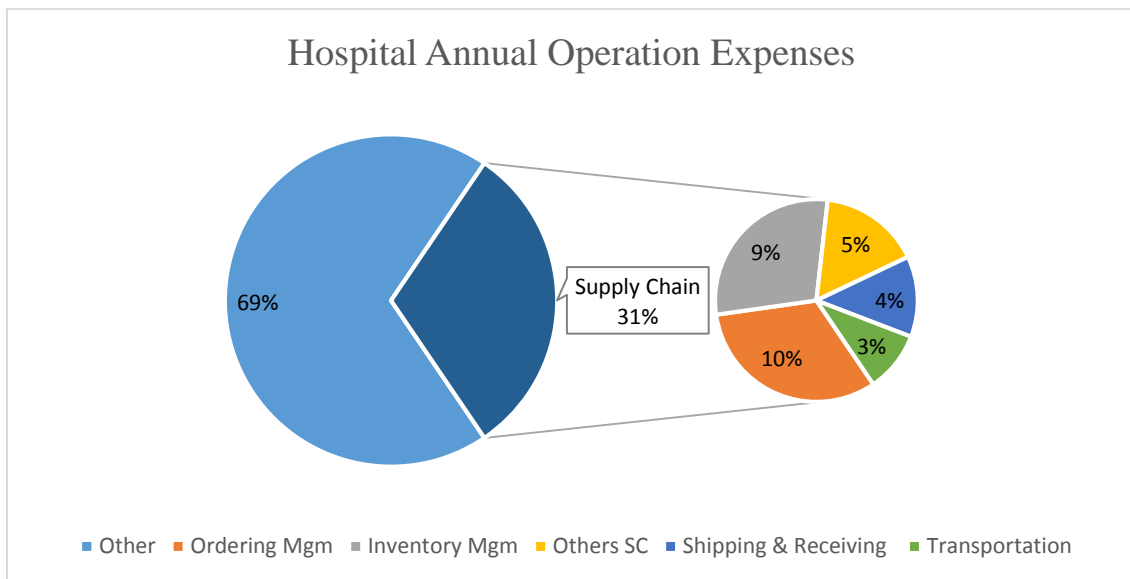


Figure 1-1 the share of supply chain practice in hospital annual expenses (based on data from Nachtmann and Pohl [14])

The aim of this study is to model procurement and inventory optimization in a modern digital hospital. The case study is a hospital in downtown Toronto. We will start by studying the current inventory and ordering management practices at the current old hospital facility using process mapping techniques. Afterwards, we apply mathematical modeling and optimization techniques to create a plan for procurement and inventory management in the new digital hospital facility.

This thesis will be presented in 5 chapters. In this chapter we review the hospital supply chain systems to better understand the health care environment. Chapter 2 will be devoted to reviewing relevant literature. In Chapter 3 we provide a background on the hospital being studied and evaluate current hospital practice by mapping out all the supply chain related processes. We then identify appropriate key performance indicators (KPIs) to assess the current hospital operations. After identifying the gaps in the literature in Chapter 2 and the needs for the new hospital in Chapter 3, we propose a mixed integer programming model to optimize procurement and inventory in Chapter 4. To solve the problem we develop a heuristic algorithm and present numerical computations to test its performance on a realistic problem data. Finally in Chapter 5 we summarize our work and suggest some future research directions.

1.2 Hospital Supply Chain systems

Hospitals supply chain systems have gone through several changes in the last two decades. For many years healthcare supply chain organizations have been trying to adopt different supply chain management (SCM) solutions but often face many hurdles. These include lack of executive support, conflicting incentives, extensive need for data collection and performance measurement, limited pool of skilled health care supply chain professionals and inconsistent relationship with supply chain partners [15]. Rivard-Royer et al. [16] reported on the attractiveness of the stockless replenishment systems in the 1980s which eventually lost its momentum by the 1990s due to the lack of incentives on the

distributors' side. The stockless idea was reintroduced again in the 2000s, after some adjustments.

By early 2000, healthcare supply chain organizations started to follow the path of SCM success stories in other industries. In some cases those attempts resulted in tremendous savings [17]. However, in general there is still a lot of potential for the healthcare supply chain to become as efficient as the retail supply chain. In 2007 the Ontario government published a report promoting e-supply chains and how they can transform a healthcare supply chain system to improve patient care, enhance service levels and at the same time reduce costs [18]. The report discussed how a traditional manual supply chain process should move towards an automated supply chain continuum. The automation activities that they proposed included the creation of an updated centralized catalogue with all the contract numbers, expiry date and item information that everyone can access through the hospital, creation and approval of the requisitions electronically, creation of purchase orders electronically, centralized receiving that can also cater for operation room supplies, streamlining the tasks of managing the hospital storerooms and inventories by the use of barcodes, handheld devices and in-house software, electronic payments, and finally extensive reporting by the use of business intelligence tools. Today most of the hospitals in Ontario have implemented many of the above automation steps but there still is a lot of room for improvement. Although the report extensively discusses the process and how they should be automated, it remained silent on the structural concepts of the envisioned modern healthcare supply chain system.

Figure 1-2 adopted from Rivard-Royer et al. [16] presents a conventional healthcare supply chain system. It contains two main components: external and internal chains. This structure has changed drastically during the past two decades [19]. Evolving the supply chain to optimize patient care operations has led the industry to take a more systemic approach that puts more emphasis on partnerships across suppliers and care providers in the supply chain network [20]. With regard to the external chain, group purchasing organizations (GPO) and shared service organizations (SSO) as well as third party logistics providers (3PL) have become the main players to leverage their purchasing power and

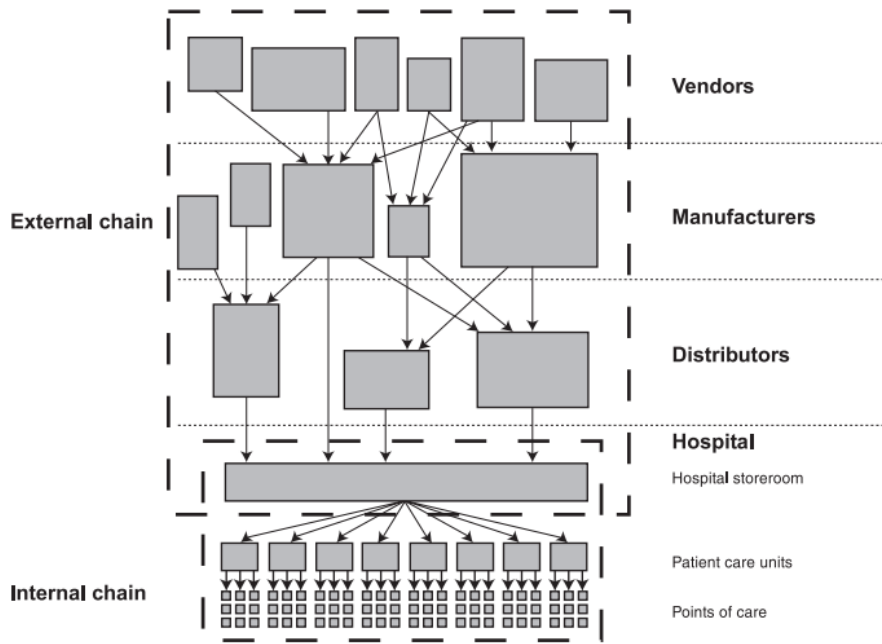


Figure 1-2 Conventional hospital supply chain network [16].

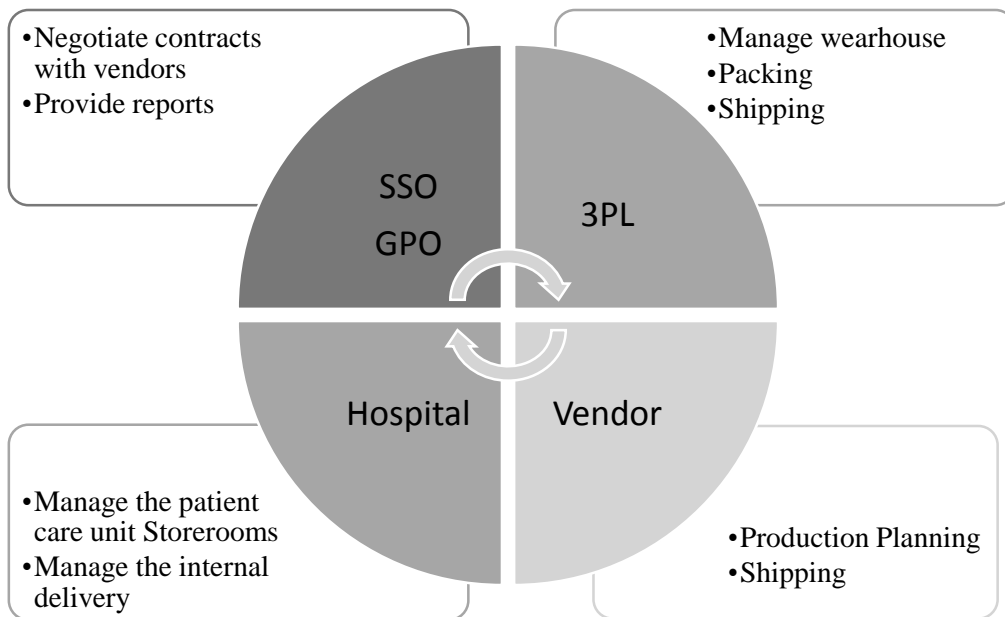


Figure 1-3 Modern hospital supply chain network

decrease the ordering cost. Although in many hospitals in Ontario the internal chain is still being managed conventionally, there is a trend towards stockless just-in-time systems

where the inventory is being owned and managed by distributors or vendors in order to decrease the hospital inventory holding cost.

Figure 1-3 adopted from an internal document in the hospital under study, represents a modern external supply chain network with more partnerships among different external partners. The main roles and responsibilities for each partner are stated on the diagram.

In the modern supply chain systems either SSO or 3PL will be responsible for holding the inventory. Therefore the hospital centralized store will be eliminated (or substantially reduced) and the supplies will be delivered to the patient care units directly from the delivery point. It then becomes vital for the hospital to be able to manage the inventory at the storerooms inside each patient care unit as well as managing the internal transportation of supplies, in a way that the mandated units service levels are met while the total cost of material management is kept in its optimal level. Neil reported on the opinion of some of the experts at the hospital CEO level and discussed the pros and cons of signing stockless or just-in-time (JIT) purchasing contracts for hospital settings [21]. The author believes that the main advantage of signing a JIT contract for a hospital will be reducing the inventory holding cost. Hospitals can also make better use of their space by reducing the storage and warehouse space commonly used to store supplies. JIT will help to increase efficiency and save costs by reducing the obsolete, stolen, spoiled, or damaged products. Therefore a modern hospital will be expected to have a JIT system in place and optimize its inventory to improve efficiency and reduce costs without negatively effecting the patients.

Chapter 2

Literature Review

In this chapter we will review some of the most relevant literature regarding the main aspects of this thesis. We will critically discuss the optimization models that have been proposed in the literature concerning multi-item inventory systems with capacity constraints. Although single-item inventory management systems have been studied rigorously, there are not many studies regarding multi-item systems. Therefore we will also review single-level single-resource multi-product capacitated lot sizing optimization models which can be interpreted as multi-item inventory management with capacity constraints. In each optimization model we will discuss the model's main assumptions and define its objective function and its constraints. In addition we will review some of the main heuristic methods used in the area of lot-sizing. Finally, we identify some gaps in the literature, with a focus on the hospital inventory management field, and describe the contributions of our thesis in that area.

2.1 Optimization Models

Karimi et al (2003), in their review of models and algorithms in capacitated lot sizing problems created a framework for all the optimization models in this field by classifying the methods in the literature. Before presenting our chronologically ordered literature review we refer to their work to provide a background for this area of research.

Karimi et al (2003) [22]

The authors reviewed and discussed different models and algorithms in the lot sizing literature. Their main focus was on single-level capacitated lot sizing which can also be translated into an inventory management system with capacity constraints.

The authors started the paper by reviewing the main characteristics of any lot sizing model such as planning horizon, number of levels, number of products, capacity or resource constraints, setup structure, deterioration of items, inventory shortage policies and finally the demand. Next they classified different lot sizing problems based on the type of demands and the capacity situation using the categories: single-level lot sizing without resource constraints (SLUR), single-level lot sizing with resource constraints (SLCR), multi-level lot sizing without resource constraints (MLUR) and multi-level lot sizing with resource constraints (MLCR). Their review then focused on a specific case of SLCR, the deterministic, single-level dynamic capacitated lot sizing problem (CLSP). After formulating the CLSP, they reviewed the related studies in detail and classified the proposed solution methods into three classes:

- 1- **Exact methods:** The goal of these methods is to improve the problem formulation by adding or modifying constraints. The authors concluded that due to the NP-hardness of the CLSP problem the current techniques may not always be able to reach to exact solutions.
- 2- **Common-sense or specialized heuristics:** In these methods, iterative item-by item strategies are used to generate solutions close to the exact solution. The authors classified these methods into two groups: period by period heuristics and improvement heuristics. Period by period heuristics start from the first period and move to the last one to produce the required products. In cases where there is any extra capacity in any of the periods, that period will be used to produce products for future and save on setup cost. On the other hand, the improvement heuristics start with an often infeasible initial solution that may be obtained by ignoring the capacity constraints and trying to improve the solution by imposing feasibility and

reducing costs. These heuristics have three major steps: (1) lot sizing step to convert the demand into production lot sizes, (2) feasibility routine to ensure that the demand is always satisfied and there is no backlogging (in this step if there is any period in which the demand exceeds the total capacity, either feedback or look-ahead mechanism should be employed to guarantee the feasibility of the solution) and (3) improvement step in which multiple rules and procedures may be used to refine and improve the current feasible solution. The main disadvantage of the improvement heuristic over the period by period method is, the time consuming computational steps which makes it harder to implement for larger problems.

- 3- **Mathematical programming-based heuristics:** The authors finally reviewed the mathematical programming-based heuristics which are known to be harder to implement but easier to adopt compared to other common-sense techniques. The main idea behind these heuristics is to try to find upper and lower bounds for the solution and get as close to the exact solution as possible. These heuristics are proven to be accurate and have the advantage of being able to utilize several commercial software packages that are available today. The programs are typically more flexible and it is more likely to be able to modify them to solve similar problems. However, sophisticated computational activities as well as the complexity of their concepts make them less likely to be implemented in real world situations.

Downs et al. (2001) [23]

Downs et al. [36], discussed an order-up-to level inventory model with multiple products, multiple resource constraints, lost sales and delivery lags. The demand distribution is assumed to be stationary. Unsold products are assumed to not lose their values and can be sold in future periods. The shortage and holding costs are assumed to be linear and the ordering cost is expected to be negligible. The latter assumption is important for the performance of the model since there will be no cost difference between placing

large or small orders. The main objective of the model is to minimize the average cost per period. They developed an approximate linear programming model and tested its performance against a special case for which they were able to find exact solutions.

Lapierre and Ruiz (2007). [24]

This paper is one of the few papers available on inventory management systems in hospital settings. Lapierre and Ruiz considered a two echelon conventional inventory system where the items are transferred to the patient care units from the central stores. They proposed a new supply chain oriented approach to modeling hospital inventory management by taking different aspects of supply chain activities into account. Two complementary models are introduced by the authors. In the first model the authors considered several factors such as demand (assumed to be constant), volume, weight and safety stock for each item. Capacity for different storerooms in each care unit and the total capacity of the central store location are also considered. Knowing the manpower capacity and operation time for different supply chain activities the model would minimize the inventory cost by solving the linear programming problem.. The second model is used to balance the schedule by considering the workload over the weekdays. Although solving their model does not generate a schedule for the staff, the authors have identified the daily percentage of total worktime for each group of activities such as purchasing, delivery and stock control, and used it to approximate the total number of FTEs required for each group of activities. They developed a Tabu search metaheuristic and used it to solve a problem of 43 “general purpose” products and 23 central units for a horizon of one month (20 working days) by considering three suppliers. They used the model to find the worktime distribution for different activities, compared it with current practice and provided recommendations.

Little and Coughlan (2008) [25]

In this paper Little and Coughlan [30] discussed the multi-item inventory system in a point of care location with capacity and service level constraints. They represented the problem as an unbounded knapsack problem containing different items with different values and weights with all the demands normally distributed. The authors then developed a model to take frequency, service level, order up to level and capacity to maximize the minimum service level. The proposed model would obtain the solution by the use of a combination of three search strategies: Choosing the items by highest importance, increasing size or increasing demand. The model was automated as a Visual Basic application within Excel and tested for a patient care unit location. The selected unit had 110 items, the space was limited to 13.7 m^3 and the lead time was assumed to be zero. They tested different scenarios to evaluate how changing the constraints on space, frequency and service level would result in different optimal policies. The authors also explored the effect of changing the objective functions and search strategies on the optimal inventory policy and provided recommendations. The authors emphasized the importance of change management for implementation of the recommended policies. In this thesis we address a similar problem. However, while they aim to reduce the service level, in our model the service level is fixed. In addition, in our work we compare our proposed solution to the exact solution while Little and Coughlan only compare approximate solutions.

Bijvank and Vis (2012) [26]

In this paper Bijvank and Vis [28] discussed hospital inventory management systems at the point of care location. Although the focus of the paper was on single-item inventory, multiple-item inventory was also discussed. The authors developed exact and heuristic inventory models to deal with service level and capacity constraints assuming some of the main hospital inventory characteristics such as lost sale, periodic review and short lead time. Their proposed exact algorithm can maximize the service level for a given capacity constraint.

The authors performed the analysis by assuming the hospital inventory system to be based on a bin system where each item i can be assigned to a bin with capacity C_i . Next, they defined a (R, s, Q) policy in which having s (reorder level) or less items in a bin signals the order. The signals will be reviewed periodically with period R and the order size is a fixed quantity represented by Q .

The models are created by decomposing the inventory system into several single item models and embedding those models to a multi-item system. They denoted TC to be the total system capacity and TC_i to be the total capacity reserved for item i . BC_i is the bin storage capacity for each item and C_i is the most number of units of item i that can be placed in each bin. Finally, a_i is the number of bin for each item hence $TC_i = a_i BC_i$. The demand-weighted average service level can then be defined by

$$\beta_{total} = \frac{\sum_i E[D^i] \beta_i}{\sum_i E[D^i]}$$

where $E[D^i]$ is the average demand for item i and β_i is the expected service level for item i . The authors then proposed a tradeoff approach between the service level for one item and the remaining capacity for the other items. Their algorithm would increase the service level for the items that have higher ratio of service level increment divided by extra capacity that is assigned to the item. The algorithm is claimed to reach the highest demand-weighted average service level. They also proposed a heuristic inventory model for a single-item (R, s, Q) inventory method that can be used for multi-item models. Their heuristic does not perform well when the capacity is tight and the item is slow moving.

2.2 Heuristic Models

In this section we discuss some of the heuristic models developed and discussed in the literature for capacitated lot sizing models in a chronological order. The methods in the following papers will be used to frame the heuristic model presented in chapter 4.

Dixon & Silver (1981) [27]

In this paper the authors presented a heuristics algorithm for a multi-item, single-level lot-sizing problem with capacity constraints. They assumed the time horizon is finite, the setup cost is fixed for each product, the production and holding cost are linear and the time to setup the machine is zero. The objective is to minimize the total cost while satisfying the capacity constraints with no backlogging. They proposed a heuristic solution that follows a simple principle where each lot-size will only satisfy the requirements of an integer number of periods. They let $AC_i(T_i)$ denote the average cost per unit time of a lot of item i which will satisfy the requirements for T_i period. That is,

$$AC_i(T_i) = (S_i + h_i \sum_{j=1}^{T_i} (j-1) d_{ij}) / T_i,$$

where S_i and h_i are the setup and unit holding cost of item i and d_{ij} is the demand of item i in period j . The heuristic would increase T_i until the first local minimum of the above equation is obtained. The time then would be reset and the same procedure would be followed until an uncapacitated feasible solution for the problem is achieved. Since the above procedure only works when there is no capacity constraints, they introduced a “greedy approach” by letting u_i be the marginal decrease in average costs per unit of absorbed capacity which can be obtained from:

$$u_i = (AC_i(T_i) - AC_i(T_i+1)) / (K_i d_{i,T_i+1}),$$

where K_i is the capacity absorption of item i . Since increasing the time supply of a lot of one item would result in decreasing the amount of capacity available for the production of other items, the heuristic would increase the time supply of the item with the greatest positive u_i . It can be seen that in each step the heuristic is trying to achieve the most benefit per used capacity. The process would stop when u_i becomes negative or there is not enough capacity to increase the time supplies. The authors also considered the scenario in which the demand for any specific period exceeds the capacity constraints for that period. Since the above procedure is not able to handle these kind of scenarios further steps are necessary to move some or all of the requirements of that period to a prior period when the capacity is not met yet. To resolve the issue one must ensure that the production of any item in any period for the periods ahead, must exceed the total amount where demand exceeds capacity in those periods. Mathematically the condition can be stated as,

$$\sum_{i=2}^t AP_j \geq \sum_{i=1}^n (CR_j - C_j) \forall t = 2, \dots$$

where CR_j is the total demand in period j and AP_j denotes the amount of production in period 1 that will be used in period j . This condition will have to be checked moving forward for all the periods.

The authors claimed that the above steps will always guarantee a feasible solution if one exists. The authors provided more steps to refine and improve the process and reduce cost. The heuristics were then tested with a variety of problem sets and shown to perform well. One important observation was that improving the solution may not always be worthy and the cost of spending time on more improvements may actually increase the total cost.

Maes and Wassenhove (1986a) [28]

In this paper the authors are tackling the same problem as Dixon and Silver (1981) which was known to be NP-hard and not have an exact solution. They aim to provide a much faster heuristic method which at the same time has a simple and flexible structure. The period by period approach was employed since the authors found it more intuitive for

further implementation. The main assumption is that the available capacity on each period exceeds the demand so the feasibility won't be a problem. The process works based on a series of strategies called East, South and South East in which demand for different products are being shifted from right to left and from bottom to top as long as they satisfy the following conditions: 1- If the demand does not exceed the capacity for that period. 2- If one of the pre-set criteria which are based on the results of previous studies to guarantee the favorability of the shift is still valid. These strategies ensure that production lot for a particular product/period is increased as much as possible before the procedure moves to the next product/period. In addition to the above strategies (C) and viability conditions (B) this heuristic is also relying on different sorting algorithms (A) to improve the solution. Any combination of ABC steps (six orderings A, four criteria B and three search strategies C) would result in different heuristics models (maximum 72) and consequently different solutions for the optimization problem.

The next step is to create a feasibility routine for the cases that capacity constraints are violated. The authors provided a two-step solution that should be carried out in a loop at the end of each period before moving to the next period if feasibility is not satisfied. Finally the heuristics models were tested against each other and their performances were evaluated by varying the time horizon. They concluded that some of the variants of their (A/B/C) model perform well most of the time and easily outperform some of the well-known heuristics algorithms such as Dixon and Silver.

Maes and Wassenhove (1986b) [29]

In this paper the authors selected three sample heuristics from the literature and compared them with a large set of test problems to analyze their performance by varying the problem parameters. The main reasons behind conducting this study are:

- 1- Most authors have used some restricted set of test problems which may or may not represent the overall quality of the model.

- 2- Most authors have not rigorously discussed the performance of their algorithm by varying different key parameters such as cost structure, demand and capacity.
- 3- The models were generally tested on small problems, which would allow the authors to compare their solutions to the exact solutions obtained by the help of mixed integer linear programming codes. This may not be a fair comparison since for small problems any single parameter can potentially have a larger effect on the final outcome.

The heuristics that were studied are from Lambrecht and Vanderveken [30], Dixon and Silver [27] and Dogramaci et al. [31]. The authors used the basic heuristics with a single improvement step to be able to compare them on a fair basis. The models were first tested for 15 sets of problems extracted from the literature. Although all the heuristic models performed well compared to the optimal solutions (i.e. as close as 99%) it should be noted that the sample sizes were as small as 3 to 8 items and 4 to 8 periods. For the sample of 20 items in 13 periods the Dogramaci algorithm was the most accurate with 95% accuracy. The authors also compared the models in terms of problem structure and concluded that the difference in performance between the models over a large set of problems is minor. They summarized the work by suggesting that

- 1- a good heuristic should have a look ahead mechanism to ensure feasibility at the initial periods
- 2- the greedy heuristics (i.e. Dogramaci et al) on average have better performance although at much larger CPU-time
- 3- the period-by-period heuristics perform better when capacities are tight and differences in capacity absorption across products are large.

Based on the conducted literature review we can conclude that there are not many studies on hospital inventory management systems. The current studies are either too complicated to be implemented in a hospital setting or they just do not give much information regarding the timing and quantity of the orders with respect to the service level agreement within each patient care unit. Given that most current hospital staff do not have

the knowledge to implement exact or metaheuristic algorithms which require extensive skills in programming and optimization, a common-sense or specialized heuristics with reasonable accuracy may offer the best solution to a hospital inventory management problem in terms of acceptance and implementation. We therefore aim to model the hospital inventory management system with a more practical approach by including the most important variables and avoiding the parameters that may increase the complexity with little value added to the objective value. For instance, although adding the parameters regarding the staff's workload can improve the accuracy of the model, without a rigorous study on the hospital staff's daily activities and the time that they spend on different tasks these parameters would not serve the purpose and would just add another layer of complexity. We will hence propose a heuristic model inspired by well-known heuristics models suggested in the literature for the capacitated lot-sizing problem and measure its performance by comparing it to the exact solution of a practical real hospital case.

Chapter 3

Current State Review

3.1 Background on Hospital

The hospital under study is located in the Greater Toronto Area and currently operates on multiple sites. This 550 bed hospital is being run by approximately 3000 staff and 600 physicians and provides different services to the surrounding neighborhood such as emergency care, ambulatory & diagnostic care, surgeries, dialysis, and acute care.

By the start of the 21st century and due to the population growth of the Toronto area, the hospital's senior management team started to believe that the current hospital is becoming overcrowded and outdated and consequently may not be able continue to provide the required quality care. Therefore a plan was developed to build a new hospital to not only provide appropriate services for the patients, but to also represent the era that we live in. The new hospital will be expected to use the most current technologies to enhance the quality of care and improve the patient and provider experience.

For the new hospital to open its doors, a smooth transition for different departments from the current sites to the new location will be a crucial step. One important aspect of this transition is to guarantee the maximum functionality of each department as a unit and all different departments as a whole. The Logistic and Purchasing department (LPD) is one of the main non-clinical departments that is responsible for providing supplies and services to all the units throughout the hospital in a timely and efficient manner with the help of 14 full-time staff.

The two primary functions addressed in this department include:

- Purchasing: This function will provide contracting and procurement services for stocked and non-stocked items (excluding pharmaceuticals), equipment, capital

projects and contracted services. The hospital under study is one of the Ontario's hospitals that have not yet outsourced their purchasing practice to COHPA (Central Ontario Healthcare Procurement Alliance) or any other shared service organizations.

- Receiving, Stores and Distribution: This function will provide all the receiving, storage and distribution of all medical, surgical supplies and other items, (e.g., disposable linen, office supplies etc.)

The inventory items in a hospital setting are categorized in three types [26]. Perishable items including medicines and blood, non-disposables (e.g. instruments) and disposable items such as gloves and needles. Perishable items are not within the scope of LPD and are handled by other departments such as the Pharmacy or Laboratory. Both disposable and non-disposable items will be part of the LPD scope. Another common categorization for the LPD items is based on the items frequency of delivery to the patient care units. The two main classes of items under this categorization are,

1. Stocked items: These items are being tracked routinely either continuously or periodically. Stocked items should be always available based on the service level that has been mandated by the unit's manager. LP departments usually use a par level or min-max policy (to be detailed in Section 3.2) to guarantee that there will not be any stockout in any patient care unit on the stocked items.
2. Non-Stocked items: These items are not tracked by the inventory control system and must be ordered manually if necessary. The non-stocked ordering starts with a requisition form that will be sent to the LP department electronically or manually. Non-Stocked items are not part of the routine ordering and should not be kept at the storerooms. The majority of the non-stocked items are one-time orders.

3.2 Logistics and Purchasing Current State

In a hospital setting the main task that is performed by the logistic staff consists of replenishment operations such as replenishing shelves at the patient care units or the central

storeroom [24]. The main activities that the LP department is responsible for can be categorized into six processes: issuing, ordering, shipping and receiving, backorder, new item request and return. We note that in some hospitals there are other activities such as linen or food delivery that may fall under the LPD scope.

Business process management analysis plays an important role in understanding of business processes by helping to recognize the sources of different gaps [32]. It can then be used to design new processes while avoiding the identified problems

To study the above mentioned processes, process mapping techniques were employed. A process map is a divisional flowchart which connects processes and illustrates the functional category of each process [33]. All the above processes were mapped in three steps. The first step was to draft the map based on shadowing and interviewing the staff to have a basic understanding of the practice. The second step was to use software to draw the map. For this purpose we used an open source process mapping software called Bonitasoft. The third step was to discuss the details with the experts and apply corrections, modifications and adjustments. The detailed maps for the hospital's LPD processes can be found in Appendix A.

Issuing: Issuing is the process of filling up the items at the storeroom for a specific unit. The process is called issuing since the items get issued to the unit's cost center. This process can start automatically via the routine scanning of the items at patient care storerooms by the LPD staff, utilizing a handheld device. Alternatively the process can start via an automatic or manual requisition send to the LPD supervisor for a non-stocked item signed by one of the staff inside the patient care unit. When the issuing is done by the LPD staff, the system will calculate the number of items that needs to be delivered to the unit based on the approved inventory level and a pick list is generated. The next step would be delivery of the items from the centralized storeroom to the unit. There are two common methods for generating a pick list in hospitals: min/max and PAR level. Landry and Beaulieu [34] provide a list of other methods that are used for inventory distribution in hospitals. The *min/max method* is also known as the (s,S) system or the reorder-level, order-up-to system

in the inventory literature. In such systems the inventory for each item is checked periodically (e.g., daily) and if it is less than the Min level then an order is placed to bring the quantity to the Max level. If the item's inventory level falls within Min and Max then the item will not be included in the pick list. The second method is the *PAR level method* where PAR stands for periodic automatic replenishment [35]. It is also sometimes referred to as the order point quantity. The PAR level is set for each item and a periodic review is used to keep the inventory level always close to the PAR level. Different hospitals may prefer either of the methods based on their policies. The main advantage of PAR level over the Min/Max system is that the inventory level can be kept above a certain minimum level. On the other hand the disadvantage would be that the system is prone to increasing the number of orders, which will increase the transportation and handling cost. In the hospital under study the issuing method for the stocked items is a Min/Max system. The minimum is based on the average weekly usage of the items during the past year and the maximum is commonly twice the minimum. The Min and Max may not follow this rule for all the items and may change based on the stores supervisor's experience. There are two main issues in the current Min/Max system:

- The system cannot capture seasonality. Although some of the items are used evenly throughout the year some other items may be used more frequently during the flu season or school months. Being able to capture the seasonality can help decrease the inventory cost by adjusting the Min and Max accordingly.
- The method to calculate the maximum is not efficient for all the items. For some items the Max value is too high which leads to higher holding cost and consequently more expired items. On the other hand for some items the Max value is too low which leads to frequent ordering. Ideally if the Min and Max system is selected to be used in a facility more sophisticated methods should be employed to calculate the thresholds. Porteus [36] provides a comprehensive review of approximate (s,S) policies.

Ordering: The process of generating purchase orders (PO) and sending them to the suppliers. The process usually starts by running a batch report on the items that have reached their minimum inventory level. The batch would then separate the items by vendors. We note that the non-stocked items should always be identified manually. The PO is then sent to the vendor before the specified deadline to make sure that the order will arrive on time. There are different ways of sending a PO to a vendor. In most cases the PO will be sent via an EDI (Electronic Data Interchange) system. If EDI is not set for a vendor the PO may be faxed or the order may be placed via a phone call. A PO is usually generated based on a requisition or when the item's inventory level decreases below a certain minimum. However, there are exceptional cases for which a PO may be generated periodically:

- Bulk Orders: These items are bulky and have frequent usage. Since there is not always enough room to keep enough inventory at the storerooms the POs for bulk orders will be generated based on average usage without going through the scanning process. For instance the bulky liquids used at the dialysis unit will be ordered periodically based on average usage. This can lead to shortages or excess inventory if for any reason the items do not follow their normal usage patterns.
- Outstanding Orders: re-ordering of the outstanding items will happen periodically unless the item has been obtained through other sources.
- Standard Orders: These items have constant guaranteed usage. Therefore the scanning process would not be necessary and the order would take place periodically to cover the usage.
- Recurring requisitions: These are some of the non-stocked items that are being ordered via requisitions periodically. These items can potentially become stocked items if the ordering periods are short.

Shipping and Receiving: Shipping is the process by which distributors ship the orders to the dock of the hospital. All the other activities by the LPD staff, from accepting the items

at the doc of the hospital to unpacking and delivering the items to the centralized storeroom is called receiving.

Backorder: This process starts by running a backorder report . The staff will then have to find a way to provide the items from different vendors or even, for a limited time, from other providers. If the backorder cannot be filled in a reasonable time then the staff will search for substitutes. If the substitute items receive the appropriate approvals from the patient care unit managers, LPD will send a hospital-wide notice to announce the replacement.

New item request: This process starts when one of the staff in a patient care unit makes a formal request for an item to be part of the stocked items. There are usually certain criteria under which the request may be accepted or rejected. If the item has multiple users with high volume or if the item is a STAT item (STAT refers to the items that are not typically kept at the store but on-hand quantity should be available for emergency) the request is usually accepted. The acceptance or rejection may depend on other conditions. For example, pandemics or CND (chemical, nuclear disasters) items may get accepted even though they would not satisfy the previously mentioned criteria.

Return: In this process one of the staff in a patient care unit makes a request to return one of the items for any reason. If the item is a stocked item, the item gets sent back to the centralized storeroom and will be placed on the shelves. If the item is a non-stock item it would get shipped back to the vendor by the LPD staff.

3.3 Logistics and Purchasing Performance Measurement

To evaluate the current practice we refer to a study done by the Broader Public Sector (BPS) Supply Chain Secretariat, an Ontario Government agency within the Treasury Board Office. This study was published in three parts from 2006 to 2009 [37, 38]. In their study, they suggested several key performance indicators (KPI) along with benchmarks for any

supply chain practice in the healthcare industry. From those suggested KPIs we have identified some metrics that we will study in this thesis. The main criteria for selecting these metrics is the ability to collect data from the different hospital departments so that we can perform reliable calculations. For some of the metrics the current data capturing practice will not be sufficient and the department may need to develop other methods to capture more data.

Before reviewing the KPIs it would be helpful to review Table 3-1 to have a better understanding of the scope of the work. This table shows the percentage of stocked and non-stocked items based on the total number of items purchased for a period of one year (July 2012 to June 2013). It can be seen that total number of items that have been purchased is around 12800. Although more than 87% of the purchased items are non-stocked items (which may have been purchased once or twice throughout the year), it should be noted that in terms of order quantity stocked items have a much bigger share of the total order quantities.

Total items purchased from July 2012-June 2013		
Groups	Number of items	Percentage
Stocked Items	1631	13%
Non-Stocked Items	11172	87%
Total	12803	100%

Table 3-1 Percentage of stocked and non-stocked items purchased in one year period.

The first performance indicator that we considered was the *percentage of active items under contracts*. Table 3-2 shows the results of this metric. Note that we assumed the active item to be any item that has been purchased during the one year period.

Type of items	Group	Number of items	Percentage	Goal
Stocked	Contract	1266	78%	100%
	No-Contract	365	22%	0%
Non-Stocked	Contract	3782	34%	<80%
	No-Contract	7390	66%	>20%

Table 3-2 Percentage of items under contract.

It can be seen that in terms of stocked items the organization is in a good standing although there is still room for improvement. There is no explanation for why the other 365 stocked items are not under contract yet. Looking at non-stocked items, we find that the percentage of under contract items is far below the threshold. Even though non-stocked items usually have highly variable usage, which makes them more difficult to put under contract, the percentage can still be improved.

According to the Ontario Government BPS performance measurement guideline [37, 38], the followings are the main advantages of having items under contracts:

- Ensuring the best price for each item that can be achieved by reducing the item cost through contract negotiations and also avoiding extra transaction costs for the non-contract items.
- Facilitating a faster ordering process and reducing errors by the help of accurate documentation for each item as well as improving the practice by reducing the activities required by supply chain staff on both hospital and vendor sides.

They also suggested the followings as the underlying leading practices that can help the organization to better manage the items that are under contract.

- Being able to estimate the demand for different items would help the managers to prioritize their tasks and develop contracts for the right items and services.
- Performing data analysis on spends would also help the organization to identify the items that would result in the most benefits from contracting.

The other important performance indicator is the *monthly inventory turnover*. The results of the inventory turnover for the two main hospital sites during a six month period are shown in Figure 3-1.

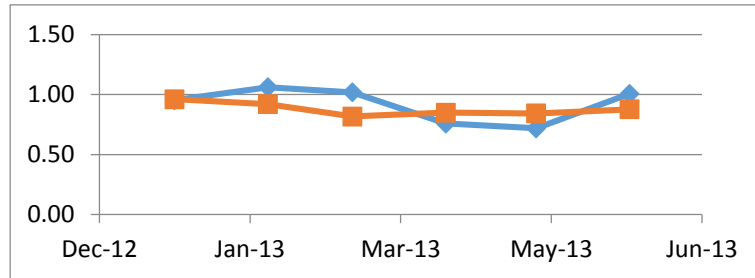


Figure 3-1 Inventory turnover for two sites

The turnovers have been calculated using the following formula:

$$\text{Turnover} = \frac{\text{Total inventory Issued}}{\text{Value of in-stock inventory}} * \frac{20 \text{ days}}{\text{Number of workdays in a month}}$$

Based on the hospitals guidelines [37, 38], the ideal turnover is around 1 ~ 1.25 for each month. It is clear from the figure that the current turnovers in average are below the ideal turnover rate and there is room for improvement. It is especially important to avoid the current pattern of inconsistency in performance. Monthly monitoring of inventory turnover enables the hospital to track and balance the cost of carrying inventory while ensuring the mandated service level for each patient care unit.

Having turnover rates above the target level results in higher ordering cost since every time a replenishment order is placed, fixed costs such as the cost of issuing the order and the cost of receiving the items would be inevitable. On the other hand having the turnover below the target would result in higher inventory holding cost. Not being able to properly manage the inventory turnover would result in either increasing the cost or even worst stock-outs. Stock-outs in a hospital setting will have several consequences. In worse cases they may risk patients' lives. They can also lead to the clinicians not trusting the supply chain management team and resorting to having multiple unofficial store rooms in patient care units.

The next performance indicator is the *number of purchase orders in a month*. Table 3-3 shows the result of this metric for a six month period.

Date	Number of Purchase Orders
Jan-13	562
Feb-13	523
Mar-13	613
Apr-13	565
May-13	547
Jun-13	560

Table 3-3 Number of purchase orders in each month.

Although the number of POs should not be seen as a standalone metric, with a target value attached to it, it can serve as an indicator that enables the organization to first compare itself with other similar organizations (for instance hospitals with the same number of beds) and also track improvement within the organization. Any supply chain process improvement within the organization, such as product standardization or order aggregation, can be reflected in the number of POs. Therefore the goal of the organization should be to reduce the number of POs in each month. The organization can also set an internal goal for itself and try to achieve it by improving the practice [37, 38].

Date	Number of Purchase Orders	Number of Lines	Average number of Lines on each PO
Jan-13	562	2040	3.63
Feb-13	523	2002	3.83
Mar-13	613	2156	3.52
Apr-13	565	1912	3.38
May-13	547	1819	3.33
Jun-13	560	1899	3.39

Table 3-4 number of lines on each purchase order

Among many other KPIs suggested in the hospitals' user guide [37, 38] the last metric that we were able to calculate was the *number of lines on each PO*. The suggested target level for this metric is to achieve more than 4 lines per PO. Table 3-4 presents the results of the metric for a period of 6 month.

Increasing the number of lines on each PO can help to improve several aspects of the supply chain system. It will help the organization by saving on ordering and receiving costs. It can also help the suppliers by reducing the number of POs that have to be processed. In addition, upfront planning and demand analysis can help the organization to increase the number of lines on each PO [37, 38].

3.4 Logistics and Purchasing Practice under JIT

One of the critical decisions to be made by the senior team of the hospital is whether or not they are going to replace their current supply chain system with a JIT (stockless) system. It is important to note that implementing a JIT system will not change all the above mentioned processes, but it will have a considerable impact on most of them. In this section we review some of those changes and comment on how those changes will improve the related supply chain practice.

At the beginning of this chapter we discussed stocked and non-stocked items as the two categories of the items in the current supply chain system. The first consequence of implementing a JIT system will be that the items will be divided into the following three categories:

Stockless or JIT items - These items will be delivered by the JIT provider. They will be scanned every other day and put away the day after for each patient care unit according to their demands.

Stocked items - Although the JIT system will shrink the centralized storeroom at the hospital it won't eliminate it completely. Some of the STAT items and also back up for some of the JIT items may still need to be kept at the centralized storeroom to avoid any

chance of stockout at the patient care unit.

Non-stocked items – There won't be any changes for the non-stocked items and they will be dealt with the same way as before.

The main goal of the JIT system is to have as many items as possible under the stockless category and improve the practice by efficiently managing those items. The stockless items will be scanned routinely. The quantity for each item to be ordered will be calculated by the policy in-place (e.g., PAR level or Min/Max). A single purchase order will be generated for all the stockless items. Then the PO will be sent to the JIT provider specifying the quantity of each item for each patient care unit. Packages will be prepared for each patient care storeroom at the JIT provider facility and will be shipped to the hospital the next day. Hospital receiving staff will check the purchase order against the received items and confirm the orders. Then the items will be delivered to the patient care storerooms by transportation carts. The transportation carts may get delivered to the storerooms by staff simply wheeling the carts to the unit or by the help of automated guided vehicles (AGV) commonly used in other industries.

Based on a number of conversations with the manager of logistic and purchasing department, the following can be mentioned as some of the key factors to successfully implement a JIT system.

- Change management is an important factor in implementing a JIT system [39, 40]. Hospital staff are used to having easy access to the central storeroom whenever they need. Even if they never need to go to the central storeroom, knowing that they always have access to the central storeroom gives them peace of mind. Implementing a JIT system will take this flexibility away from them to improve and optimize practices and save money. Hence it is expected that it will take some time and training before the staff and nurses get used to the new changes.
- Designing all the patient care units' storerooms will be crucial. Considering that most of the items cannot be found at the hospital's central storeroom, it becomes inevitable that nurses or other staff may need to borrow items from different units

in case of emergency. Therefore the standardization of storeroom layouts and grouping the products will help the staff to search and find items in different storerooms quickly.

- The same logic will apply to the design of the carts and shelves in each unit. Using appropriate carts and layout can also improve other aspects of hospital practice. For instance selecting the right type of shelves with enough distance from the ground can help infection control practices in an emergency situation.

Although the stockless items should be scanned routinely, in practice it may not happen every other day. In some hospitals the LPD staff will scan the item on Mondays and Wednesdays but for Fridays a dummy purchase order will be generated based on the information from the past two days. Reducing the number of scanning trips helps the department to save on labor cost. The use of new technology has also improved the scanning practice in some ways. In some storerooms the scanner is installed conveniently on the wall so that it is easy for staff to scan the picked item on their way out. In this way the scanning happens in real time and the POs will be generated more accurately. The main risks involved with these technology solutions are increasing the cost, lack of commitment from the staff and uncertainty of the responsibilities in case of shortage. Another way to decrease the number of scanning trips is to analyze the demands and orders based on the optimum order quantities. For this scenario the LPD department needs to make sure that the following can always be satisfied:

- Service levels mandated by the patient care units' managers. The importance of complying with service level in a hospital setting is apparent. Although not all the supplies may need to have high service levels, it is safe to say that most of the items need to be always available and if we plan to not scan the items very often, we need to make sure that we can always meet the demand.
- Capacity constraints. Although ordering based on the optimal order quantity will reduce the cost of the practice, the storage space is limited in each storeroom and hence any ordering method should take into account the storage capacity constraints.

In the next chapter we will select one of the patient care units and try to perform all the necessary analyses to be able to eliminate the frequent scanning process as well as finding the optimal ordering plan while maintaining appropriate service level and satisfying the capacity constraints. We will use real data and make a comparison between current practice and the future hospital plan in terms of number of patients, number of storerooms and number of shelves and carts.

Chapter 4

Model and Analysis

4.1 Dialysis Clinic – Pre-analysis

In this chapter we chose the dialysis clinic as a pilot to perform all the necessary analysis for sourcing and inventory. It should be noted that although the dialysis unit has many features that are common to other units in the hospital, there are still some aspects that are different. We will address practical implementation issues of our model to other departments later on.

The main reasons behind selecting the dialysis unit include:

- The dialysis clinic is known to have a steady demand with a small variance throughout the year and factors such as seasonality will not affect the demand and can be ignored.
- The dialysis unit consumes a variety of different supplies and can be a better representative of the hospital supply chain compared to the units that may just consume a few specific items.
- The size and volume of the supplies for the dialysis department may vary from very large to very small which makes it a better candidate to represent the whole hospital.
- Although in some departments supplies are being issued to each patient chart and demand analysis is more straightforward, it is not the case in the dialysis department and the patient demand is unknown. Handling this complexity in this pilot model will be helpful for other departments that have similar patient demand characteristics.

We start the analysis by discussing a number of important factors, such as demand and ordering cost estimation that are needed to develop the model. We focus on the stocked items which are planned to become stockless (JIT) items in the new facility.

4.1.1 Demand Analysis

The main barrier to accurately estimate demand for the supplies in the dialysis unit is that in current practice staff do not keep records of the supplies that are used for each patient. The only step at which the data are recorded is when the items are about to be delivered to the dialysis store room. At that point the store's staff should make sure to issue the items to the department's cost center in order to guarantee the accuracy of the invoices.

We started the analysis by looking at different Meditech (the Health Information Management software currently used in the hospital under study) reports to be able to capture the delivery of the supplies for a period of one year (August 2012 to August 2013). The report that we found to be most appropriate to use is the "delivery based on the units' cost centers" report. We ran the report for the period of study by restricting the cost center field to the cost centers that the dialysis department had used during that period. After some data cleaning we analyzed the data and came across some inconsistencies for some of the items. For instance there were items that had been used heavily for the first nine months but there was no sign of usage for the last three months. We discussed the issues with the department managers and realized that around May 2013 new dialysis equipment had been purchased by the hospital. Consequently, the unit had stopped ordering some of the old supplies and instead started ordering some new items that were used by the new equipment. To take those changes into account we looked at the three month period (Jun 2013 to Aug 2013) in which there were no significant changes.

After some more data cleaning activities we managed to generate a report for the period of June to August 2013 with the following information: Item number, item description, number of items in each package, the dollar value of each package, number of deliveries

for each month, the volume of delivery for each month and finally the number of packages delivered to the unit during the specified period.

Having seen some inconsistencies with the delivery of less frequently used items, we wanted to further investigate the reliability of our data. To this end we calculated the mean, standard deviation and coefficient of variation (CV) for each item. Assuming a distribution with a CV of less than 1 to be considered low-variance and those with a CV higher than 1 to be considered high variance, we realized that around 90% of the items are low variance, hence reliable. We then generated a one year period report for the items with high variances and calculated the CV for one year. If the new CV was less than 1, we divided the new usage by 4 (to estimate a three month period usage) and updated our table with the new value. If the CV was still high we eliminated those items from our calculation assuming that the items with such a high variance should not be part of the stockless items. The items that were eliminated from this list can be considered as stocked items (being kept at the central storeroom) or non-stocked items (being ordered when needed).

Subsequently, we needed to know which of the items should be carried on the shelves (stockless items). To do so, we extracted a report from the in-house software that is used for shelf replenishment at the stores and identified all the items that are being carried in any of the current dialysis storerooms. We then ran a cross match report utilizing Microsoft Access to identify the items that had been used during the past three month but do not need to be on the shelves (i.e. are not currently on the shelves based on the information from the in-house software). Those items were removed from our list. To confirm the list, we sat down with one of the dialysis technicians to review all the items again. During these two steps we removed 1/3 of the items from our list and finalized the list with 100 items that needed to be on the shelves in the new facility.

Barring an inaccuracy in this data, we still need more information to estimate the item demand. What we have so far is estimates for the usage of each item during the specified period based on analysis of the unit cost center data. Other information that we needed to estimate demand is patient arrivals. Fortunately, the dialysis unit had begun keeping

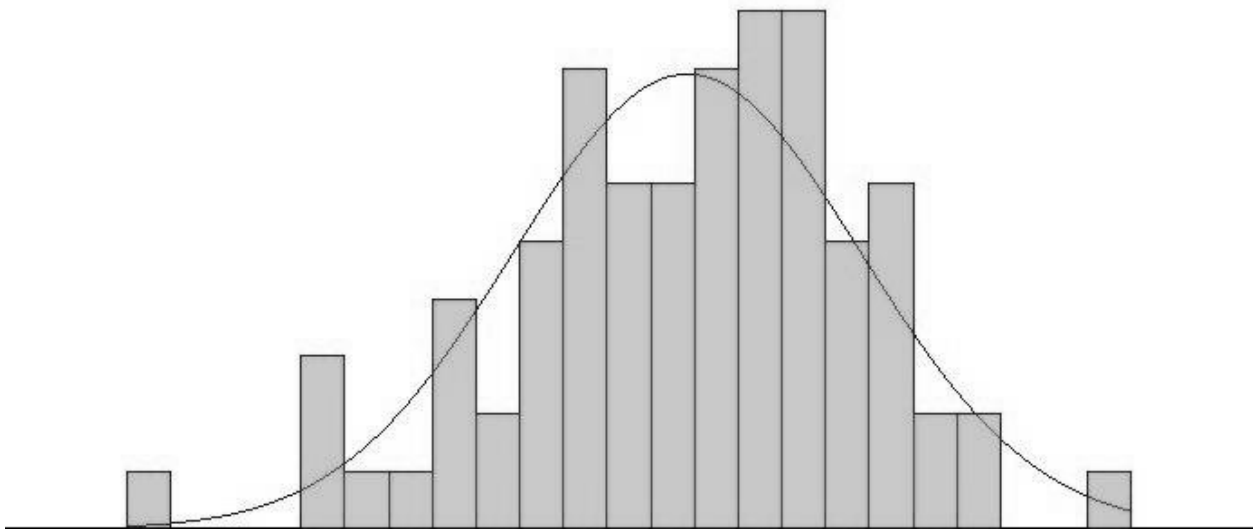
records of the patients' daily visits and we were able to gather patients' arrival data for the past three months.

There are two main types of patients that are being treated at the dialysis clinic. The Standard patients on average spend 3 hours at the clinic. The clinic accepts around 52 standard patients each working day. Conventional patients spend on average 5 hours at the clinic as they do not necessarily get treatment on a regular basis. On average the clinic accepts 135 conventional patients each day.

The question that we faced was how to relate the patients' arrival data with the usage data. The first option was to consider the time that the patients spend at the clinic and assume that the more they stay at the clinic, the more supplies are needed for them. The second option was to treat the patients equally no matter what kind of treatment they receive and assume that demand has a direct correlation with the number of patients. Consulting with the dialysis technicians and subject matter experts we realized that some of the items, such as dialyzers, are being used equally (one unit per patient) regardless of the type of patient. We were thus advised that in general it is safe to treat both types of patients identically, instead of giving weight to the time that they spend in the clinic.

Therefore we created a list for the period of June to August 2013 with the number of patients that get treatment in each working day for a total of 79 working days.

Using the Input Analyzer of the simulation software Arena we found that a Normal distribution, with mean 187 and standard deviation 3.98, would best describe the patients' arrival with a square error of 0.006313. Details about curve fitting are included in Figure 4-1.



<u>Distribution Summary</u>	<u>Chi Square Test</u>	<u>Data Summary</u>	<u>Histogram Summary</u>
Distribution: Normal	# of intervals = 6	# of Data Points = 79	Range = 175 to 198
Mean = 187	Degrees of freedom = 3	Min Data Value = 175	# of Intervals = 23
Std Dev = 3.98	Test Stat = 3.08	Max Data Value = 197	
Square Error:0.006313	p-value= 0.397	Sample Mean = 187	
		Sample Std Dev = 4.01	

Figure 4-1 Curve fitting for patient's arrival.

We note that a total of 14798 patients received treatment during the three month period. Dividing the three month usage of each item by the number of patients we were able to estimate the usage per each patient for each item. We then assumed that the demand for all the dialysis items follows the same distribution as that of the patient's arrival and used it to estimate the demand for all the items.

4.1.2 Ordering Cost

In our analysis we assigned the cost of ordering to each line of each purchase order. Although the cost of issuing each purchase order may be the same, each purchase order has a different number of lines and as such it is not possible to estimate the cost of ordering an individual item by only considering the cost of issuing a purchase order. We know that before any purchase order leaves the hospital the system will check all the purchase orders and identify duplicates. If two or more purchase orders contain the same items, they are combined in one purchase order.

From the data we found that on average each PO contains 3.4 lines. To have a valid estimate of a purchase order cost we needed information about the salary of LPD staff, the amount of time they spend on each PO and any related purchasing overhead costs. Due to the lack of information we accepted the hospital's current PO cost estimate of \$150. This number appears to be based on some unpublished studies that were done several years ago, but there is a consensus from managers on the use of this estimate. Although it is likely that the cost may have decreased due to the increasing use of technology, we performed our analysis using the \$150 figure to maintain consistency with the current costing system in the hospital. Consequently the cost of each line of each PO is estimated to be \$44. To inform management on the effect of lower (or higher) ordering costs we will later perform a parametric analysis on our model results.

It should be noted that JIT providers usually deliver two types of products; franchises and non-franchises, where the ordering cost for non-franchise items are usually higher. Since the JIT provider has not been identified yet, in our model, we treated all items as franchises as it was difficult to accurately identify which items fall under which category. Once these categories have been identified, it is not difficult to incorporate them in our model.

4.1.3 Transportation Cost

In this thesis the transportation cost is considered to be the cost of delivering the packages from the hospital dock to the unit. Items are transported by carts. The carts are usually taken to the unit by the LPD staff. The carts can also be transported by automated guided vehicles (AGV) commonly used in industrial settings. Unfortunately we were not able to collect reliable data on transportation volumes and trip costs. Therefore we decided to not include the transportation costs in our model, but they can be easily incorporated once they are available.

4.1.4 Grouping

Grouping the items can improve practice in many aspects. For example, in case of shortage. Staff may need to borrow items from different storerooms and standardizing the storerooms will help the staff find the items quicker. Especially if the hospital is considering the use of universal workers [41, 42] which is a concept that is already being used in other healthcare facilities such as long term care. Thus, in our model we allow for groupings and offer flexibility for hospital management to standardize storage layouts in the different units. Borrowing from the practice at the material management department of the Peterborough hospital, where they have already started implementing JIT, we created the following 14 groups:

Briefs, Dialysis, General Care, General Supply, Glove, IV Solutions, Lab, Med Lines, N95, O2 Tanks, Respiratory, Suction, Syringes, and Wound Care.

4.1.5 Size Categories

Being able to measure the size of each item would help us to estimate how much supplies we can fit in any given storeroom. It also helps to estimate the number of trips that a transportation cart with a given size has to take in order to deliver the daily supplies from the dock of the hospital to the storeroom inside the patient care unit. Since it was not practical to measure every single item accurately, we identified five different size

categories (see Table 4-1). Note that size category 4 was assigned to the bulkiest item and size 0 was assigned to the smallest items.

Size Categories	4	3	2	1	0
Width (m)	0.35	0.12	0.1	0.05	0.025
Depth (m)	0.55	0.4	0.2	0.1	0.1
Height (m)	0.25	0.1	0.05	0.05	0.012
Volume (m ³)	0.048125	0.0048	0.001	0.00025	0.00003

Table 4-1 Size categories.

4.1.6 Future Store Rooms

The drafted layout of the dialysis unit of the new hospital suggests that the dialysis clinic will have two storerooms with the following supply equipment (see Table 4-2).

Room 1		Room 2	
Equipment	Size	Equipment	Size
Cart, Supply, 5 tier	73''wx25''dx77''h	Cart, Supply, 6 tier	73''wx25''dx77''h
Cart, Supply, 8 tier	74''wx25''dx77''h	Cart, Supply, 5 tier	75''wx24''dx70''h
Cart, Supply, 7 tier	73''wx25''dx77''h	Cart, Supply, 6 tier	74''wx24''dx77''h

Table 4-2 – Supply Equipment.

After converting from imperial to metrics units, we can conclude that the total available space for storing supplies at the dialysis storerooms in the future clinic will be around 13.32 m³. This number will be a key factor in all of our future calculations.

In Table 4-3 we compare the current and future hospitals' practices. It can be observed that while the number of dialysis seats will change only by one seat, which means the demand

for dialysis supplies almost remains the same, the number of storerooms and available space for the new hospital will drastically decrease (from 1.16 feet per seat to 0.67). This highlights the importance of optimization and process improvement activities before moving to the new hospital, as well as change management to prepare the staff.

Dialysis Clinic	Room	Size of Shelves (Foot)	6	5	4	3	2	Total Space (Foot/Seat)
		Number of seats in each room						
Current State	1	10	2	3				71/61
	2	34	3		1		1	
	3	17	2		2			
Future State	1	30	3				1	40/60
	2	30	3				1	

Table 4-3 current and future practice storeroom comparison

4.1.7 Safety Stock

Safety stock is always taken very seriously in hospitals since stockouts may lead to loss of patients' lives. Natural disasters, such as the 2010 Iceland volcano eruption, can disrupt supply flows. Safety stocks may also be needed in other circumstances like pandemic events or labor strikes. On the other hand, limited space availability, operating budgets and the growing cost of healthcare are pushing managers to avoid unnecessary storage of supplies. Finding an optimum point for the safety stock that would balance service levels and costs is very challenging.

For this thesis we considered both demand and supplies uncertainties to calculate the safety stock. The method used to calculate the safety stock was adopted from Chopra and Meindl [43]. We use the following notation.

D : Average demand per period

σ_D : Standard deviation of demand per period

L : Average lead time for replenishment

s_L : Standard deviation of lead time

CSL: service level mandated by the department

We would like to determine the distribution of patient demand during the lead time given that both lead time and demand are uncertain. The demand during the lead time is normally distributed with the following mean and standard deviation:

$$D_L = DL$$
$$\sigma_L = \sqrt{L\sigma_D^2 + D^2s_L^2}$$

Hence the desired safety stock for each item i can be obtained with the help of the following equation:

$$ss_i = F_s^{-1}(CSL) * \sigma_L$$

We note that the above formula should be applied to all the items (in this case 100) to be able to estimate the space required for them. For this analysis the average demand and standard deviation of the demand per period is obtained from the normal distribution that was best fitted to the patient arrivals. The average lead time is 1 day for all the items, considering that the delivery arrives one day after the order takes place. The standard deviation of lead time was assumed to be 0.05, representing the fact that there is only one incident in each year that an item would arrive late by one day. The mandated customer service level is assumed to be 0.99999 for all items. The case where different items require different service levels can be handled easily in our model. We will later discuss the effect of decreasing the service level on the total cost.

4.2 Optimization Model

In this section we develop an optimization model to find the optimal ordering practice for the dialysis clinic by minimizing procurement and inventory costs while meeting the capacity constraints. We note that we are not optimizing for service levels, since in healthcare settings there is no cost that can be assigned for missing service levels of critical items. Thus, we indirectly handle service level requirements by keeping the required safety stock for each item at the storerooms.

Notation

We need some additional notation to complete the model formulation:

$$i \in I = \{1, 2, \dots, 100\}$$

represents the dialysis stockless items selected to be kept on the shelves at the dialysis storeroom. These are the items that will be delivered by the JIT provider.

$$j \in J = \{2_M, 4_W, 6_F, 9_M, 11_W, 13_F \dots\}$$

represents the ordering days and , *M: Monday, W: Wednesday and F: Friday*. Since orders take place only in one of those days and the clinic is closed on Sundays.

A_i : average daily usage of item i

V_i : dollar value of item i

PV_i : package volume of item i

AS : A constant, representing the available space at the storeroom and can be obtained from the following formula:

$$AS = \text{Max shelf space at the storerooms} - \sum_{i=I} (ss_i * PV_i) \forall i \in I$$

M : A large number.

N : A random integer used to calculate the opening inventory.

Z_j : Number of trips that a transportation cart should make in order to deliver all the packages from the dock station to the dialysis storeroom for each day.

α : Carrying cost as a percentage of inventory value assumed to be 0.2.

$X_{i,j}$: Integer variable representing the number of packages of item i that need to be ordered on day j .

$D_{i,j}$: A binary decision variable which decides whether or not the item i should be ordered on day j .

OI_i : Opening inventory for item i . We assume that we have N days of average demand as the opening inventory at the start of the period. Therefore,

$$OI_i = N * A_i \text{ where, } \sum_{i=1}^{100} PV_i * OI_i \leq AS$$

$PI_{i,j}$: Physical inventory of item i at day j . The physical inventory can be obtained from the following formula:

$$PI_{i,j} = X_{i,j} - 2 * A_i + PI_{i,j-1}, \text{ Where: } PI_{i,0} = OI_i$$

OC : Constant cost associated with every line of each purchase order.

OP : Percentage of items that are allowed to be ordered on each day. This is to give the managers flexibility to decide on the maximum number of items that can be ordered at any single day.

F_i : Maximum number of packages that can be ordered each day for item i .

TCV : Volume of a transportation cart.

TCC : Cost associated with each trip of each transportation cart. The cost varies by the method of the transportation.

Assumptions

Although we strived to represent the real world problem as much as possible, we still needed to make some assumptions:

- 1- Based on the storeroom measurements, in total the maximum shelf space at the storerooms is equal to $13.32117 m^3$
- 2- The safety stock will take $6.09542 m^3$ of the space, resulting in $7.22575 m^3$ of available space at the start of the period.
- 3- The ordering cost is equal to 44\$.
- 4- The Total Inventory Cost is based on the costs associated with ordering, holding the supplies on the shelves and transportation.
- 5- The daily demands for items will be rounded to the closest number with 0.5 significance to avoid unnecessary decimals. We note that the items with very low demand have already been removed from the list.
- 6- The inventory holding cost ratio is assumed to be 0.2. Note that our ordering and inventory holding costs are high and one can divide both values by a common factor to reduce them.
- 7- Since there was no data on the transportation carts' volume and the cost of each trip, we assumed the size to be 0.5 and the cost to be zero.
- 8- The percentage of the items that can be ordered in each day is assumed to be 100%.
- 9- There is no daily limit for any of the items, Adding such limits to the model is not difficult.
- 10- Based on existing JIT provider practice we assumed that the purchase orders will be issued on Mondays, Wednesdays and Fridays. Considering that the clinic is

closed on Sundays, the model should have a tendency to avoid keeping extra items during the weekend to decrease the inventory cost.

11- The opening inventory is assumed to be 3 days of average demand for each item.

Objective Function

Our objective is to minimize the total cost (TC):

$$Min : TC = \alpha \left[\sum_{j \in J} \sum_{i \in I} \left[\frac{J(j) - J(j-1)}{2} \right] V_i * PI_{i,j} \right] + \left[OC * \sum_{j \in J} \sum_{i \in I} D_{i,j} \right] + TCC * \sum_{j \in J} Z_j \quad (4-2-1)$$

Note that the fraction $\left[\frac{J(j) - J(j-1)}{2} \right]$ is used to account for inventory holding cost over the weekend where $J(j)$ stands for the index of order j in the set J . (e.g. $J(4_w) = 4$)

Constraints

The constraints to be satisfied include:

1. Making sure the ending inventory will be at least equal to the opening inventory:

$$OI_i \leq PI_{i,j} \quad \forall i \ \& \ j = |J| \quad (4-2-2)$$

2. Guaranteeing the space availability at the storeroom:

$$\sum_{i \in I} PV_i * X_{i,j} \leq AS \quad \forall j \quad (4-2-3)$$

3. Ordering only during selected days:

$$X_{i,j} \leq M * D_{i,j} \quad \forall i, j \quad (4-2-4)$$

4. Ensuring that the transportation carts make enough trips to deliver all the packages to the storeroom:

$$\sum_{i \in I} PV_i * X_{i,j} \leq Z_j * TCV \quad \forall j \quad (4-2-5)$$

5. Respecting the packages daily order limit:

$$X_{i,j} \leq F_i \quad \forall i,j \quad (4-2-6)$$

6. Limit on total number of daily orders. This limit can be instituted by the JIT provider to control the complexity of its order assortments.

$$\sum_{i \in I} D_{i,j} \leq Round(|I| * OP) \quad \forall j \quad (4-2-7)$$

4.3 Optimization results and Analysis

GAMS and EXCEL were employed to solve the above mixed integer programming (MIP) optimization problem. EXCEL was initially used for data entry and setting the initial conditions. GAMS is used to solve the problem. GAMS optimization results were then exported to EXCEL for presentation purposes. A snapshot of the EXCEL interface that was created to capture the initial model entry conditions can be seen in Figure 4-2.

Figure 4-2 Excel data input interface.

The input data is Table B-1 in Appendix B.

GAMS

The General Algebraic Modeling System (GAMS) is a modeling system for mathematical programming problems such as Linear Programming, Mixed Integer Programming, Mixed Integer Non-Linear Programming, and different forms of Non-Linear Programming. Our model (4-2-1: 7) is a linear mixed integer program and we use CPLEX 12 to solve it. The following are the solver options that we used in GAMS:

Option Optca = 0.001; the solver will stop if the absolute gap between the best integer solution and the “best estimate” calculated by the relaxation drops below *optca*.

Option Optcr = 0.01; the solver will stop if the relative gap calculated by the formula $\frac{\text{best estimate} - \text{best integer}}{\text{best estimate}}$ drops below *optcr*.

OPTION RESLIM = 1000; the solver will terminate after 1000 seconds even though it may not have reached any of the above thresholds. The full GAMS code can be found in appendix C.

Results

CPLEX is able to close the relative gap by 14% in a few seconds but it takes much more time to achieve any further improvements afterwards. When it reaches to a relative gap of 12% it becomes evident that it has difficulty in improving the solution and usually terminates shortly after due to the time limit of 1000 seconds. The model input and output can be found in Appendix B in Tables B-1 and B-2, respectively. Table 4-4 has a summary of the optimal costs as obtained from CPLEX.

Total Cost	Ordering Cost	Inventory Holding Cost
\$35,908	\$17,820	\$18,088

Table 4-4 The exact solution of the Dialysis unit optimization problem

Table 4-5 shows the details of the delivery schedule for the first 20 items, sorted from largest to smallest based on the average daily usage, for a one month period.

Items	Grouping	Ordering days through the one month period													
		M:Monday – W:Wednesday – F: Friday													
		M	W	F	M	W	F	M	W	F	M	W	F	M	
1	Lab		836						1140						
2	IV Solutions		33	66	66	66	66	66	66	66	66	66	66	165	
3	Syringes		25	53	53	53	53	53	53	53	53	53	187		
4	General Supply		140				200					180			
5	Wound Care		45		60		60		60		60		105		
6	Dialysis		12	24	24	24	24	24	24	24	24	24	24	60	

7	General Care		114						159					
8	General Care		72				105					96		
9	General Care		10	20	20	20	20	20	20	20	20	20	20	50
10	IV Solutions		40			48			32		32		56	
11	Glove		21		15	15	30		15	30		15	54	
12	Dialysis		6	15	15	15	15	15	15	15	15	15	15	39
13	Glove		5	26		26		13	13	26		26		34
14	General Care		5	26		13	26		13	26		26		34
15	General Care		156											
16	Syringes		15		20		20		20		20		35	
17	Dialysis		3	9	9	9	9	9	9	9	9	9	9	24
18	N95		20			24			32				28	
19	General Care		16			21			21			14		19
20	Glove		16			21			14		14		26	

Table 4-5 Ordering schedule for the first 20 items

In Figure 4-3 we see that the percentage of items that we order each day did not exceed 60% of the items in any day. The average percentage number of items ordered each day is 31%. Being able to order around 35% of the items in each day is considered as good practice by the LPD manager.

Another important factor to consider is the inventory holding cost for safety stocks. This

can be calculated as $\alpha \sum_{i=1}^{100} (ss_i * V_i)$.

This cost should be added to the total cost obtained from the optimization problem to be able to report on the real cost of inventory, depending on the required service level. In our application we find that the safety stock holding cost is \$23,462, resulting in a total cost of

\$59,370 for each month. Figure 4-4 shows the annual savings associated with decreasing the service level.

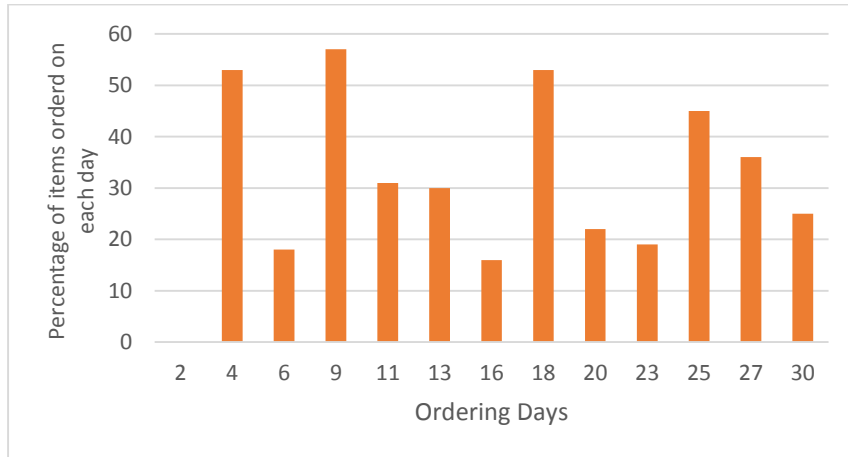


Figure 4-3 Percentage of items ordered on each day.

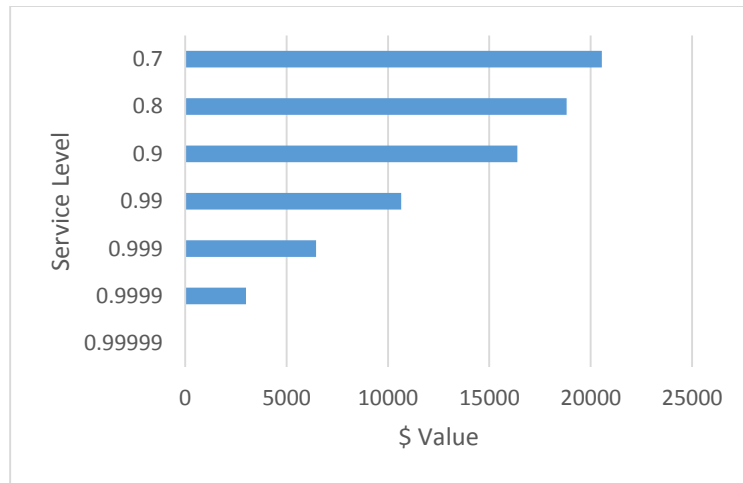


Figure 4-4 Annual saving associate with decreasing service level.

As it has been mentioned before, one of the expected outcomes of this model is to help us to build and design the shelves in a way that can accommodate the supplies in the future. We note that $6.09542 m^3$ of the space at the storeroom will be assigned to the safety stock and the remaining $7.22575m^3$ will be available for daily inventories. We looked at the maximum space needed for items in each group and identified the percentages of the dialysis storerooms that should be assigned to each of the dialysis groups. Figure 4-5 shows

the result of our analysis. The majority of space (~67%) is assigned to dialysis (39%) and general care (28%).

Figure 4-6 shows the space availability during the period of study. It can be observed from the figure that in the first and the last days of period we experience the most inconsistencies in terms of space availability. This phenomenon can be a direct cause of opening and closing inventory in a one month ordering system. Expanding the period will reduce the inconsistencies and make the problem more realistic considering that the ordering will be continuous and the demand for the supplies will have a very small variance. In addition JIT providers guarantee the delivery of the supplies with a high service level. Therefore, it is safe to say that any interruption to the flow of supplies will be highly unlikely. We can conclude from the Figure 4-6 that the available daily space is around $3 m^3$. The available space will provide more flexibility for the LPD managers and staff to make ordering decisions.

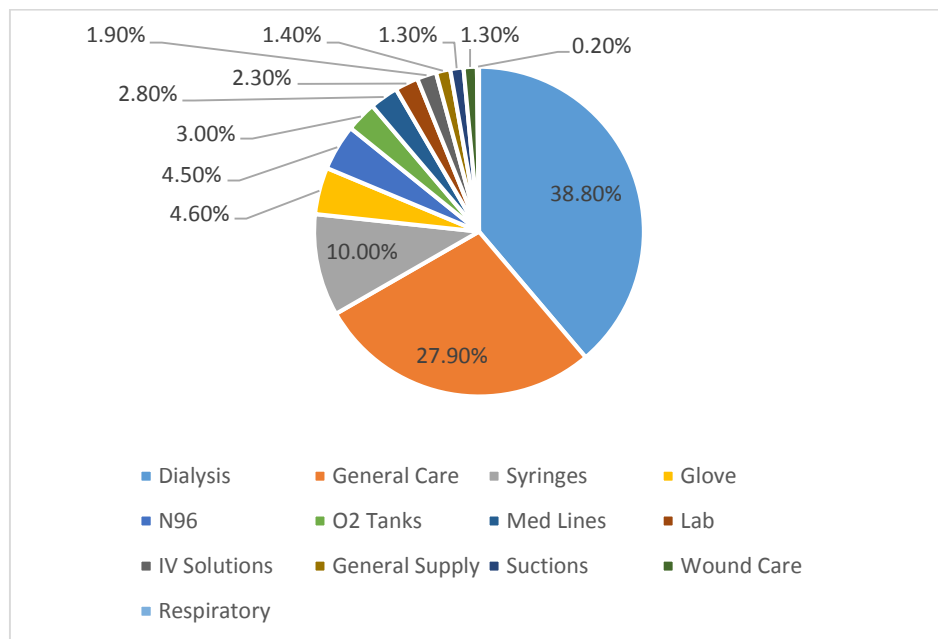


Figure 4-5 Percentage of the storerooms' space that should be assigned to each group

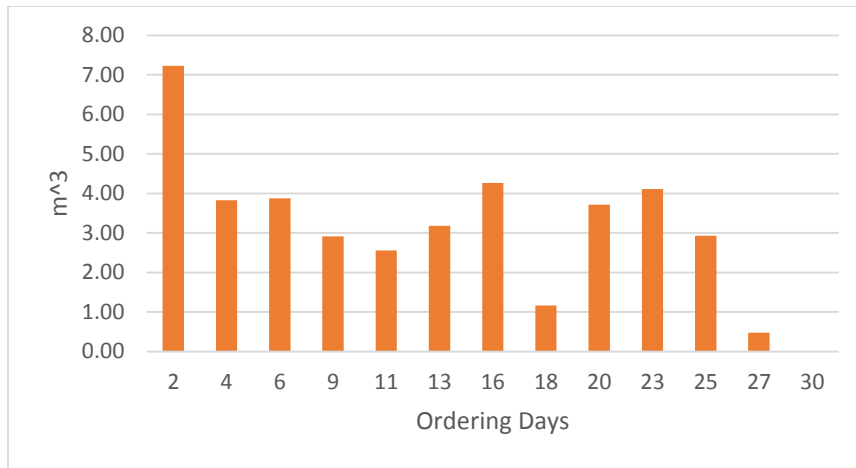


Figure 4-6 Daily available space at the storeroom based on the schedule.

Re-evaluation

Ideally the goal of this model is to avoid unnecessary scanning practice and LPD staff should be able to use Table 4-5 as a fixed schedule for ordering without scanning the items. However, we know that the demand analysis was based on some estimations and assumptions. There may also be other factors that we have not captured which may affect the demand or the other parameters in our model. Therefore the performance of the model should be tested periodically to detect any inconsistencies and improve it. Hence, LPD staff should periodically scan the items. If the safety stock is more than it is supposed to be, the extra safety stock will be deducted from the pre-scheduled order and if the safety stock is less than it should be, the shortage will be added to the pre-scheduled order. The changes should be tracked and analyzed to be able to find the items that have the most significant changes during a long period. The underlying factors which may cause those behaviors then need to be investigated and the results incorporated into the model for optimization.

4.4 A Heuristic Solution Approach

In this section we propose a heuristic approach to solve the inventory and delivery JIT model. Our motivation for constructing such a heuristic is to achieve computational efficiency and ease of implementation. Even for moderate sizes of 100 items we have observed that the CPLEX solver can take a considerable time to solve the problem. In addition, we believe that the current staff in the hospital is not equipped to use sophisticated commercial solvers in their decision making; they do not have access to commercial licenses and they are not trained in using advanced analytics solutions. Finally, a commercial implementation of CPLEX is estimated to cost the hospital around \$50,000/year. The proposed heuristic will offer an affordable, easy to implement and accurate tool to solve the model presented earlier.

If we look at the solution provided in Table 4-5, we can visualize the solution as converting a given vector of demands \mathbf{A} to a matrix of order deliveries \mathbf{X} . As such our problem can be seen as a special case of the general capacitated lot sizing problem, where instead of setup costs we use ordering costs. Heuristics for such problems can be classified into two types: step by step or improvement heuristics [22]. The main difference between the two types is that in the step by step heuristics, at each period after satisfying the demand for that period the algorithm tries to use excess capacity to satisfy the demand for future periods while in improvement heuristics the process starts with a usually infeasible initial solution obtained by ignoring the capacity constraints. Numerical tests have shown that a step by step heuristic produces better solutions but at the expense of longer computation times for large size problems [28]. Considering that we are usually dealing with a large number of items in a hospital we decided to employ improvement heuristics to avoid the lengthy computational times.

Heuristics in the area of capacitated lot sizing generally constitute of three main steps: lot sizing, feasibility routine and improvement [27, 28, and 29]. Lot sizing is the process of combining demands into a lot which can be interpreted as combining demand into orders by replacing the setup cost with the ordering cost. In the improvement heuristic the lot

sizing step is to find an initial plan that may not satisfy the capacity constraints. The feasibility routine step is to ensure all the demand and constraints are satisfied by left-shift or right-shift procedures [31] where the extra quantities on each period will be shifted to the left or right periods to meet the capacity constraints. In the improvement step the heuristic tries to improve the solution by the help of several steps that could lead into reducing the total cost.

We designed an improvement heuristics that on average found solutions that are 97% of the optimal solution for a 100 item problem in a one month period.

We first describe the steps and then review the performance of the heuristic for different samples. The flow chart for the heuristic steps is presented in Figure 4-7.

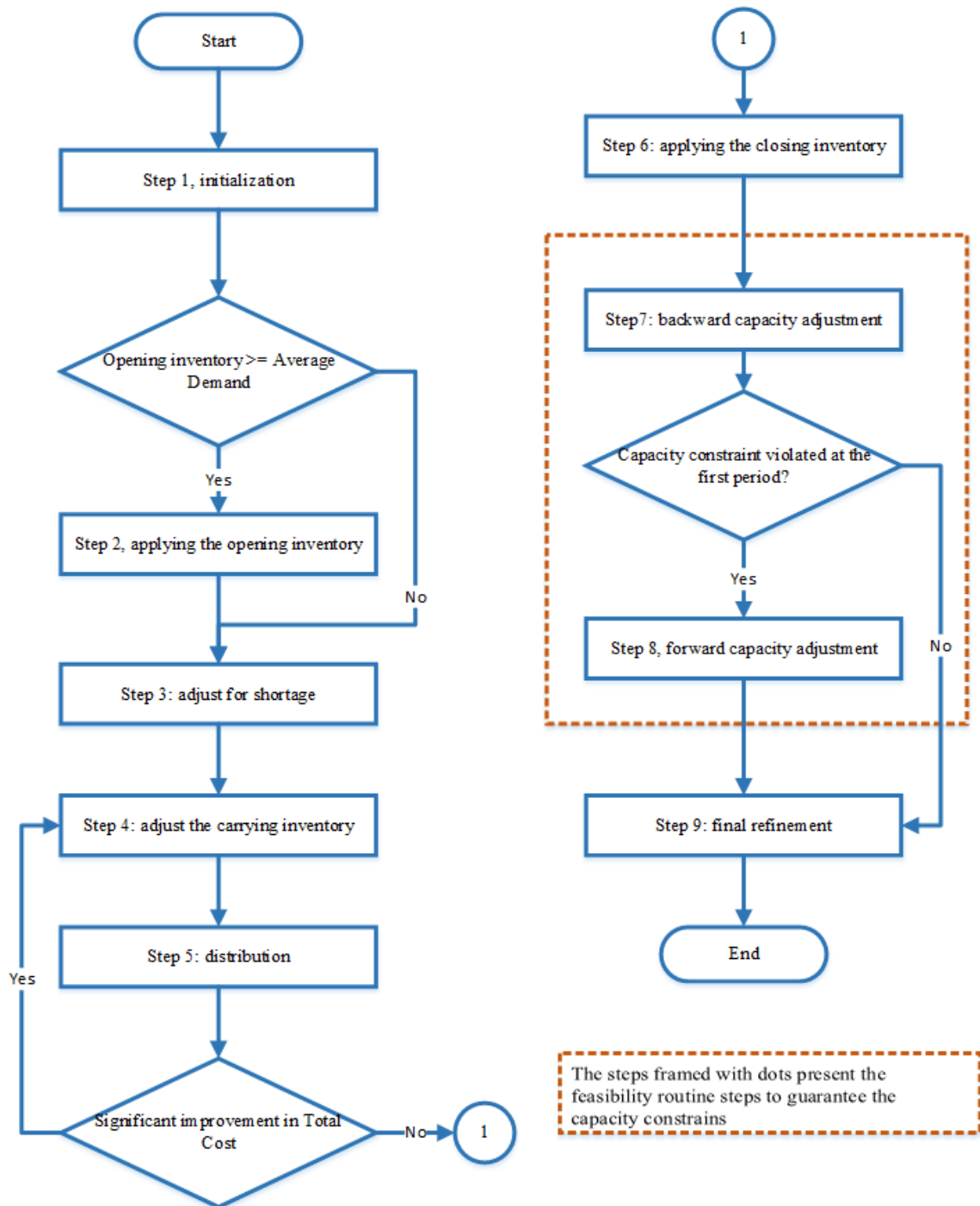


Figure 4-7, Flowchart of the heuristics

Step 1, initialization: As a first step, we start with finding an admissible solution for the problem as an initial plan by ignoring the capacity constraints. Since the proposed heuristic is sensitive to the initial plan, finding a good solution is the key to the successful implementation of the heuristic. For generating the initial plan there are two main factors to consider. On one hand we should note that this heuristic is based on moving the order quantities forward and backward in time to find a better solution. Therefore the more the orders are distributed throughout the period the closer we can get to the optimal solution. On the other hand, if the orders are overly distributed throughout the period, it takes much longer for the method to perform, which contradicts our goal of achieving shorter computational times. Chopra and Meindl [43] described a method to facilitate aggregation planning with capacity constraints. They used information such as demand per product A , holding cost α , unit cost V_i , common order cost OC and supplier specific order cost s_i to find out the frequency with which different products should be ordered. We use this method to approximately identify how often each item should be ordered. Then we will find a logic to categorize them and distribute the orders for each item based on the categories.

The Chopra and Meindl method starts with evaluating the order frequency for each product while assuming that each product is ordered independently. Let us denote

$$\bar{n}_i = \sqrt{\frac{\alpha V_i A_i}{2(OC + s_i)}}$$

to be the optimal order frequency for each item. Dividing the length of the period J by \bar{n}_i will identify how often each product should be ordered.

$$f_i = \frac{J}{\bar{n}_i}$$

Next, we use the categorization in Table 4-6 to distribute the orders throughout the period.

Ordering frequency categories	Number of batches throughout the period
$f_i > 1.5 L$	1
$L < f_i < 1.5 L$	2
$\frac{L}{6} < f_i < L$	4
$\frac{L}{6} > f_i$	6

Table 4-6 Initial condition set-up

The batches will be evenly distributed throughout the period. We predict that this kind of distribution will help us to achieve an accurate result in a reasonable time since the orders are locally optimized, i.e., the number of orders are close to what an ordering practice for independent orders would suggest. It should be noted that other methods for multi-item replenishment inventory control systems can be found in the literature [e.g., 44 and 45]. Since our heuristic is very sensitive to the initial plan we do not claim that the above method will always result in better solutions compared to other replenishment policies. The main reasons that we preferred this method over others in the literature are simplicity of calculations and flexibility to handle different ordering frequency distributions.

Step 2, applying the opening inventory: Through the initialization process all the items will be ordered at the first day of the period. Hence, at the second step we take the opening inventory into consideration. For each item we check the number of demand days that are covered by the opening inventory and postpone their orders accordingly.

Step 3: adjust for shortage: In this step, we check if there is any inventory shortage on any day. In case of shortage we increase the quantity of the last order before the shortage to avoid it.

Step 4: adjust the carrying inventory: At this step we review the days that orders take place for each item to make sure that we are not carrying extra inventory. For example, assume that X_{ij} represents the order of item i at day j . If there is extra inventory on day $j - 1$, clearly the orders that happened before X_{ij} should be reduced. But the packages that are

taken off from those orders should be added to X_{ij} to avoid shortages at the end of the period. This process continues for all the items and all the days until we make sure that the amount of extra carrying inventory is minimum. Note that the only parameter that will be changed at this step is the quantity of the orders; ordering dates will not change.

Step 5: distribution: At this step we try to find the economic order quantity and date for each item by cutting the quantity of each order by half and investigating the possibility of moving the other half of the orders to the next day. This process continues for all the orders and all the days, as long as it results in decreasing the total cost. We note that the quantity of each order that should be moved to the next day can be obtained accurately by moving quantities by the smallest units and measuring the changes in total cost. But this approach would be very time consuming and not practical. By applying this step, costly items are more likely to be ordered more frequently and less expensive items will be ordered occasionally.

Note: we will repeat Steps 4 and 5 until the improvement in the total cost is negligible (i.e. less than 5\$).

Step 6: applying the closing inventory: This step is to make sure that the closing inventory is satisfied. This can be done by checking the shortage and excess of each item at the end of the period. In case of excess we decrease the last order that has taken place. If the last order is less than the amount of excess, we remove the last order and decrease the previous order. This process continues until there is no excess for any of the items. In case of shortage we have two scenarios. If there is already an order on the last day, we increase the last order to avoid the shortage. If the last order did not take place at the last day we try two different options and select the one that results in less total cost. Option one is to place a new order at the last day and option two is to add the quantity to the last order.

Step 7: backward capacity adjustment: At this phase we take the first step towards applying the capacity constraints. We first sort the items based on their volume decreasingly and their value increasingly. Then we can start by the last day j and check if the capacity constraint for that day is met. If it is not met, meaning that we have placed more orders

than we could carry, we start from the top of the list, choosing the cheapest item among the bulkiest, and move the items to day $j - 1$. If moving a portion of the item to day $j - 1$ results in satisfying the capacity constraint for day j , we stop the process. Otherwise we move the whole order to day $j - 1$ and continue the process using the next item on the sorted list. When the capacity constraint of day j is met we can repeat the same procedure for day $j - 1$. At this step, depending on the distribution of the orders, we will either meet the capacity constraints for all the days or in the worst case scenario only at the first day the capacity will be exceeded.

Step 8, forward capacity adjustment: The second step to satisfy the capacity constraints will be to take care of the capacity of the first day in case it has exceeded the limit. We again start by sorting the items. This time the items will be sorted decreasingly based on their volume and package value. Then we start with the most expensive and bulkiest item and move portions of its order forward to the days where there is room for more items. Under two conditions we would leave the first item and go to the second item on the list to repeat the procedure. First, if all the items from the order have been moved and the capacity constraint is not met yet. Second, if removing more items from those items will result in shortage. The step will be repeated for the items based on the new sorting until all the capacity constraint for the first day is met.

Note that the two sorting methods employed in Steps 7 and 8 are to guarantee that the capacity constraints are being met by the minimum cost possible. It can be achieved by moving the bulky items to expedite the procedure and keep the ordering structure as close as possible to the one that we obtained before applying the capacity constraints. We also try to postpone the ordering of the expensive items to avoid the extra carrying cost.

Step 9: final refinement: The last step is to try to improve the solution after applying the capacity constraints. At this step we use the last sorting that we had for Step 8 and check the days with extra inventory to see if moving the items to the days ahead, without causing shortage or exceeding the capacity, will improve the total cost. We note that if the capacity

constraints were met at Step 7, Step 8 will be skipped. Hence for Step 9 we need to sort the items again based on their volume and their package value both decreasingly.

The main assumption for successfully implementing this heuristic are as follows:

- The available capacity should be at least equal to the volume of the items that are needed to satisfy the demand for the whole period plus the volume of one of the bulkiest items.
- If the percentage of the number of infrequent items to the total number of items is large in Step 1, it is likely that the model would not be able to land on a good result. This is because most of the items will be piled up at the start of the period which is not a good initial plan to start the process. In this case we may need to change the initialization rules to achieve better results.

4.5 Implementation and Testing

To successfully implement and test the above algorithm for different samples we employed VBA in Excel to create a program to automate the heuristic steps. Although the automation is not necessary for adopting the model, it can serve as an effective demonstration tool for the hospital management.

Since the initial driver for this heuristic was the hospital data, to test the model we will define a set of conditions for generating samples that are similar to the real data from the dialysis department.

The first parameter to generate are the package values V_i . After analyzing the unit prices of the hospital's items we categorized the package values to four categories and assigned the following probability to each price category. Table 4-7 shows the data used to generate values for the samples.

Package volume PV_i is the second parameter. As it has been discussed before we identified 5 different categories and assigned each package size to one of those categories. Dialysis

data suggests that the volumes should be generated by following the probabilities in Table 4-8.

Price Range (\$)	The probability of selecting from the range
0.1 to 1	17%
2 to 20	58%
21 to 100	16%
101 to 700	9%

Table 4-7 rules to generate sample values

Volume (m ³)	The probability of selecting from the each category
0.048125	12.5%
0.0048	12.5%
0.001	37.5%
0.00025	12.5%
0.00003	25.0%

Table 4-8 rules to generate sample volume for items

Finally the last parameter will be the daily demands D_i for different items. Daily demand for the items is randomly selected from 0.5 to 76 and the numbers are rounded to multiples of 0.5. We exclude the items with demand less than 0.5 a day since not all the items should be ordered through the JIT system. The main condition to accept or reject a generated set of parameters is to satisfy daily capacity constraints. This condition can be obtained by checking the following formula for each generated set:

$$\sum_{i=1}^n PV_i D_i \leq AS$$

#	CPLEX			Heuristic			Accuracy			RG	AS
	TC	OC	IC	TC	OC	IC	TC	OC	IC		
1	\$ 100,648	\$ 29,348	\$ 71,300	\$ 102,138	\$ 29,216	\$ 72,922	99%	100.5%	97.8%	3.69	0.64
2	\$ 126,958	\$ 29,744	\$ 97,214	\$ 129,271	\$ 29,612	\$ 99,659	98%	100.4%	97.5%	2.44	0.87
3	\$ 68,715	\$ 24,728	\$ 43,987	\$ 70,756	\$ 24,508	\$ 46,248	97%	100.9%	95.1%	5.35	1.23
4	\$ 145,967	\$ 31,240	\$ 114,727	\$ 147,561	\$ 31,152	\$ 116,409	99%	100.3%	98.6%	1.24	1.47
5	\$ 152,890	\$ 25,872	\$ 127,018	\$ 154,994	\$ 25,564	\$ 129,430	99%	101.2%	98.1%	2.52	0.09
6	\$ 96,878	\$ 27,236	\$ 69,642	\$ 106,356	\$ 27,324	\$ 79,032	91%	99.7%	88.1%	3.16	1.07
7	\$ 190,987	\$ 28,028	\$ 162,959	\$ 192,861	\$ 27,720	\$ 165,141	99%	101.1%	98.7%	1.68	0.57
8	\$ 53,491	\$ 24,156	\$ 29,335	\$ 54,754	\$ 24,024	\$ 30,730	98%	100.5%	95.5%	7.09	0.73
9	\$ 186,042	\$ 29,788	\$ 156,254	\$ 187,504	\$ 29,568	\$ 157,936	99%	100.7%	98.9%	1.72	1.08
10	\$ 84,613	\$ 27,940	\$ 56,673	\$ 87,001	\$ 27,588	\$ 59,413	97%	101.3%	95.4%	3.92	0.68
11	\$ 128,337	\$ 25,608	\$ 102,729	\$ 130,340	\$ 25,388	\$ 104,952	98%	100.9%	97.9%	2.87	2.18
12	\$ 174,546	\$ 26,928	\$ 147,618	\$ 179,381	\$ 26,620	\$ 152,761	97%	101.2%	96.6%	1.95	0.07
13	\$ 163,585	\$ 33,880	\$ 129,705	\$ 166,560	\$ 33,616	\$ 132,944	98%	100.8%	97.6%	1.71	0.22
14	\$ 113,628	\$ 29,744	\$ 83,884	\$ 115,487	\$ 29,612	\$ 85,875	98%	100.4%	97.7%	2.68	2.17
15	\$ 112,227	\$ 25,696	\$ 86,531	\$ 114,203	\$ 24,508	\$ 89,695	98%	104.8%	96.5%	3.21	2.22
16	\$ 194,197	\$ 29,964	\$ 164,233	\$ 195,954	\$ 29,392	\$ 166,562	99%	101.9%	98.6%	1.52	2.33
17	\$ 156,550	\$ 28,292	\$ 128,258	\$ 166,332	\$ 27,984	\$ 138,348	94%	101.1%	92.7%	1.96	0.13
18	\$ 92,507	\$ 28,248	\$ 64,259	\$ 107,942	\$ 28,248	\$ 79,694	86%	100.0%	80.6%	2.93	0.10
19	\$ 112,759	\$ 29,128	\$ 83,631	\$ 114,760	\$ 29,084	\$ 85,676	98%	100.2%	97.6%	2.48	1.29
20	\$ 110,688	\$ 27,192	\$ 83,496	\$ 112,006	\$ 26,224	\$ 85,782	99%	103.7%	97.3%	3.18	2.79
21	\$ 178,433	\$ 30,888	\$ 147,545	\$ 181,166	\$ 30,536	\$ 150,630	98%	101.2%	98.0%	1.74	0.19
22	\$ 132,521	\$ 29,260	\$ 103,261	\$ 133,994	\$ 28,864	\$ 105,130	99%	101.4%	98.2%	2.47	3.57
23	\$ 126,796	\$ 31,460	\$ 95,336	\$ 128,133	\$ 31,548	\$ 96,585	99%	99.7%	98.7%	2	3.19
24	\$ 185,390	\$ 30,140	\$ 155,250	\$ 187,361	\$ 29,744	\$ 157,617	99%	101.3%	98.5%	1.61	1.17
25	\$ 74,970	\$ 25,124	\$ 49,846	\$ 76,401	\$ 25,256	\$ 51,145	98%	99.5%	97.5%	3.79	2.96
26	\$ 160,464	\$ 31,108	\$ 129,356	\$ 165,180	\$ 31,108	\$ 134,072	97%	100.0%	96.5%	2	0.93
27	\$ 107,032	\$ 28,292	\$ 78,740	\$ 109,677	\$ 28,732	\$ 80,945	98%	98.5%	97.3%	3.39	0.37
28	\$ 68,731	\$ 25,388	\$ 43,343	\$ 70,267	\$ 24,992	\$ 45,275	98%	101.6%	95.7%	4.42	1.09
29	\$ 63,812	\$ 25,872	\$ 37,940	\$ 66,182	\$ 25,212	\$ 40,970	96%	102.6%	92.6%	6.48	0.96
30	\$ 123,262	\$ 28,512	\$ 94,750	\$ 125,632	\$ 28,688	\$ 96,944	98%	99.4%	97.7%	2.82	0.54

Table 4-9 Comparison between the performances of exact solution vs. heuristic solution.

TC: Total cost, IC: Inventory Cost, OC: Ordering Cost, RG: Relative Gap, AS: Available space

Table 4-9 presents the performance of exact and heuristic solutions for 30 generated samples. The summary of the performance results is presented in Table 4-10. It can be seen that on average the results of the heuristic get as close as 97% to the exact solution

with a standard deviation of 3%. We also note that for some instances CPLEX may take a long time to find a solution and we had to terminate it after 300 seconds.

	TC	OC	IC
Average Accuracy	97%	100.9%	96.2%
Std. dev. of Accuracy	3%	1.2%	3.7%

Table 4-10 Summary of performance results.

One main observation from Table 4-10 is that the heuristic model has the tendency to perform better in terms of ordering costs and worst in terms of inventory holding costs. The heuristic in general places less orders than the optimal solution which results in more holding cost. It can hence be concluded that increasing the ordering cost would increase the performance of the model and decreasing the ordering cost may decrease its performance.

To evaluate the effect of expanding the time horizon, the same analysis was conducted on the above samples while the time horizon was increased from one month to two months (the detailed table can be found in appendix B). The following are some of the main observations:

- The average relative gap for GAMS for the above 30 samples will increase from 2.9 to 9.3 for the termination time of 300 seconds.
- The average accuracy for a heuristic will drop to 96%, from 97%, which still could be considered as accurate.
- On average for a two month period the total inventory holding cost decreases when the time horizon is expanded (18% decrease in CPLEX and 16% decrease in heuristic). It shows how the effect of opening and closing inventory is fading by increasing the time horizon. Surprisingly for some of the samples even the total cost will decrease when the time horizon is expanded.

To investigate the effect of different generated samples on the performance of the heuristic model we introduce a parameter denoted by T as

$$T = A_i * V_i * PV_i$$

which represents the multiplication of usage, price and volume of each item i . We observed that the standard deviation of T has a negative correlation (-0.71) with the accuracy of the heuristic model. It suggests that having high usage, expensive, bulky items as well as low usage, cheap, small items at the same time has a negative impact on the performance of the heuristic model.

4.6 Further implementation

As discussed at the start of this chapter, we piloted the dialysis department to create and test the optimization model but the same approach can be employed for different sections of the hospital. Although all different sections should be fairly similar to the dialysis department there are still some important points to factor in.

- Demand analysis may vary from one department to another. The dialysis department was identified to have a steady demand with a small variance but other units do not necessarily follow the same pattern. For instance seasonality may play a role for the demand of the items in the emergency department and consequently more rigorous analysis should be performed to estimate their demand. The accuracy of the analysis is also important. If any of the departments use the electronic medical record system to issue different supplies to the patients the demand analysis will be based on more accurate information, hence resulting in a more realistic schedule.
- Alternative items may also play a more important role in the analysis if a department commonly uses the alternative supply. As an example it may be more affordable for a department to use a 200 milligram supply for a patient that needs 100 milligram and discard the rest of the bottle instead of using two 50 milligram supply for the same patient. Therefore a different approach on the demand analysis should be undertaken in the case of alternative supplies.
- Different departments may have different procedures in terms of delivery and timing of the orders and methods of delivery. For instance the operating room may

prefer a shorter time horizon since most of the items are extremely expensive and the department does not want to order those items unless an operation has been scheduled already.

Chapter 5

Conclusion and Future Work

5.1 Thesis Summary

In this thesis we have reviewed a hospital supply chain management system and proposed a lean purchasing optimization model to improve its efficiency. We started by discussing some of the motivations behind this study and comparing traditional and modern approaches in hospital supply chain systems. We then reviewed the relevant literature regarding hospital inventory management systems, including single-level single-resource multi-product capacitated lot sizing optimization. Since we focused our study on a selected hospital, we provided a background on the hospital being studied and evaluated current hospital practice by mapping out all the supply chain related processes and identifying appropriate key performance indicators (KPIs) to assess the current hospital operations. A mixed integer programming (MIP) model to optimize procurement and inventory management was then proposed. Utilizing CPLEX we obtained the exact solution to the problem using real data from the hospital. To overcome the complexity of implementing a MIP model in a hospital setting, we developed a heuristic algorithm and presented numerical computations to test its performance on realistically generated data. A visual basic application was developed in Excel to automate the steps of heuristic model and facilitate the implementation. Finally, the performance of the heuristic model was tested against the exact solution.

5.2 Future Work

The key component of this thesis is the MIP model proposed to optimize the procurement and inventory systems. To develop the model we piloted the dialysis department at the subjected hospital and made several assumptions based on the characteristics of the pilot. Since the logistic and purchasing department provides services to all the hospital's units, identifying the characteristics of different units and implementing the model for all of these makes the model more realistic.

It should be considered that a transportation cart may be able to deliver supplies to different units on each trip. Therefore optimizing the schedule of the deliveries for the whole hospital would be beneficial.

Applying simulation techniques will reveal useful information regarding the number of required transportation carts for a hospital and also the timing and the path of each cart. This kind of information can be helpful for designing a hospital as well as implementing an optimized and modern supply chain system in the hospital setting.

References:

- [1] Eysenbach, G. (2001, June 18). What is e-health. . Retrieved July 2, 2014, from <http://www.jmir.org/2001/2/e20/>
- [2] Oh, H., Rizo, C., Enkin, M., & Jadad, A. (2005, February 24). What Is eHealth (3): A Systematic Review of Published Definitions. . Retrieved July 1, 2014, from <http://www.jmir.org/2005/1/e1/>
- [3] Oxley, H., MacFarlan, M., & Gerdtham, U. G. (1994). Health care reform: controlling spending and increasing efficiency (Vol. 149). Paris: OECD.
- [4] The digital hospital evolution Creating a framework for the healthcare system of the future. (2013, April 1). . Retrieved July 2, 2014, from <http://www.himss.eu/sites/default/files/IBM%20Digital%20Hospital%20Evolution%20GBW03203-USEN-00.pdf>
- [5] Hollingsworth, B., Dawson, P. J., & Maniadakis, N. (1999). Efficiency measurement of health care: a review of non-parametric methods and applications. *Health care management science*, 2(3), 161-172.
- [6] Landry, S., & Beaulieu, M. (2013). The challenges of hospital supply chain management, from central stores to nursing units. In *Handbook of Healthcare Operations Management* (pp. 465-482). Springer New York.
- [7] Jones, D. (2009). Hospital CEOs manage staff time, inventory to cut costs. *USA Today Online*, September, 10.
- [8] Munshi, S. (n.d.). Health Spending Projections through 2015: Changes on the horizon. *Health Spending Projections through 2015: Changes on the horizon* - . Retrieved July 2, 2014, from <http://www.hmgglobal.com/knowledge-bank/articles/health-spending-projections-through-2015-changes-on-the-horizon>
- [9] The Changing demographic structure. (2013, May 22). *Web Experience Toolkit*. Retrieved July 2, 2014, from <http://www.horizons.gc.ca/eng/content/changing-demographic-structure>
- [10] Facts and figures. (2014, June 23). Government du Canada, Citoyenneté et Immigration Canada, Communications. Retrieved July 2, 2014, from <http://www.cic.gc.ca/english/resources/statistics/menu-fact.asp>

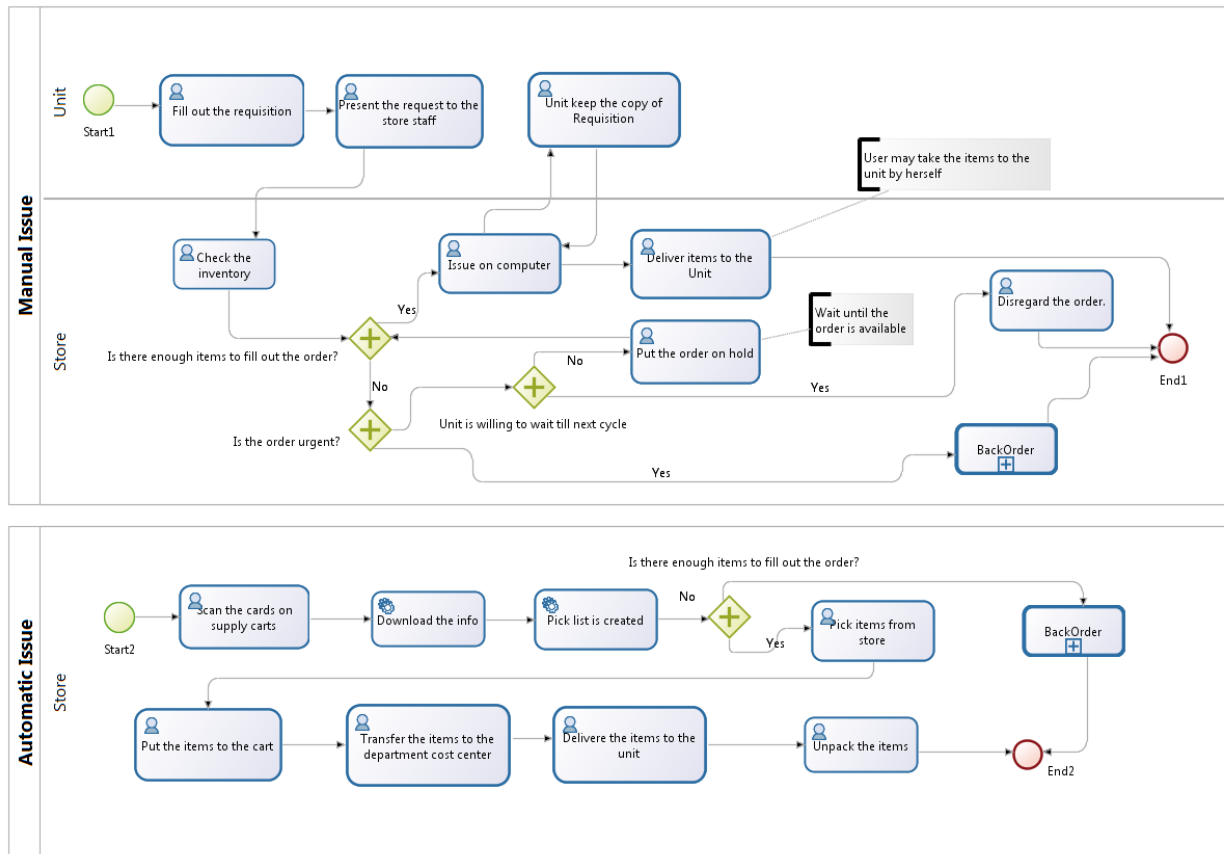
- [11] Boyle, T. (2013, May 2). Ontario budget will see more hospital downsizing and community upsizing, health minister says. *Thestar.com*.
- [12] How do new technologies impact on workforce organisation?. (2011, August 1). . Retrieved July 2, 2014, from http://www.skillsforhealth.org.uk/component/docman/doc_view/1834-how-do-new-technologies-impact-on-workforce-organiastion-082011.html
- [13] Our Redevelopment. (2014, January 1). HRH. Retrieved July 2, 2014, from <http://www.hrh.ca/redevelopmentobjective>
- [14] Nachtmann, H., & Pohl, E. A. (2009). The state of health care logistics: cost and quality improvement opportunities. Center for Innovation in Health care Logistics, Arkansas.
- [15] McKone-Sweet, K. E., Hamilton, P., & Willis, S. B. (2005). The ailing healthcare supply chain: A prescription for change. *Journal of Supply Chain Management*, 41(1), 4-14.
- [16] Rivard-Royer, H., Landry, S., & Beaulieu, M. (2002). Hybrid stockless: A case study: Lessons for health-care supply chain integration. *International Journal of Operations & Production Management*, 22(4), 412-424.
- [17] Burt, T. (2006). Seeing the future: Innovative supply chain management strategies. *Healthcare Executive*, 21(1), 16-6.
- [18] Supply Chain Modernization in Ontario Health Care: Improving Patient Care, Enhancing Service Levels and Reducing Costs: a Report on the E-supply Chain Project. (2007) Ontario Ministry of Finance,.
- [19] Rodrigue, J., & Notteboom, T. (2013). Containerized Freight Distribution in North America and Europe. *Handbook of global logistics transportation in international supply chains* (). New York, NY: Springer.
- [20] Keeping the Patient First A Dialogue with Suppliers. (2011, January 1). . Retrieved July 2, 2014, from http://www.hscn.org/Data/Sites/1/conferencearchives/2011/hscn_2011_keeping_the_patient_first-mark_fam_and_panel.pdf
- [21] Neil, R. (2004, February). The ups and downs of inventory management. *Materials Management in Health Care*, 13(2), 22-26.
- [22] Karimi, B., Fatemi Ghomi, S. M. T., & Wilson, J. M. (2003). The capacitated lot sizing problem: a review of models and algorithms. *Omega*, 31(5), 365-378.
- [23] Downs, B., Metters, R., & Semple, J. (2001). Managing inventory with multiple products, lags in delivery, resource constraints, and lost sales: A mathematical programming approach. *Management Science*, 47(3), 464-479.

- [24] Lapierre, S. D., & Ruiz, A. B. (2007). Scheduling logistic activities to improve hospital supply systems. *Computers & Operations Research*, 34(3), 624-641.
- [25] Little, J., & Coughlan, B. (2008). Optimal inventory policy within hospital space constraints. *Health care management science*, 11(2), 177-183.
- [26] Bijvank, M., & Vis, I. F. (2012). Inventory control for point-of-use locations in hospitals. *Journal of the Operational Research Society*, 63(4), 497-510.
- [27] Dixon, P. S., & Silver, E. A. (1981). A heuristic solution procedure for the multi-item, single-level, limited capacity, lot-sizing problem. *Journal of Operations Management*, 2(1), 23-39.
- [28] Maes, J., & Van Wassenhove, L. N. (1986b). Multi item single level capacitated dynamic lotsizing heuristics: A computational comparison (Part I: Static case). *IIIE transactions*, 18(2), 114-123.
- [29] Maes, J., & Van Wassenhove, L. N. (1986a). A simple heuristic for the multi item single level capacitated lotsizing problem. *Operations Research Letters*, 4(6), 265-273.
- [30] Lambrecht, 41. R., and Vanderveken, H., "Heuristic Procedure for the Single Operation Multi-Item Loading Problem", *AIIE Transactions*, Vol. II, No. 4, December 1979, pp. 319-326
- [31] Dogramaci, A., Panayiotopoulos, J. E., and Adam, N. R., "The Dynamic Lot Sizing Problem for Multiple Items under Limited Capacity", *AIIE Transactions* Vol. 13, No. 4, December 1981, pp. 294-303
- [32] Iannone, R., Lambiase, A., Miranda, S., Riemma, S., & Sarno, D. (2013). Modelling hospital materials management processes. *Int J Eng Bus Manag*, 2013, 5-15
- [33] Anderson, C. (2009). What is a Process Map, Bizmanualz
- [34] Landry, S., & Beaulieu, M. (2013). The challenges of hospital supply chain management, from central stores to nursing units. In *Handbook of Healthcare Operations Management* (pp. 465-482). Springer New York.
- [35] Koprowski, T. L. (1987). Computers in materiel [sic] management: A case study for the administrator. *Hospital Materiel Management Quarterly*, 8(3), 24.
- [36] Porteus, E. L. (1985). Numerical comparisons of inventory policies for periodic review systems. *Operations Research*, 33(1), 134-152.
- [37] Performance Measurement A Report by the Hospital Supply Chain Metrics Working Group. (2006, August). . Retrieved July 2, 2014, from [https://www.doingbusiness.mgs.gov.on.ca/mbs/psb/psb.nsf/attachments/bpsbperformance-metrics-report-pdf-eng/\\$file/bpsbperformancemetrics-report-eng.pdf](https://www.doingbusiness.mgs.gov.on.ca/mbs/psb/psb.nsf/attachments/bpsbperformance-metrics-report-pdf-eng/$file/bpsbperformancemetrics-report-eng.pdf)
- [38] Performance Measurement Phase II — A Framework for Action. (2009, January). . Retrieved July 2, 2014, from [https://www.doingbusiness.mgs.gov.on.ca/mbs/psb/psb.nsf/attachments/bpsbperformance-metrics-report-pdf-eng/\\$file/bpsbperformancemetrics-report-eng.pdf](https://www.doingbusiness.mgs.gov.on.ca/mbs/psb/psb.nsf/attachments/bpsbperformance-metrics-report-pdf-eng/$file/bpsbperformancemetrics-report-eng.pdf)
- [39] Higgins, J. M., & Mcallaster, C. (2004). If you want strategic change, don't forget to change your cultural artifacts. *Journal of Change Management*, 4(1), 63-73.
- [40] Oliveira, J., & Nightingale, D. (2007). Adaptable enterprise architecture and long term value added partnerships in healthcare.
- [41] Perla, L. (2002). The future roles of nurses. *Journal for Nurses in Professional Development*, 18(4), 194-197.

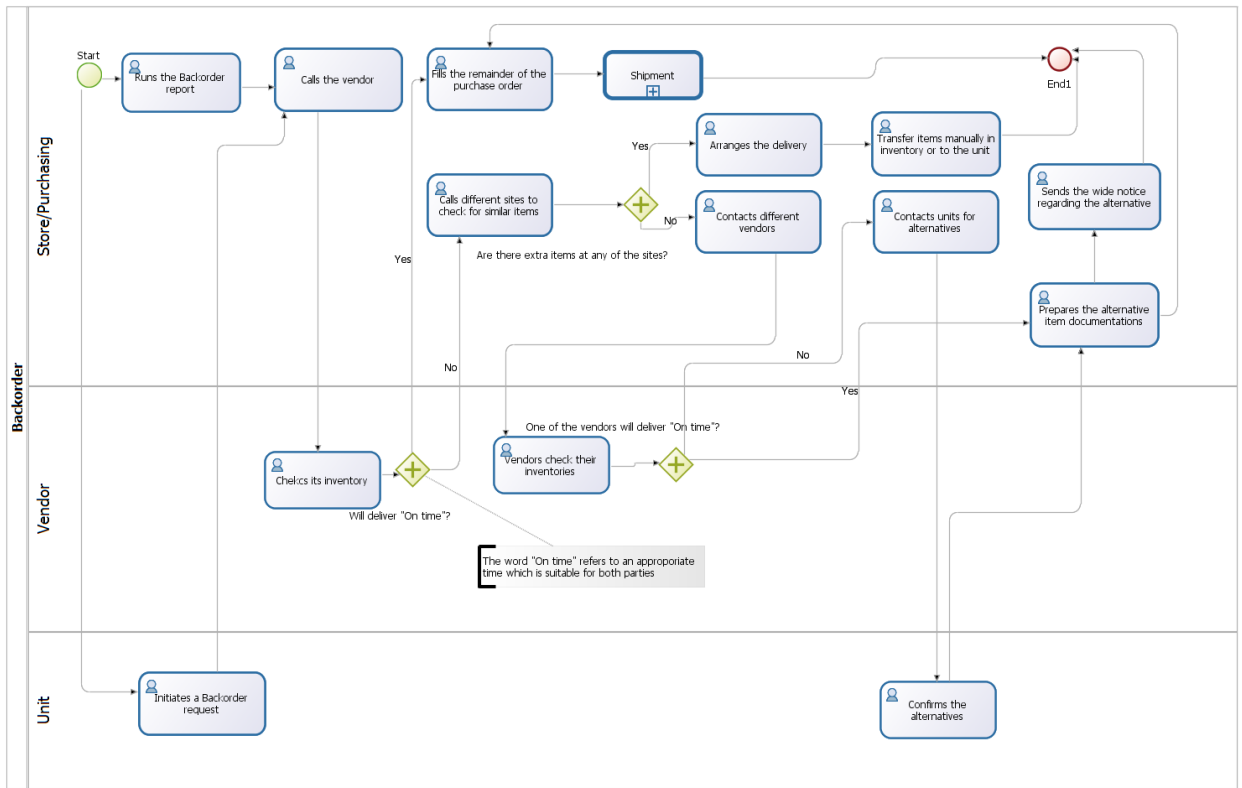
- [42] Bowers, B., Nolet, K., Roberts, T., & Esmond, S. (2007). Implementing change in long-term care: A practical guide to transformation.
- [43] Chopra, S., & Meindl, P. (2010). Supply chain management: strategy, planning, and operation (4th ed.). Boston: Prentice Hall.
- [44] Silver, E. A. (1974). A control system for coordinated inventory replenishment. *International Journal of Production Research*, 12(6), 647-671.
- [45] Goyal, S. K., & Satir, A. T. (1989). Joint replenishment inventory control: deterministic and stochastic models. *European Journal of Operational Research*, 38(1), 2-13.

Appendix A:

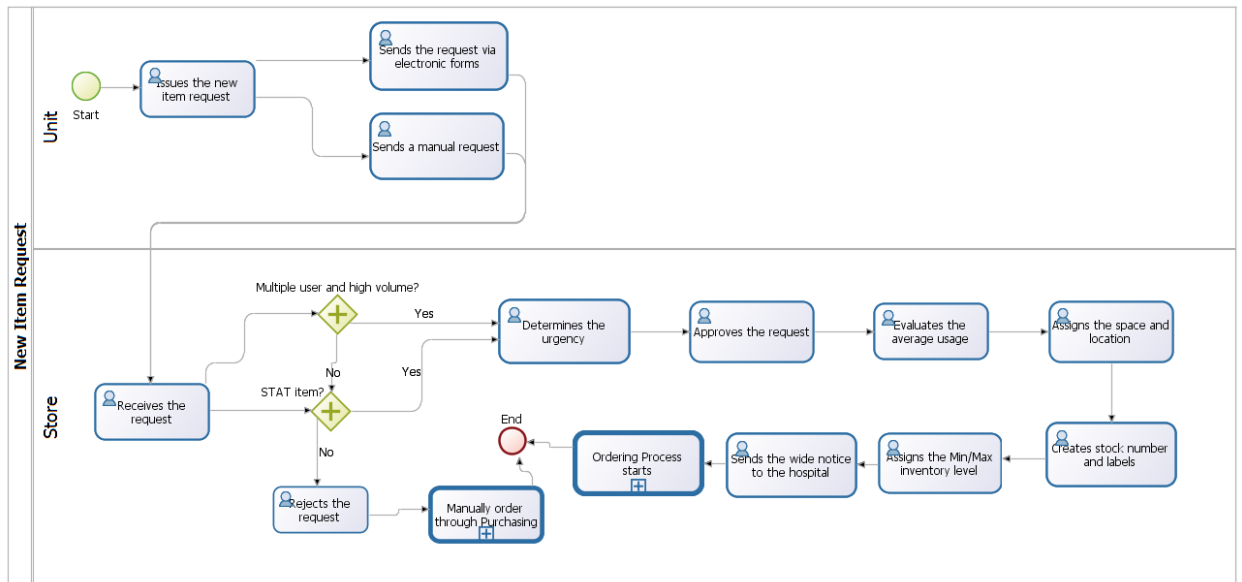
This appendix contains the process diagrams for all the main processes performed by the Logistics and Purchasing Department.



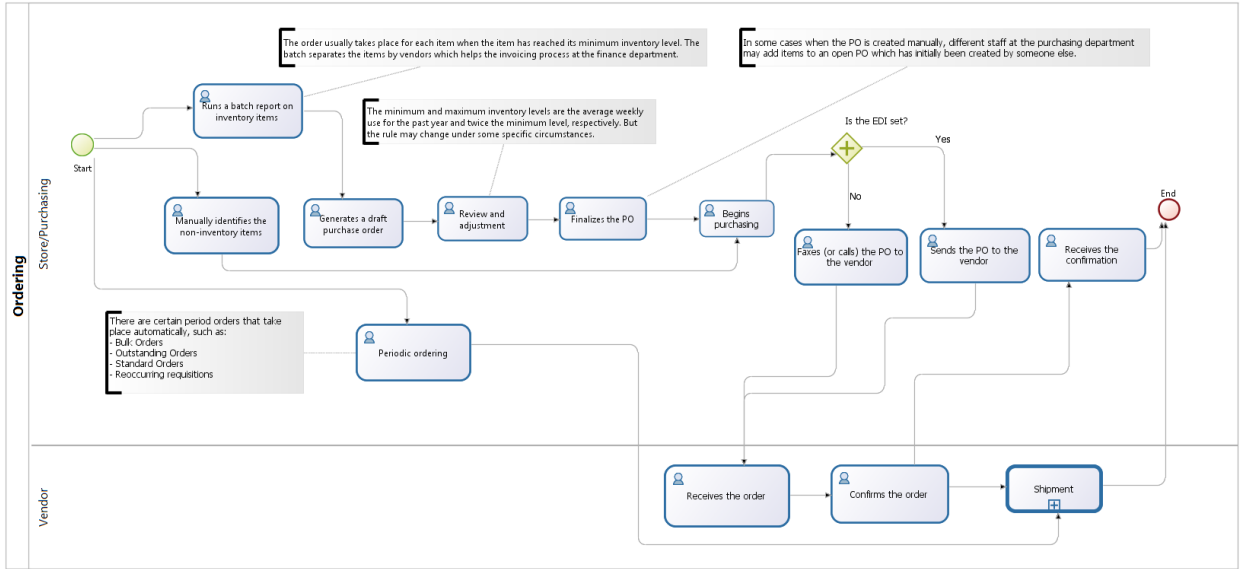
Appendix A- Figure 1: The map for the process of issuing items to the department through a requisition



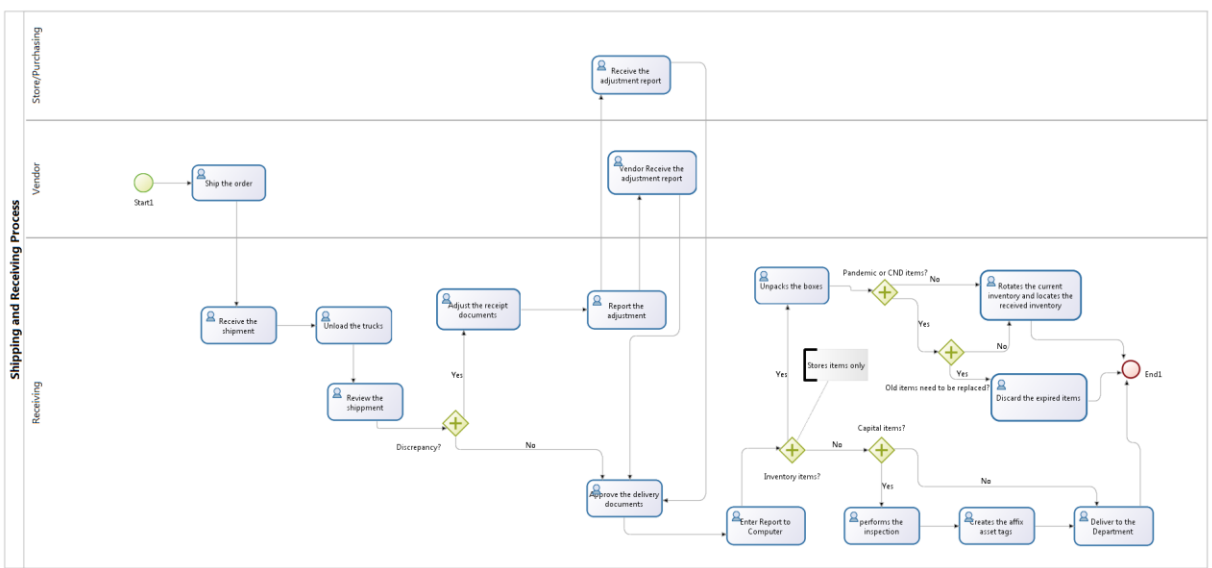
Appendix A- Figure 2: The map for the process of dealing with backordered items



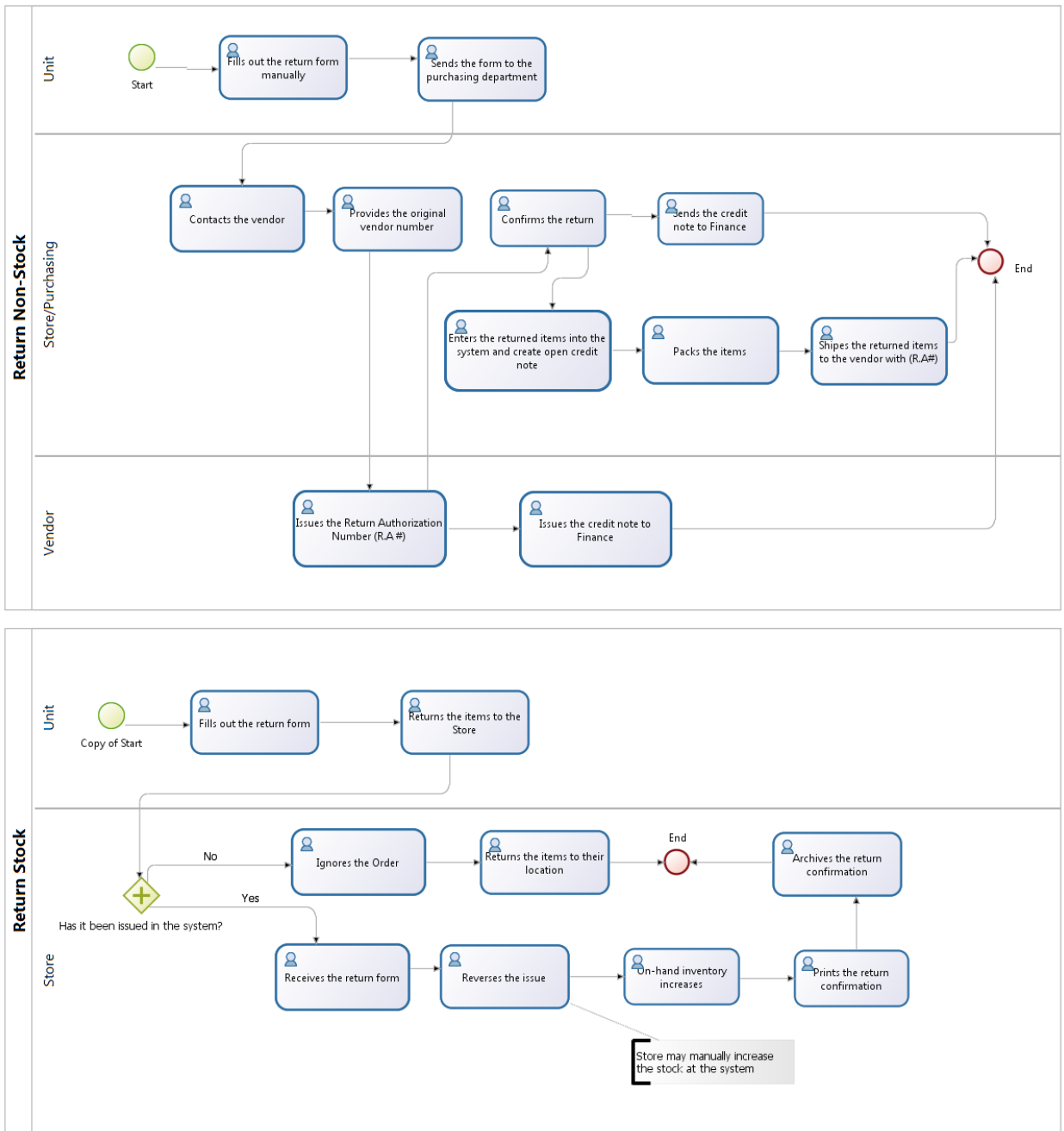
Appendix A- Figure 3: The map for the process of dealing with new item requests



Appendix A- Figure 4: The map for the process of ordering items



Appendix A- Figure 5: The map for the shipping and receiving process



Appendix A- Figure 6: The map for the process of dealing with returned items

Appendix B

Optimization Model: Data and Results

Item #	Description	items in PKG	Size Category	PKG Value	Daily usage	Safety Stock
1		1	0	\$ 0.04	76	248
2		12	2	\$ 15.75	33	107
3		30	3	\$ 9.60	26.5	85
4		1	0	\$ 0.46	20	64
5		100	2	\$ 2.95	15	48
6		25	2	\$ 26.65	12	38
7		1	2	\$ 0.30	10.5	34
8		1	2	\$ 0.90	10.5	34
9		18	4	\$ 162.00	10	33
10		4	2	\$ 4.98	8	26
11		200	3	\$ 11.51	7.5	24
12		12	4	\$ 135.00	7.5	23
13		200	3	\$ 11.51	6.5	21
14		100	2	\$ 11.50	6.5	21
15		1	0	\$ 0.13	6	19
16		100	3	\$ 8.91	5	16
17		12	4	\$ 138.00	4.5	14
18		50	2	\$ 3.41	4	13
19		96	2	\$ 7.82	3.5	11
20		200	3	\$ 11.51	3.5	10
21		50	2	\$ 20.00	3	9
22		1	2	\$ 0.10	3	9
23		100	2	\$ 8.22	3	9
24		1	2	\$ 7.25	2.5	8
25		100	2	\$ 130.18	2.5	7
26		24	3	\$ 87.39	2.5	7
27		1	2	\$ 6.00	2.5	7
28		1	4	\$ 7.30	2.5	7
29		12	2	\$ 4.20	2.5	7
30		100	3	\$ 3.01	2	6
31		1	2	\$ 1.19	2	6
32		200	2	\$ 1.40	2	6
33		50	3	\$ 32.18	2	6
34		100	2	\$ 15.14	2	6
35		1	2	\$ 1.10	2	6
36		1	2	\$ 6.05	2	5
37		50	3	\$ 32.18	1.5	5
38		1	2	\$ 4.42	1.5	5
39		48	2	\$ 10.40	1.5	4
40		24	4	\$ 572.87	1.5	4
41		100	3	\$ 3.16	1.5	4
42		50	4	\$ 12.49	1.5	4
43		100	2	\$ 1.30	1	3
44		48	4	\$ 83.52	1	3
45		1	0	\$ 0.27	1	3
46		1	0	\$ 0.28	1	3
47		33	3	\$ 33.00	1	3
48		50	2	\$ 71.07	1	3

49		33	3	\$ 33.00	1	3
50		1	2	\$ 6.90	1	3
51		24	4	\$ 240.00	1	3
52		1	3	\$ 0.43	1	3
53		100	3	\$ 3.04	1	3
54		1	0	\$ 4.45	1	2
55		1	2	\$ 1.20	1	2
56		1	0	\$ 0.70	1	2
57		1	0	\$ 0.10	1	2
58		1	4	\$ 11.71	1	2
59		1	0	\$ 0.01	1	2
60		24	4	\$ 672.74	0.5	1
61		100	2	\$ 18.10	0.5	1
62		25	2	\$ 5.94	0.5	1
63		126	3	\$ 5.76	0.5	1
64		100	2	\$ 18.80	0.5	1
65		25	2	\$ 11.35	0.5	1
66		1	2	\$ 4.19	0.5	1
67		100	2	\$ 8.08	0.5	1
68		4	2	\$ 4.97	0.5	1
69		100	0	\$ 10.36	0.5	1
70		250	4	\$ 9.97	0.5	1
71		50	3	\$ 17.50	0.5	1
72		250	3	\$ 45.00	0.5	1
73		1	0	\$ 0.72	0.5	1
74		1	2	\$ 1.91	0.5	1
75		100	0	\$ 45.00	0.5	1
76		24	4	\$ 384.00	0.5	1
77		1	2	\$ 0.45	0.5	1
78		1	2	\$ 1.38	0.5	1
79		1	2	\$ 25.00	0.5	1
80		100	0	\$ 1.11	0.5	1
81		200	3	\$ 10.60	0.5	1
82		5	2	\$ 8.80	0.5	1
83		1	0	\$ 2.75	0.5	1
84		1	0	\$ 8.44	0.5	0.5
85		1000	4	\$ 14.31	0.5	0.5
86		1	2	\$ 1.39	0.5	0.5
87		1	2	\$ 0.46	0.5	0.5
88		120	2	\$ 63.60	0.5	0.5
89		100	3	\$ 117.07	0.5	0.5
90		1	3	\$ 47.20	0.5	0.5
91		1	0	\$ 1.00	0.5	0.5
92		1	0	\$ 0.25	0.5	0.5
93		5000	4	\$ 34.00	0.5	0.5
94		12	2	\$ 1.63	0.5	0.5
95		100	3	\$ 3.16	0.5	0.5
96		1	2	\$ 2.75	0.5	0.5
97		180	3	\$ 11.51	0.5	0.5
98		56	3	\$ 13.99	0.5	0.5
99		50	3	\$ 32.18	0.5	0.5
100		100	3	\$ 34.84	0.5	0.5

Table B-1: The list of all the items with their PKG size, Volume category, Daily usage, Value and safety stock

Item	Item Descriptions	Group	Ordering days during the one month period											
			M	W	F	M	W	F	M	W	F	M	W	F
1		Lab	836						1140					
2		IV Solutions	33	66	66	66	66	66	66	66	66	66	66	165

3		Syringes	25	53	53	53	53	53	53	53	53	53	187	
4		General Supply	140				200					180		
5		Wound Care	45		60		60		60		60		105	
6		Dialysis	12	24	24	24	24	24	24	24	24	24	24	60
7		General Care	114						159					
8		General Care	72				105					96		
9		General Care	10	20	20	20	20	20	20	20	20	20	20	50
10		IV Solutions	40			48			32		32		56	
11		Glove	21		15	15	30		15	30		15	54	
12		Dialysis	6	15	15	15	15	15	15	15	15	15	15	39
13		Glove	5	26		26		13	13	26		26		34
14		General Care	5	26		13	26		13	26		26		34
15		General Care	156											
16		Syringes	15		20		20		20		20		35	
17		Dialysis	3	9	9	9	9	9	9	9	9	9	9	24
18		N95	20			24			32				28	
19		General Care	16			21			21			14		19
20		Glove	16			21			14		14		26	
21		General Care	9		12		12		12		6	12		15
22		General Care	78											
23		Syringes	15			18			18			12		15
24		General Care	11			15			20				19	
25		Syringes	1	5	5	5	5	5	5	5	5	5	5	14
26		Dialysis	1	5	5	5	5	5	5	5	5	5	5	14
27		Wound Care	11			15			20				19	
28		General Care	11			15			20				19	
29		Wound Care	16				25					24		
30		Glove	22						30					
31		IV Solutions	22						30					
32		General Care	22						30					
33		Syringes	2	8		8		8		8		8		10
34		Wound Care	10			12			12			8		10
35		IV Solutions	22						30					
36		Lab	14				20					18		
37		Syringes		6		6		6		6		6		9
38		Lab		15					12				12	
39		Syringes		9			9			9			12	
40		Dialysis	3	3	3	3	3	3	3	3	3	3	3	9
41		Glove		18						21				
42		N95		6		9			12				12	
43		Wound Care	26											
44		Med Lines	3		2	2	4		2	4		2	7	
45		General Supply	26											
46		General Supply	26											
47		Dialysis	5			6			6			4		5
48		Wound Care	3		2	4		4		4		4		5
49		Dialysis	5			6			4		4		7	
50		Med Lines	7				10					9		
51		Dialysis	1	2	2	2	2	2	2	2	2	2	2	5
52		General Care	26											
53		Glove	11						15					
54		Med Lines	11						15					
55		Wound Care	26											
56		General Supply	26											
57		Wound Care	26											
58		O2 Tanks	7				10					9		
59		General Care	26											
60		Dialysis			1	1	1	1	1	1	1	1	1	4
61		Lab			4				4				5	
62		Lab			7							6		
63		N95			7							6		
64		Lab			4				4				5	
65		IV Solutions			7							6		

\$ 109,338	\$ 61,072	\$ 48,266	\$ 111,832	\$ 58,124	\$ 53,708	98%	105%	90%	11.48
\$ 136,145	\$ 53,460	\$ 82,685	\$ 140,848	\$ 54,604	\$ 86,244	97%	98%	96%	10.41
\$ 174,874	\$ 57,376	\$ 117,498	\$ 183,530	\$ 56,188	\$ 127,342	95%	102%	92%	7.93
\$ 175,103	\$ 70,488	\$ 104,615	\$ 179,192	\$ 71,280	\$ 107,912	98%	99%	97%	6.34
\$ 131,099	\$ 61,776	\$ 69,323	\$ 133,286	\$ 63,360	\$ 69,926	98%	98%	99%	8.83
\$ 124,865	\$ 53,416	\$ 71,449	\$ 127,100	\$ 53,548	\$ 73,552	98%	100%	97%	11.67
\$ 189,465	\$ 62,480	\$ 126,985	\$ 193,346	\$ 62,964	\$ 130,382	98%	99%	97%	6.03
\$ 163,418	\$ 61,204	\$ 102,214	\$ 175,378	\$ 59,664	\$ 115,714	93%	103%	88%	7.62
\$ 130,038	\$ 61,776	\$ 68,262	\$ 152,047	\$ 59,796	\$ 92,251	86%	103%	74%	9.75
\$ 129,999	\$ 61,600	\$ 68,399	\$ 132,697	\$ 60,632	\$ 72,065	98%	102%	95%	9.73
\$ 126,082	\$ 56,188	\$ 69,894	\$ 127,849	\$ 58,124	\$ 69,725	99%	97%	100%	10.52
\$ 183,504	\$ 64,856	\$ 118,648	\$ 189,719	\$ 65,692	\$ 124,027	97%	99%	96%	6.39
\$ 143,189	\$ 60,764	\$ 82,425	\$ 145,199	\$ 61,556	\$ 83,643	99%	99%	99%	8.37
\$ 141,488	\$ 65,252	\$ 76,236	\$ 144,817	\$ 66,440	\$ 78,377	98%	98%	97%	6.37
\$ 183,430	\$ 63,052	\$ 120,378	\$ 186,074	\$ 63,624	\$ 122,450	99%	99%	98%	6.53
\$ 96,163	\$ 52,052	\$ 44,111	\$ 97,536	\$ 52,536	\$ 45,000	99%	99%	98%	12.27
\$ 166,819	\$ 64,768	\$ 102,051	\$ 181,107	\$ 65,912	\$ 115,195	92%	98%	89%	7.06
\$ 123,728	\$ 59,796	\$ 63,932	\$ 127,974	\$ 60,808	\$ 67,166	97%	98%	95%	10.41
\$ 90,832	\$ 52,712	\$ 38,120	\$ 93,863	\$ 52,976	\$ 40,887	97%	100%	93%	11.83
\$ 89,440	\$ 53,460	\$ 35,980	\$ 92,382	\$ 55,308	\$ 37,074	97%	97%	97%	15.72
\$ 139,644	\$ 60,676	\$ 78,968	\$ 144,471	\$ 62,480	\$ 81,991	97%	97%	96%	9.3

Table B-3 Comparison between the performances of exact solution vs. heuristic solution for a two month time horizon.

Appendix C

GAMS code

* Optimization model to find the best ordering practice

Set

 i items

 j days ;

\$Call 'Gdxxrw i=D:\Users\mabdi\Desktop\Data\DialysisData.XLSM skipempty=0 trace=2
index=Index!A1'

\$GDXIN DialysisData.gdx

\$Load i j

Option Optca = 0.001;

Option Optcr = 0.01;

Option Reslim = 1000;

Parameters

 A(i) Average daily usage i in cases

 V(i) Price Value of i in cases

 PV(i) Package Volume of i in cases

 s(j) Inventory carrying weight

 Maxim(i) Maximum daily order

Result

 C1

 C2

 C3

 Optimum

 OrderingPrac

 AvaSpac

 AveDItem

TRansCarts;

Scalar

AS Constant Availabe space

M A Large Number

OC Ordering Cost

OP Ordering Percentage

Alpha Inventory hoding cost percentage

N Number of days of supplies for Opening Inventory

TrCrV Transportation Cart Volume

TrTC Transportation Trip Cost;

\$Load A V PV AS M OC OP Alpha s N Maxim TrCrV TrTC

\$GDXIN

scalar starttime;

starttime = jnow;

display A;

Parameter

OI(i) Opening Inventory

U(i) Opening Inventory;

$OI(i) = N * \text{round}(A(i),0) ;$

$U(i) = \text{card}(j) * \text{round}(A(i),0);$

Variables

X(i,j) Number of packages ordered each day

D(i,j) Binary decesion variables for ordering decesion

PI(i,j) Physical inventory

TC Total Inventory cost

TC1 Ordering Cost

TC2 Inventory Cost

TC3 Transportation Cost

AI Average Number of Items ordered each day

Z Number of transportation carts;

Integer Variable X;

Binary Variable D ;

Positive variable Z,PI;

PI.lo(i,'1')=OI(i);

PI.up(i,'1')=OI(i);

X.up(i,j)=2000\$(ord(j)<>1);

Equations

ordering(i,j) ordering condition

physicInv (i,j) physical inventory

cost1 ordering Cost

cost2 inventory cost

cost3 transportation cost

cost define objective function

BestPractice(j) following the best practice for each j

endinv(i,j) ending Inv

space (j) to guarantee the space availability for each j

AverageItems

TraCondition(j)

MaximumDO(i,j);

ordering(i,j)\$(ord(j)<>1) .. X(i,j) =I= M*D(i,j) ;

physicInv(i,j)\$(ord(j)<>1) .. PI(i,j)=e=X(i,j)-2*A(i)+ PI(i,j-1);

cost1.. TC1 =e= OC*sum((i,j)\$(ord(j) <> 1), D(i,j));

cost2.. TC2 =e= Alpha*(sum (j\$(ord(j)<>1),s(j)*sum(i,V(i)*PI(i,j)\$(ord(j)<>1))));

cost3.. TC3 =e= Z*TrTc;

cost .. TC =e= TC1+TC2+TC3 ;

BestPractice(j)\$(ord(j)<>1) .. sum(i, D(i,j)) =I= round(OP*card(i),0) ;

endinv(i,j)\$(ord(j) eq card(j)) .. PI(i,j)=g= OI(i);

space (j)\$(ord(j)<>1) .. sum(i, X(i,j)*PV(i)) =I= AS ;

```

AverageItems.. AI =e= TC1/(OC*card(i)*(card(j)-1));
TraCondition (j)$ (ord(j)<>1).. Z*TrCrV =g=sum(i, X(i,j)*PV(i));
MaximumDO(i,j).. X(i,j)=I=Maxim(i);
MODEL Dialysis /all/
Solve Dialysis using mip minimizing TC ;
Optimum('Optimal TC')=TC.L;
Result('Item',I,J)=X.L(I,J);
C1('Ordering Cost')=TC1.L;
C2('Inventory Cost')=TC2.L;
C3('Transportation Cost')=TC3.L;
OrderingPrac('Best Practice')=OP;
AvaSpac('Max daily delivery')=AS;
AveDItem('Ave Daily Item')=AI.L;
TRansCarts ('Number of Trips')=Z.L;
scalar elapsed; elapsed = (jnow - starttime)*24*3600;
display elapsed;
Execute_Unload
'GDX.gdx'Optimum,Result,C1,C2,C3,OrderingPrac,AvaSpac,AveDItem,TRansCarts,A,V,PV;
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=Optimum
RNG=Result!A1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=C1
RNG=Result!B1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=C2
RNG=Result!C1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=C3
RNG=Result!D1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=OrderingPrac
RNG=Result!E1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=AvaSpac
RNG=Result!F1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=AveDItem
RNG=Result!G1'
Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=TRansCarts
RNG=Result!H1'

```

Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=Result
RNG=Result!A5'

Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=P
V
RNG=Result!Q1'

Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=V
RNG=Result!Q3'

Execute 'Gdxxrw I=GDX.gdx O=D:\Users\mabdi\Desktop\Data\DialysisData.XLS Par=A
RNG=Result!Q5'

Execute '=shellExecute D:\Users\mabdi\Desktop\Data\DialysisData.XLS';