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Improving healthcare supply chains and decision making in the management of pharmaceuticals

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**IMPROVING HEALTHCARE SUPPLY CHAINS AND DECISION MAKING IN THE
MANAGEMENT OF PHARMACEUTICALS**

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Interdepartmental Program in Business Administration
(Information Systems and Decision Sciences)

by

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May 2009

DEDICATION

This work is dedicated to my family, especially...

to my fiancé, Amanda, for her love, support, patience, and friendship all of which make me a stronger person and a better man;

to my parents, Barbara and Dwight, for teaching the value of hard work and for giving me their unyielding support, encouragement, and love which helped me become the man I am today and without which none of this would have been possible;

to my brother, Robert, for challenging me and helping me find my path in life;

to my niece, Madilyn, for being so very special and always reminding me what is truly important; and

to Pogo and Tiger for reminding me when to stop working.

.

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Dr. Peter Kelle is a scholar and a gentleman, and I consider it an honor and a privilege to have him serve as my advisor. He provided advice, guidance, and motivation necessary to keep me focused and on my path. I will always be grateful for his commitment to helping me complete of this work and my degree. More importantly, I am lucky to call him a friend.

Dr. Helmut Schneider has my sincerest gratitude for giving me the opportunity to join the ISDS Department and to pursue this degree. I appreciate the confidence you have shown in me over the years and will always value the experience I gained from working with you. I could not have asked for a better mentor.

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ABSTRACT

The rising cost of quality healthcare is becoming an increasing concern. A significant part of healthcare cost is the pharmaceutical supply component. Improving healthcare supply chains is critical not only because of the financial magnitude but also because of the fact that it impacts so many people. Efforts such as this project are essential in understanding the current operations of healthcare pharmacy systems and in offering decision support tools to managers struggling to make the best use of organizational resources.

The purpose of this study is to address the objectives of a local case hospital that are typical general problems in pharmacy supply chain management. We analyze the pharmacy supply network structure and the different, often conflicting goals in the decisions of the various stakeholders. We develop quantitative models useful in optimizing supply chain management and inventory management practices. We provide decision support tools that improve operational, tactical, and strategic decision making in the pharmacy supply chain and inventory management of pharmaceuticals.

On one hand, there is considerable progress to support pharmacy product distribution by advanced computerized technology that manages the dispensation of medications, and automates the ordering. On the other hand, the available information is not utilized to help the managers in making the appropriate decisions and control the supply chain management.

Quantitative methods are presented that based on the available data provide simplified, practical solutions to pharmacy objectives and serve as decision support tools. For the operational inventory decision we provide the min and max par levels (reorder point and order up to level) that control the automated ordering system for pharmaceuticals. These parameters are based on two near-optimal allocation policies of cycle stock and safety stock under storage space constraint. For the tactical decision we demonstrate the influence of varying inventory

holding cost rates on setting the optimal reorder point and order quantity for items. We present a strategic decision support tool to analyze the tradeoffs among the refill workload, the emergency workload, and the variety of drugs offered. We reveal the relationship of these tradeoffs to the three key performance indicators at a local care unit: the expected number of daily refills, the service level, and the storage space utilization.

CHAPTER 1: INTRODUCTION

A recent visit to a local emergency room (ER) motivated the author of this work to literally investigate the crucial element of supply chain management (SCM) within the healthcare system. After experiencing eight hours of delays in the ER waiting room and witnessing incredible lags in the medication dispensing process and even further impediments to the delivery of treatment modalities, the researcher became outraged with the thought of a high-performing healthcare system's lack of better supply chain management and service delivery. As a healthcare consumer, this scenario is likely to happen to all of us.

One might contemplate how an industry based on customer service falls short in the arena of inventory, patient and materials management? According to business researcher Vicki Smith-Daniels (2006) in a field where precision is literally a matter of life and death, it seems strange, that a crucial supportive function like inventory control and purchasing is often a hit-or-miss process. Healthcare, unlike other industries has not given supply chain management the detailed attention that it so rightly deserves and needs to ensure patient safety and reduce overall healthcare costs.

Inventory management in the healthcare industry presents several interesting challenges both from a managerial and operational perspective. The stakeholder relationships, product considerations, and managerial and regulatory policies typically seen in healthcare are unique and worth investigation. Before delving into specific inventory control issues or demand characteristics that make healthcare supply chain management (SCM) particularly difficult, it is important to recognize the magnitude of this industry.

1.1 Magnitude of Healthcare Industry and Impact of Pharmaceutical Costs

According to statistics published by the Centers for Medicare and Medicaid Services, healthcare spending topped \$2 trillion or 16% of its Gross Domestic Product (GDP) in the

United States in 2005 (Centers for Medicare and Medicaid Services 2007). In addition, this percentage is projected to increase to 18.7% in ten years (Heffler et al. 2005). Catlin et al. (2007) state that healthcare expenditures increased at an annual rate of 6.9%. In addition, there has been a shift from public to private healthcare financing in the United States, as well as other countries around the world. Most of these efforts are an attempt to continuously find new ways of both controlling healthcare expenditures and paying for prescribed treatments and pharmaceuticals.

Especially given the current economic crisis, a growing amount of attention is being given to the rising costs of healthcare and specifically pharmaceuticals. Healthcare providers, insurance companies, government agencies, and consumers alike are forced to address this issue and to explore alternative methods of cost reduction or cost containment (Marmor and Okma 1998; Jönsson and Musgrove 1997; Culyer 1990). To gain a better understanding of the significance of this issue, it is prudent to first identify the magnitude of healthcare expenditures. According to The Plunkett Research Group (2008), “The health care market in the U.S. in 2007 was made up of hospital care (about \$697.5 billion), physician and clinical services (\$474.2 billion), prescription drugs (\$229.5 billion), nursing home and home health (\$190.0 billion), and other items totaling \$668.8 billion.”

As shown above, the financial aspect of the healthcare and pharmaceutical industries is quite staggering. Much of the research in this field has focused on the relevant costs of healthcare (Castles 2004; Comas-Herrera 1999; OECD 1994; OECD 1995; OECD 1996); however, Rothgang et al. (2005) examined data reported by the Organization for Economic Co-operation and Development (OECD) from 1970 to 2002 to investigate trends in the level of governmental involvement with healthcare systems. Although some shifting has occurred over the years, convergence towards a mixed system of both public and private healthcare seems apparent.

A significant area of healthcare costs is the pharmaceutical area, which represents approximately ten percent of annual healthcare expenditures in the United States and about \$550 billion globally in 2007 (Plunkett Research 2008). Despite the size and importance of this industry around the world, especially in developed countries, the area of healthcare supply chain management (SCM) and inventory management has been given relatively little attention. Several researchers have estimated that inventory investments in healthcare range between 10% and 18% of total revenues (Holmgren and Wentz 1982; Jarrett 1998). Any measures taken to control expenditures in this area can have substantial impacts on the overall efficiency of the organization and its supply network and, as a result, the profitability of healthcare providers.

In 2003, Guillén and Cabiedes examined the pharmaceutical policies of European Union (E.U.) countries from the mid-1980s through the 1990s. As explained in their research, the costs of pharmaceuticals continue to increase while countries struggle to find financing to support these drugs. They noted that much of the healthcare services are shaped by the pharmaceutical policies, and they also identify three reasons justifying a focus on pharmaceuticals when examining healthcare supply chains: the reliance of modern medicine on drugs to both prevent and cure sickness; the significance of pharmaceutical expenditures around the world; and the pharmaceutical industry characteristics (i.e. use of technology, innovation, etc.). Almarsdóttir and Traulsen (2005) also identify a number of reasons why pharmaceuticals deserve extraordinary consideration in controlling inventory. These specific characteristics make the pharmaceutical industry a very powerful force in its own right.

As with any industry the range of products can vary tremendously depending on the market, customer demand, the scope of services, and other managerial decisions. For the purposes of this project and the specific research case presented, the focus is mainly on the supply chain of pharmaceuticals within the hospital.

1.2 Special Conditions and Terminology of Healthcare SCM

The stakeholders and their interrelationships, the product characteristics, and the policies employed all have some impact on the healthcare supply chain management and inventory control. An explanation of some specific conditions and terminology used in healthcare are discussed in more detail below.

- **Stakeholders**

Here is a brief summary of some unique factors influencing how healthcare stakeholders interact, how they are controlled, and how they manage operations. A detailed analysis is provided in the next section.

Doctors are the primary caregivers in the healthcare system; however, it is important to recognize that physicians, in many cases, are contracted service providers. They are not actual employees of hospitals in which they work. Although this enables hospitals to expand their service capacities and offer better customer service, they must also relinquish some measure of control to these doctors. Autonomy, as it relates specifically to customer care, is valued above all else by doctors. Patients trust that physicians are prescribing treatments and medicines that will address their individual medical needs. Attempts to restrict the choices or influence the conditions of medical treatment meet with a great deal of resistance.

Another consideration is that, unlike many industries of this size, **hospital administrators** and pharmacy managers have to manage very complicated distribution networks and inventory control problems without the proper training or educational backgrounds to do so efficiently. This in no way implies that these individuals lack the intelligence to perform these tasks. Most hospital administrators and pharmacy directors are themselves doctors, which means they are highly skilled and educated in medicine; however, they are not engineers or supply chain professionals that are commonly employed to manage similar systems in other industries.

The hospitals order the majority of the supply from a selected **group purchasing organization (GPO)** that purchases directly from the production companies.

- **Products**

The **product formulary** is the term used to identify the variety of drugs offered by the hospital pharmacy and is a source of both conflict and cost for the hospital. This formulary is comprised of specific medicines each designed to address a particular medical need, but physicians' opinions may vary on the most effective drugs at satisfying patient requirements. Providing prescription options for the doctors is important, both to the doctors and hospital; however, this increases the number of drugs that must be carried by the hospital pharmacy for patient treatment if it desires to maintain such a high level of customer service. In addition, the product formulary changes quite frequently as physicians' prescribing behavior reacts to advancements in medical research and technology.

It is also important to recognize that pharmaceuticals have a number of other requirements. They must be handled by trained personnel and experts in this field. Extraordinary resources are committed to developing these items, to manufacturing them, and to controlling their distribution and usage. All of these aspects are highly regulated by governments and other regulatory agencies, and they may require additional documentation. Finally, unlike other areas, customers have a limited role in the product selection process. As patients become more aware of alternative treatments, they may influence doctors as they prescribe medications; however, more times than not these choices are made for them.

Many of these items are also **perishable** and must be destroyed if not used. Perishable items have a limited shelf life and in many cases have special transportation and storage requirements. Part of the concern with pharmaceuticals is that outdated or expired items may be overlooked and dispensed to patients, which could have potentially disastrous effects both in

patient care and public relations. The perishable item inventory control problem is a difficult one and has been studied many times using a periodic review approach (see Fries 1975, Nahmias 1975, Nahmias 1982) with less attention being given to continuous review systems; however, there have been a number of works in this area in recent years (see Weiss 1980; Schmidt and Nahmias 1985; Chiu 1995; Liu and Lian 1999; Lian and Liu 2001). Although these studies provide valuable insight into the management of such products, none of these models have been tested in pharmaceutical inventory control. Given the combination of high costs and perishability of prescription drugs, it seems that more study is warranted as pharmacy managers look for help in setting optimal order policies.

- **Policies**

Substantial efforts are made to regulate the healthcare industry. Government involvement is high as it can provide both oversight of caregivers and funding for care recipients. Previously, healthcare systems have paid little attention to the management of inventories. However, with the implementation of **Diagnostic-Related Groups (DRG)** in 1983 by the United States government, these systems have turned their attention to cost containment as a means of increased profitability. The original objective of diagnosis-related groupings (DRGs) was to develop a patient classification system that related types of patients treated to the resources they consumed. Hospital cases are segmented into one of approximately 500 groups expected to have similar hospital resource use. DRGs are used to determine how much Medicare pays the hospital, since patients within each category are similar clinically and are expected to use the same level of hospital resources.

Interestingly, public and managerial policies targeted at cost-control have failed in many cases to produce the necessary changes in stakeholder behaviors to achieve such outcomes. Efforts to control pharmaceutical prices have provided little relief as drug manufacturers attempt

to recover the resources spent researching and developing these products. These companies also target physicians and patients with advertising campaigns as they attempt to influence prescribing behavior. Another reason policy has been somewhat ineffective at cost-restraint is the conflicting stakeholder goals that appear throughout the supply chain. Doctors and hospital administration are often at odds as they try to balance the issues of prescribing autonomy and product variety. While the doctors want a large variety of brand name drugs, the hospital management strives to minimize costs in the overall system by seeking generic drugs as substitutes for medicines preferred by physicians. Hospital and GPO have different objectives. Hospitals focus on negotiating the best prices for a wider selection of drugs from different pharmaceutical companies while the GPOs are interested in larger orders from only a few pharmaceutical production companies.

Inventory control variables are called “**par levels**” in healthcare inventory management. The min par level is equivalent to the reorder point: if the inventory level decreases to or below this level, an order is triggered. The max par level is equivalent to the order up level (or base stock).

1.3 Traditional Operations in Hospital Pharmacy

Traditionally, hospital pharmacies operated in a centralized manner. Medications were stored in a central pharmacy and then distributed by pharmacy technicians using dose carts to make deliveries to the various hospital floors and Care Units (CUs). A setup such as this requires large amounts of inventory to be stored in a single location while also allowing for quick, easy access to items. These technicians were charged with the task of moving the various medicines in the correct amounts or in individual cassettes for each patient. These dose carts contained individual cassettes of medications for each patient, which the nurse or caregiver was then charged with administering to the patient. If for some reason the patient’s drug order

changed, a special trip would be required to retrieve the necessary medications and then return to the CU. Thus, changes in medication or dosage may have taken hours to satisfy resulting in time delays in care, increased labor requirements, and an overall increase in system costs associated with wasteful or excess operations.

To avoid prolonged delays in administering medications, it was common practice for nurses to borrow a medication from another patient. That resulted in additional problems in the distribution process and in potentially dangerous situations where patients may have received the improper medications. Other difficulties associated with the specific pharmaceutical types existed. Specifically, federal and state regulations require a variety of documentation associated with the dispensation of narcotic drugs. From the time a narcotic is delivered to the hospital until it is administered to the patient, the drug must be tracked by the hospital and is surrounded by a number of tasks such as checking the ordered medication against the patient's medical record, searching for narcotic keys to the cabinet, documenting for administrative records and reconciling narcotic records after each shift. This example demonstrates some specific challenges in controlling and monitoring items in healthcare SCM.

Pharmacists are highly paid professionals being asked to spend long amounts of time handling excessive documentation and a labor intensive drug dispensation and distribution process rather than practicing pharmaceutical care. The opportunity to reduce repetitive and tiresome tasks was very appealing to administrators and pharmacists alike. As such, the ability to automate these processes and take advantage of computer information systems was valued by stakeholders.

1.4 Research Objectives

The hospital participating in this investigation employs an inventory management solution driven by information technology (IT). The specific solution and operating procedures

are discussed in more detail in Chapter 3; however, it is prudent to provide a simple overview of this system at this point. Specifically, this solution, *Pyxis MedStation*® allows for local storage depots to be distributed at the various CUs around the hospital. These *Pyxis*® machines house the drugs needed for patient care in that CU, as well as, track every inventory transaction, prompt replenishment orders, generate necessary documentation, and facilitate the billing processes related to pharmaceutical treatments. While these *Pyxis MedStations*® allow for the automation of a number of tasks associated with this supply network, it is important to recognize that pharmaceutical inventory management is still a very labor-intensive process due to the number of *Pyxis*® machines in the hospital (~85), the large volume of drugs housed in each depot (250-500), and the workload required during the restocking process. As such, the following research objectives are identified:

1. Service Level_{*i*} \rightarrow max, $> \alpha_i$

Here we are trying to maximize or set a lower limit for service levels for each item in the *Pyxis*® machine. The service level is defined as an appropriate measure of customer service for each of the n items (i.e. 90%, 95%, or 99%). Alpha (α) service levels are associated with items based on the number of shortage occasions that managers are willing to accept during a period of time. If for some reason the hospital pharmacy is out of this item, it can place an emergency order with its supplier to replenish this item. However, the hospital would like to avoid these emergency orders if possible because they are very costly for the organization. For this objective we are considering the service level, α , for each item separately. To consider all items in the machine as a whole would result with lesser demanded items being unavailable more often to accommodate the higher demanded goods. In addition, these levels reflect the average service level for the item rather than the worst-case scenario level as set by the hospital.

2. $\sum_i(\text{Orders per Day}_i) \rightarrow \min, \leq N(\text{workload constraint})$

Here we are trying to minimize the number of orders per day (refill occasions) or at least keep this number less than the number of orders a worker can handle during a shift. This is an attempt to account for the workload constraint. Workers can perform a limited number of restocking activities during a given shift. There is an incremental workload constraint, which only increases with the addition of trained pharmaceutical technicians. As such, the goal here is to find inventory control values that will minimize the number of required refill occasions per day and not exceed the work capacity for a single worker.

3. $\sum_i(v_i S_i) \leq M \rightarrow \min$ (space constraint)

Here the goal is to allocate space for each item in the *Pyxis*® unit such that the unit contains the necessary drugs but does not exceed the available space. The goal is to determine the appropriate amount of space necessary for each item within a *Pyxis*® unit by first assigning space to accommodate s_i (safety stock) and then determine the additional space required to house D_i , which is the difference between the order-up-to-level (S_i) and the minimum stock level (s_i). This is done to provide support for reorganizing dividers within the *Pyxis*® unit to allocate the available space appropriately amongst all of the required items.

1.5 Organization of the Dissertation

The remainder of this document is divided into several chapters with each addressing specific topics related to this research. Chapter 2 offers a review of relevant managerial and quantitative modeling literature, as well as, presents practical solutions employed to address challenges specific to hospital inventory control. Chapter 3 presents the research environment and the modeling approaches used to satisfy the investigation objectives. Chapter 4 provides the analysis and findings of this study. In addition, the impacts of these results are examined for

managerial decision support purposes. Chapter 5 brings the conclusion of this dissertation, as well as, promotes areas of future study.

CHAPTER 2: LITERATURE REVIEW

This research focuses specifically on supply chain management issues **from the perspective of the hospital**. Other members of the supply network in this industry are important; however, the subject is simply too voluminous to cover adequately in this setting without restricting the scope somewhat. As such, the authors have selected to focus on supply chain problems as they are viewed by hospitals, which is appropriate given their significance in the supply chain and the costs they incur. In the following sections critical managerial areas are identified that distinguish the healthcare environment from other industries that have received attention in the past.

Pharmacy directors are turning their attention to controlling costs in the areas of supply chain management and pharmaceutical inventory control. Supply and purchased services account for the second largest cost component for a hospital, and it is clearly recognized that SCM is one of the principal areas for improvement in organizational performance. Supply chain management in hospital systems all over the world shows a great variability both in performance and in focus. Such a variability combined with the growing cost of care and pharmaceuticals determines relevant differences in health service efficiency and unacceptable annual increases in healthcare costs.

The remainder of this chapter will serve to address several key areas of healthcare SCM and pharmaceutical inventory management. A review of the relevant managerial and quantitative modeling literature is provided. Here attention will be given to both the overall study of healthcare SCM and the quantitative approaches to inventory optimization. The practice of pharmacy operations will be described with specific attention given to the movement and distribution of prescribed medications within a hospital. Solutions focused on addressing SCM

challenges will be presented along with the Multiple Criteria Decision Making (MCDM) nature of decision making in this context.

2.1 Managerial Research in Healthcare SCM

Traditionally researchers have taken two approaches to studying healthcare SCM: analyzing the managerial concerns and evaluating various quantitative models. First, the managerial aspects of such supply chain systems are discussed. The stakeholders in healthcare supply chain and value chain are examined along with the conflicting goals in the system. Thereafter the most common managerial approaches in healthcare SCM are summarized including outsourcing and vendor managed inventory (VMI). In existing research, the focal point has primarily been on description of the system rather than developing innovative models or performing quantitative analyses. However, these descriptive studies are important to document the actual healthcare supply practices.

2.1.1 Stakeholders and Relationships

The financial aspects of the healthcare industry are significant, but it is also an industry very important to all members of society as it involves a wide range of stakeholders. Burns (2002) examined the healthcare industry for three years to investigate its value chain, to uncover significant industry trends, and to identify the major stakeholder groups involved with healthcare services. Evidence showed that both vertical and horizontal integration were present in healthcare. Vertical integration was illustrated by hospitals teaming with insurance agencies or ambulatory services to combine various portions of this delivery network. Noticeable horizontal integration manifested in the form of hospitals purchasing other hospitals or in the formation of groups purchasing organizations. A significant result of this research was the identification of the following groups as stakeholders in this industry: 1) payers, 2) fiscal intermediaries, 3)

providers, 4) purchasers, and 5) producers. Each of these groups is explained in more detail below.

Any person or organization responsible for supplying the funds to pay for medical expenses is identified as a *payer*. Based on this definition, examples of payers would include government, employers, individuals and employer coalitions. Insurance agencies, health maintenance organizations (HMOs), and pharmacy benefit managers fall under the category of *financial intermediaries*. Any group supplying healthcare screening, treatment, or any other healthcare related provisions are considered to be *providers*. Such entities would be physician offices, hospitals (or hospital systems), surgical centers, alternative and satellite facilities, ambulatory services, and pharmacies. Individuals or groups procuring any of these services are viewed as *purchasers*; however, it is important to note that this category extends beyond the basic consumers of healthcare services. This group also includes a wide variety of product resellers, independent distributors, pharmaceutical wholesalers, etc. The final group is the *producers* whose responsibility is the manufacturing of healthcare products, equipment, and technology. This includes pharmaceuticals, surgical equipment, information technology services, medical devices, and other capital equipment found throughout the healthcare system.

Tarabusi and Vickery (1998) state that attitudes and habits of local pharmacists and physicians must be known for good access to markets. This research identifies the importance of cost-containment programs in the pharmaceutical industry by comparing the approaches employed by the United States and countries of the European Union. Globalization and international partnerships have grown as pharmaceutical companies strive to control the research and development costs associated with these drugs.

2.1.2 Value Chains

The notion of value in the healthcare service value chain can be described by the interrelations of relevant stakeholders. Value chains were first introduced by Porter (1985) and are significant marketing tools because they afford managers the opportunity to assess the specific value added by each member of the supply network. Supply chains provide a mechanism for delivering that value to consumers. The original view of a value chain focused on a company's internal activities specifically designed to create value for customers; however, this concept has been extended to include the entire product and service delivery system (Bower and Garda 1985; Evans and Berman 2001).

Pitta and Laric (2004) provide a model of the healthcare value chain and supply chains as they exist in many practical situations. Figure 2-1 below illustrates that this supply chain is not linear or sequential in nature but closely follows the flow of information through the system. The success or value created is linked to the transfer of quality information as the medical care received by patients relies heavily on information processing.

The first two groups interacting in this network are the patients and physicians. This stage of the process is generally initiated by the patient and provides valuable information necessary to adequately address whatever needs they might have. This research showed that individuals are much more likely to share very personal information with their healthcare providers when they believe this information is needed for medical purposes and when they trust the confidential nature of the patient-doctor relationship. The next link in the chain is created by the addition of pharmacists and other providers of medical equipment and services. In this stage the pharmacist creates value by further investigating the medical history, specifically as it relates to medications, of patients to determine any potential risks or interactions that may result from

the addition of new, prescribed drugs. This is a very important step in customer service and patient care.

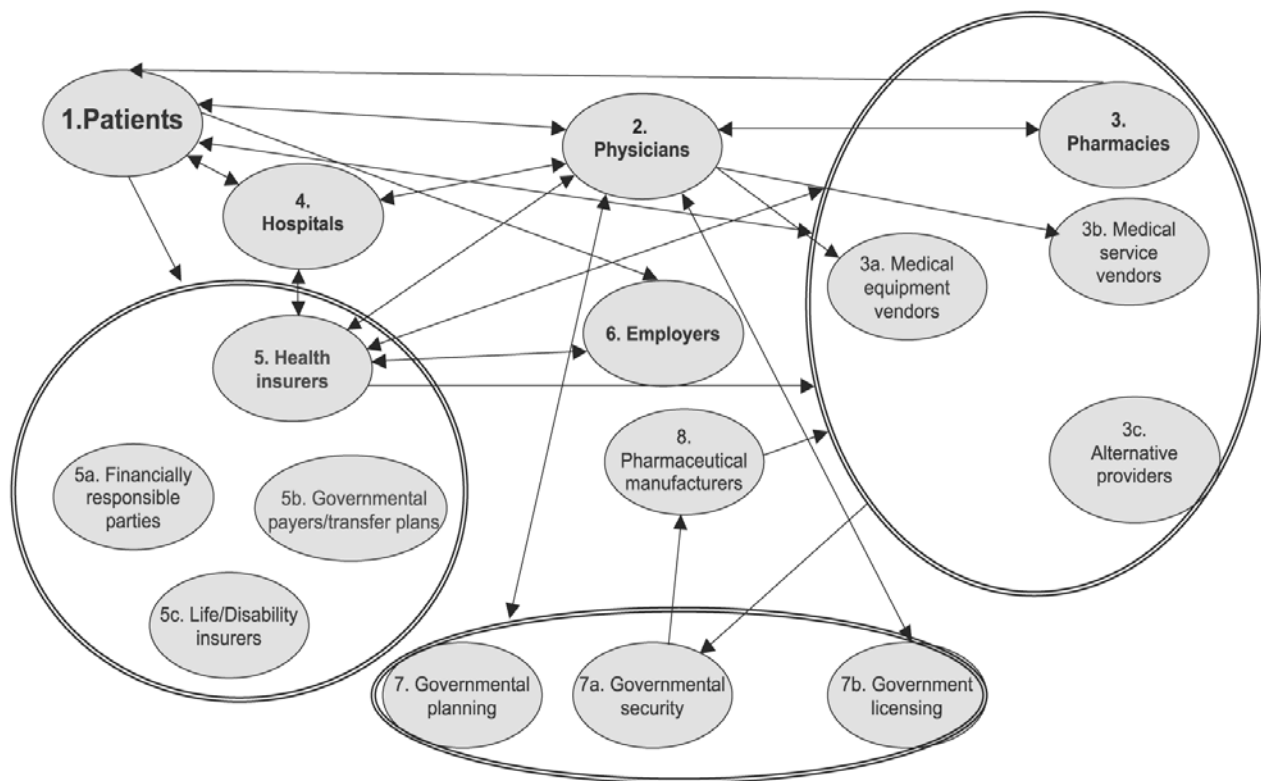


Figure 2-1: Stakeholders in the Healthcare Value Chain (Pitta and Laric 2004)

The next addition to the value chain is that of the hospital and the related services and procedures that may be included in diagnosing patient symptoms. As explained by Pitta and Laric (2004), doctors often request batteries of tests be performed on patients even when symptoms and other indicators suggest a course of treatment. Hospitals create and store vast amounts of medical data for patients, which can be useful going forward. The fifth member of the healthcare value chain is the health insurers, which includes both public and private entities responsible for providing financial support to those receiving care. Since many insurers require a series of diagnostic tests and related data be completed before approving potentially costly procedures, patient data continues to grow. The addition of insuring groups or companies can also be a negative influence on the value chain. As one can see with the addition of new

members to the network and the creation of data at each stage, the healthcare system and participant interactions are becoming more and more complex.

Employers are the sixth group added to create another value chain. In the United States (US) employers are the most often used source of medical insurance for employed persons and their families. Here the value is obtained by negotiating better benefits for groups of people as opposed to those offered to individuals. When the US Government introduced its Federal Medicare and Medicaid programs in the 1960s, it became the largest medical insurance provider in the United States. A result of this involvement is the increasing influence of government regulation and policy in the healthcare industry. As such, government becomes the seventh participant of interest here as it influences various parts of this system. The final member of the model is the pharmaceutical manufacturers. It has already been established pharmaceuticals represent a significant area of cost in the healthcare industry, as well as being the primary means of preventative and curative medical treatment.

2.1.3 Stakeholder Conflicts

Physicians and pharmacists/pharmacy directors clash over medications offered by the hospital. The basic conflict here revolves around the issue of product variety versus economies of scale. The doctors have professional and personal preferences that are reflected in their prescription decisions. They value their individual freedom of choice in selecting the medications that they feel best address the specific needs of the patients under their care. Physicians are also influenced by drug manufacturers, sales representatives, and the appearance of new drugs in the market. In contrast, the pharmacy directors pay more attention to the costs associated with specific medications and promote the usage of generic rather than brand drugs when available. They strive to take advantage of economies of scale whenever possible in the selection of drugs offered.

In 2005, Prosser and Walley examined the extent to which cost influenced prescribing behaviors of general practitioners (GPs) in the UK healthcare system. According to the authors, Primary Care Organizations (PCO) involvement has steadily increased as a means of providing more unified, controlled budgets for these physicians and to provide a monitoring mechanism of prescribing activities with this cost-containment objective in mind. The primary goal of this investigation was to measure the cost-awareness of doctors and to evaluate the attitudes of these GPs towards cost-restraint policies. Another goal was to determine what affect this managerial objective might have on their professional behavior. In this case the evidence demonstrated that all of the physicians were aware of pharmaceutical costs when prescribing treatments for their patients and that these costs should be considered when making prescription choices. However, there appeared to be a great deal of variation in the amount of influence these costs actually had on modifying medical decisions. As expected, physicians identified patient care as their primary focus during the treatment process with cost being a secondary concern.

Prosser and Walley (2007) continued their research in this area and employed qualitative methods to examine the managerial influence of healthcare administrators on the prescribing autonomy of general care practitioners. In general, physician prescribing autonomy has been challenged recently due to the greater sophistication of patients in the ability to direct medical decisions and the increased bureaucratic involvement in service delivery in healthcare. This research showed that the objective of cost-containment presents a formidable obstacle for caregivers striving to offer the highest level of care and individualized service to those they serve.

The above analysis showed that managerial involvement will have limited success in influencing GPs' prescribing autonomy. The conclusion was that the GPs directly resisted the attempts administrators made to modify their prescribing behaviors because the GPs maintain it

is their responsibility to offer the best medications and treatment available to their patients and that this autonomy is a component of providing individual care. In many cases this is an area of great conflict between doctors and hospital/pharmacy administrators since larger product formularies desired by doctors usually result in higher inventory costs and reduce the opportunity for cost savings. When asked, doctors acknowledged the importance of controlling the costs of pharmaceuticals, but they identified the quality of patient care as being the paramount objective. Managers placed a great deal of importance on keeping prescribing costs within established budgets.

Another divergence appears between hospitals and the group purchasing organization (GPO) on the issue of product variety. Hospitals focus on negotiating the best prices for a wider selection of drugs. The attention is shown to the brand name medications in most cases. The GPO, on the other hand, strives to minimize costs in the overall system by seeking generic drugs as substitutes for medicines preferred by physicians. Again, a great deal of effort is given to the achievement of economies of scale for demanded items by considering a limited formulary (narrower selection of drugs).

The importance of product standardization for managing costs and improving clinical performance is outlined with respect to physicians' unwillingness to accept products alternative to branded ones, even in the face of evidence regarding equivalence. As such, hospitals persist in the argument for wider drug selections. Both physician and nurse involvement and leadership in product analysis is necessary for successful standardization to occur and for the provision of metrics pertaining to products and their relationship to the performance of the supply chain.

2.1.4 Managerial Approaches in Healthcare SCM

In this section of the chapter, the focus shifts to the various strategic approaches that have been pursued in the area of supply chain management and inventory control. Some of the topics

to be discussed are the outsourcing of distribution activities, allowing suppliers to manage inventory levels at various distribution points, and the use of common statistical techniques to achieve organizational and system goals.

2.1.4.1 Outsourcing

Kim (2005) presents an explanation of an integrated supply chain management system developed to specifically address issues related to pharmaceuticals in the healthcare sector. Many industries have recognized the importance of improved information sharing throughout the supply chain, and this work considers it as the most critical success factor. Here the supply network is composed of pharmaceutical companies, a wholesaler, and hospitals. The hospital's operating procedures and policies were reviewed to determine system requirements in an effort to improve the management efficiencies of the supply chain.

Jayaraman et al. (2000) present several tools and practical ideas to improve the flow of materials in a small healthcare facility. Traditional techniques, such as Pareto diagrams and department-product-type (DPT) matrices, were employed to track item flows and identify sources of errors or difficulties. Researchers suggested several procedural and policy changes be implemented to reduce inventory management problems. Landry and Beaulieu (2000) present a descriptive study of logistics systems at hospitals from three countries – France, Netherlands and The United States – to identify the best practices for replenishment policies, equipments, and handling technologies.

Nicholson et al. (2004) compared the inventory costs and service levels of an internally-managed three-echelon distribution network and contrasted it with an outsourced two-echelon distribution network. Their research revealed that a general trend in healthcare is the outsourcing of specific organizational activities, inventory management, and materials distribution to “expert” third-party providers. To this point very little attention has been given to inventory

management; however, changes in pharmaceutical regulations and the formation of the DRGs prompted a shift in approach.

When outside entities can provide needed products or services more efficiently than internal departments, it can prove very rewarding. In other instances outside providers may demonstrate the ability to provide the desired products or services at a higher level of quality than an organization may be capable of achieving (Lunn 2000). A long-term benefit of outsourcing is the ability to reduce the number of suppliers in the system, which will eventually lower the procurement costs for the downstream members of the supply chain. As such, the short-term benefits of increased efficiency and higher quality along with the long-term benefit of lower procurement costs make outsourcing a logical approach to overall cost containment in the healthcare industry and consistent with current practices in inventory management (Veral and Rosen 2001).

Outsourcing decisions in this area are motivated by three factors: the magnitude of investment, the impact on service quality and delivery, and the availability of qualified service providers. Quality of service is arguably the paramount goal of healthcare providers (Li and Benton 1996), and it has been suggested that outsourcing various functions allows organizations to improve the quality of its internal operations. Jarrett (1998) identified several areas in which providers were able to improve internal performance. Patient care was improved, which can influence customer satisfaction and perceptions related to the quality of service provided by an organization. As the expertise develops and the capabilities of external sources grow, outsourcing becomes an increasingly attractive option. Another motivation for healthcare providers considering outsourcing the inventory management functions are the “success” stories similar to those described by Rivard-Royer et al. (2002).

Rivard-Royer et al. (2002) examined the changing role of distributors in the healthcare industry in recent years by investigating how operational processes had changed at a Quebec hospital. As reported by Jarrett (1998), the ever-increasing desire to control healthcare costs have led hospitals to re-evaluate many of their previous policies and operations. Inventory control is a logical area where substantial gains can be realized. Pharmaceuticals represent a significant cost equation related to both hospital inventory and quality patient care. As such, many hospitals and hospital systems have focused on this specific material management issue when restraining costs. US pharmaceutical distributors were offering “stockless” replenishment where the distributors would prepackage items based on usage at individual care units and would often provide direct delivery of drugs to these CUs (Henning 1980). By employing such a system the distributors share in the benefits and risks associated with pharmaceutical savings or costs. The reduction in pharmaceutical inventory located at the hospital central pharmacy saved hospitals valuable resources, and the shifting of duties from the pharmacies to the distributors allowed the hospitals to reduce their workforce. Another improvement was noticed in enhanced customer service. However, as one would expect, a critical success factor in achieving any benefits from such a relationship and process is the continuous exchange of information between the point of use and supplier (Bolton and Gordon 1991).

2.1.4.2 Supply Coordination and Vendor Managed Inventory

According to Rivard-Royer and colleagues (2002), by the late 1990s stockless replenishment was a thing of the past as hospitals sought a balance between the amount of effort being spent in replenishing hospital inventories and the hospitals’ inventory savings. The hospital involved with this study employed a “hybrid approach” since high-demand items were purchased in bulk (at the case level) for delivery directly to the patient CUs from distributors and low-volume items were handled by the pharmacy Central Storage (CS). For these low-demand

items the CS was charged with breaking-down the bulk purchases into smaller quantities for distribution to the various CUs as items were used. However, this hybrid approach was found to have limited benefits to both the hospital and distributors. Distributors were asked to perform additional work without receiving a comparable level of additional revenue. The hospital was still unpacking, repacking, and preparing drugs for distribution to the CUs and failed to realize significant workload reductions as a result of this replenishment approach. Overall, the gains were very limited in this particular study.

One managerial shift has been to vendor managed inventory (VMI), which has been shown to have benefits in SCM related to enhanced material handling efficiency. Other trends in supply coordination have included online procurement systems and the availability of real-time information sharing. These advances have demonstrated an ability to reduce total pharmaceutical inventory by more than 30% (Kim 2005). In addition, the improved information sharing throughout the supply chain allowed for more timely and accurate inventory data, which resulted in better demand forecasts and materials management.

The research of Meijboom and Obel (2007) investigated supply chain coordination in a global pharmaceutical organization. The authors looked at the issues facing a pharmaceutical company with a multi-location and multi-stage operations structure. Simulations are used to explore various coordination activities focusing specifically on “tactical control” in the firm. Their results suggest that a functionally organized operations structure will be unsuccessful in a multi-location, multi-stage environment. According to the authors, firms can employ one of two methods. They can either use a centralized approach relying heavily on information systems or maintain a decentralized structure that relies on transfer prices as the coordination device.

Lapierre and Ruiz (2007) developed two modeling approaches for improving healthcare inventory management by examining the impact of scheduling decisions on the coordination of

supply activities while recognizing inventory capacities. Specifically, the researchers concentrated on timing issues ranging from the purchasing and delivery of inventory to the work schedules and job assignments of employees. A significant outcome of this work is the promotion of coordinated activities throughout the purchasing and procurement process such that schedules can be expanded to include more specific details for improving the resource utilization across the organization. The models were tested in a hospital in Montreal, and hospital managers believed that the schedules generated by the models were both efficient and well balanced. Again, this evaluation furthered this approach as a favorable method to improving inventory management activities in the healthcare industry.

2.2 Quantitative Modeling in Healthcare SCM and Inventory Control

One of the primary goals of our initiative is to model and improve inventory management practices being employed by hospitals. There are a number of relevant inventory models in the current body of supply chain literature that are related to this effort, and those models are examined and described herein. In this review most of the attention will focus on models addressing multi-item, single-location and multi-echelon coordination given the unique conditions germane to the industry considered. Inventory models have been collected that have been formulated to address healthcare problems, have been applied, or have a high relevance to healthcare related inventory management.

After summarizing the specifics of inventory control policies and planning frameworks in hospital pharmacies, the demand specifics are described in this section. A major portion of this section is devoted to inventory modeling; models of specific interest are multi-item, single-location, and single-item, multi-location models. Literature associated with each of these modeling approaches is discussed, as well as, how these models have been employed in the past.

2.2.1 Inventory Control Policies and Planning Framework in Healthcare SCM

Efficiently managing pharmaceutical inventory systems requires another approach than a continuous review reorder point model. There are at least three limitations for using the continuous replenishment model in the context of healthcare supply systems: (a) the model does not account for the limited human resources, (b) it does not account for physical storage capacities, particularly the one at the CS level which is critical in most hospitals and (c) the decisions are only based on costs, not accounting for inventory control activities and their restricted capacity. Each of these limitations is elaborated on below.

Continuous replenishment inventory management is usually not applicable in hospitals since visits to CUs take a lot of the employees' time. To make it more efficient, tours are made such that several CUs are visited consecutively for rounds of stock control or supply distribution. The *periodic replenishment* model seems more appropriate for healthcare organizations as each CU is replenished according to a schedule instead of when reaching a reorder point. However, with this inventory management approach, the frequencies of the visits are determined based on the order period and the economic order quantity (EOQ). Storage capacities at CUs and the CS are important factors when deciding how frequent a CU should be replenished and how frequent a supplier should be called. An undersized CS and open shelves able to contain very limited quantities of the voluminous products is often the reality most hospitals have to face. This situation calls for more frequent orders to suppliers and/or keeping more stocks at the CU than these suggested by the EOQ model in order to satisfy requirements and respect capacities. In that context, CU's stocks are kept higher to compensate for a small CS. Thus, greater volumes of items can be stored on-site by keeping these extra quantities. Another reason for keeping more stock in the overall system is that *stockouts* are time expensive for the supply service that needs to make extra emergency visits, internally referred as *hot-picks*, to CUs but also for the medical

staff who waste their time making extra calls to the supply department or chasing the products at other CUs.

One of the distinct features of material management in a hospital is the use of a periodic review *par level* (or order-up to level) servicing approach. A major issue in setting par levels for various items in a healthcare setting is that these levels tend to reflect the desired inventory levels of the patient caregivers rather than the actual inventory levels needed in a department over a certain period (Prashant 1991). In most cases these par levels are experience-based and politically driven, rather than data-driven. This poses a problem for warehouse managers since the inventory they hold is typically based on aggregate hospital demands while requirements of departments when aggregated are not in line with such estimates. The literature analyzing the setting of optimal par levels and review periods for multiple echelons draws upon prior work in multi-echelon inventory systems which are discussed in the next sections.

On the quantitative side, among one of the first healthcare inventory models was published by Michelon et al. (1994) who developed a tabu search algorithm for scheduling the distribution operations in a hospital. In their application, the number of replenishment visits is given a priori, and the problem consists of finding the schedule that minimizes the number of carriers given several time windows and practical constraints. Another investigation concentrating on this type of inventory control situation was Banerjea-Brodeux et al. (1998) who looked at an application of a routing model to match the different CUs to be visited by a laundry department in a hospital. Here the authors used a combination of quantitative techniques and common sense to minimize the number of routes while respecting the volume capacity constraint of a cart.

Supply chain management can be fit into a planning framework. Vissers et al. (2001) defined a planning framework for hospitals. One of the primary objectives of this research was to

balance service and efficiency throughout the organization. As identified by the investigators, there are three characteristics that fit hospital production control settings. They are as follows: *(1) a demand that is, generally speaking, larger than supply, (2) by restrictions on supply defined by contracting organizations, and (3) by higher patient expectations on service quality* (Vissers et al. 2001). As with many organizations the quandary then becomes how to maximize resources while still achieving higher levels of customer service. The developed framework consists of five levels of planning and control: *patient planning and control, patient group planning and control, resources planning and control, patient volumes planning and control, and strategic planning* (Vissers et al. 2001). The researchers describe the framework, as well as explain instances where current hospital policies and practices deviate from their suggestions and where changes may benefit the organization.

Another attempt is to include SCM into an Enterprise Resource Planning (ERP) framework. Implementation of ERP in healthcare is very challenging due to the special characteristics to consider. van Merode et al. (2004) explain the planning function of the hospital environment and identify facets of the healthcare industry that make ERP implementations and utilization more difficult. Some attention is given to explaining areas in which ERP can or cannot be used. According to the authors, hospital functions should be divided into “a part that is concerned only with deterministic processes and a part that is concerned with non-deterministic processes” (van Merode et al. 2004). It is their contention that the deterministic process can be handled very well by ERP.

2.2.2 Demand Specifics for Hospital Pharmacy

The usage of pharmaceutical products in hospitals has specific characteristics. Typically, 40 to 60% are high demand items that are relatively easy to handle based on usage statistics. Though, much care is to be taken on the frequent changes in the used medication, on the so

called “formulary changes”. New items come frequently, and an initial qualitative forecast is required. A large proportion of the items are only rarely used, and the usage times and quantities are changing. Another group of items is used by patients for only a few days and finished afterwards. Here the auto-correlation of the demand time series is challenging to consider.

Intermittent demand refers to the usage pattern of items that have extended time gaps separating irregular or sporadic periods of demand. If the quantities of the usage are also variable we have the so-called “lumpy” demand that is a major challenge in pharmacy inventory management. The study of intermittent and lumpy demand has typically been approached from either a forecasting or inventory control perspective with a number of studies incorporating both of these areas to examine practical issues related to inventory system performance. The body of work discussed in this section provides examples of this.

Sani and Kingsman (1997) provide a good review and compare various periodic inventory policies like the Normal Approximation (Roberts 1962), Naddor’s Heuristic (Naddor 1975), Power Approximation (Ehrhardt 1979), and several others. In addition, a variety of forecasting methods were reviewed with the authors attempting to determine which are best for low and intermittent demand items. Before discussing specific inventory control approaches or models, it is important to recognize two fundamental notations commonly used in this literature. The minimum inventory parameter, or the re-order point, is commonly denoted as s while the maximum inventory parameter, or the order-up-to value, is represented by S . In situations where item demand appears to be low or intermittent, variations of the (s, S) form of the periodic review inventory control system have been promoted as the optimal approach to inventory management. As the authors state in their review, forecasting demand for such items can also prove very challenging.

The research presented by Sani and Kingsman (1997) examines the management of spare parts for agricultural machinery, which includes many items with seasonal demand characteristics displaying vastly different demand from summer to winter months. After examining the various (s, S) inventory policies with respect to annual inventory costs and customer service levels, the Ehrhardt's (1979) Power Approximation proved to be a good inventory system for managing items with low overall demand. This method not only scored well in evaluations of cost minimization but also offered reasonable service levels for items with low to medium demand. From the comparisons seems that the Croston estimator (Croston 1972) is one simple forecasting method that performs adequately in most cases (using the exponentially smoothed inter-demand interval, updated only if demand occurs). One surprising result was that a basic 12 month moving average of demand yielded adequate forecasting results when examining both annual costs and service level with exponential smoothing performing the worst on this measure; however, exponential smoothing performed best on the customer service level measure alone. It is important to note that both of the aforementioned techniques were utilized along with updates every review period and the Croston forecast. Finally, the authors concluded that achieving customer service levels greater than 95% for lumpy demand items is impossible unless high materials stocks are kept as a means to satisfy this objective.

Hollier et al. (2005) developed a modified (s, S) inventory model to address cost control issues specific to lumpy demand patterns. This approach integrated a maximum issue quantity restriction and a critical inventory position as constraints influencing the inventory control policy. Here the primary objective was to minimize the system replenishment costs. These authors applied two algorithms, one being a tree search and the other a genetic based, to optimize the decision variables. The numerical examples and results illustrate the benefits of employing

such algorithms, as well as, demonstrate the utility of the maximum issue quantity and critical inventory position constraints when managing lumpy demand items.

Syntetos and Boylan (2006) employ simulation models to provide an evaluation of various forecasting techniques, specifically simple moving average, single exponential smoothing, Croston's estimator, and a new technique introduced in their paper, when handling lumpy or intermittent demand items. Service level and stock volume were evaluated using a number of performance measures related to customer service and inventory costs. In this case the authors reported that the new estimator they developed outperformed other forecasting techniques as an inventory control method; however, it is important to recognize that the simple moving average technique yielded favorable results as well compared to the other two methods.

2.2.3 Multi-item, Single-location Models for Pharmacy Inventories

We found few papers that applied multi-item models to control healthcare inventories. Dellaert and van de Poel (1996) derived a simple inventory rule, a (R, s, c, S) model, for helping buyers at a university hospital in the Netherlands. The notations of s and S were defined previously, and their meanings remain the same. Here R represents the length of the review period (time between orders) while c is the can-order level. Since most items have a joint supplier and the orders for a certain supplier are always placed on the same day of the week, they extended an EOQ model to a so-called (R, s, c, S) model, in which the values of the control parameters s , c and S are determined in a simplistic manner. This approach resulted in substantial gains, which were observed in improved service levels, reductions in supplier orders, smaller total inventory levels and holding costs, and substantially lower system costs, for the participating hospital.

However, we could not find other multi-item inventory applications in healthcare; we summarize next the models that seem to have the best application potential for this specific area.

The majority of results for the multi-item problem are for the deterministic demand case where the sizes and the multi-product sequence of orders have to be determined. The problem is known to be NP-complete and therefore many heuristics have been proposed. For an overview on the approaches, see e.g. Gallego et al. (1996), Hariga and Jackson (1996), Minner and Silver (2005).

The early investigations in stochastic multiproduct inventory problems were generated by Veinott (1965), Ignall (1966), and Ignall and Veinott (1969). Later in the study of Beyer et al. (2001) the researchers examined the management of multiple items with a warehousing (storage) constraint, which was based on the early model of Ignall and Veinott (1969), and generated results for finite-horizon and infinite-horizon discounted-cost problems. This work demonstrates optimal policies suitable for the various conditions that occur in healthcare.

Ohno and Ishigaki (2001) examined a continuous review inventory system for multiple items exhibiting compound Poisson demands and created a new algorithm for determining the optimal control policy. This alternative method was derived using the policy iteration method (PIM) and resulted in a substantial decrease in processing time needed to evaluate and improve the optimal policy. In addition, the new algorithm was tested using three joint ordering policies.

Minner and Silver (2005) analyzed the stochastic demand, continuous review lot-size coordination problem for Poisson demand and negligible replenishment lead times. A formulation as a semi-Markov-decision-problem was presented to find the optimal replenishment policy and several heuristics were suggested and tested in a numerical study. However, the results only apply for pure Poisson demand and cycle inventories (i.e. without safety stocks). With the assumption of negligible lead times, safety stocks here serve to avoid the negative consequences of transaction sizes that exceed available inventory rather than covering against demand uncertainty over the replenishment lead time.

In a recent paper, Minner and Siver (2007) analyze a replenishment decision problem where each replenishment has an associated setup cost and inventories are subject to holding costs. The solution of this trade-off results in order batch sizes. The warehouse space for keeping inventories is limited which generally restricts these batch sizes. A second aspect of their analysis is that demands are random, here being modeled by a compound-Poisson demand process. This further complicates the analysis because now, safety stocks and cycle stocks share the limited warehouse space.

2.2.4 Single-item Multi-location Models - Multi-echelon Coordination in Pharmacy

The literature analyzing the setting of optimal par levels and review periods for multiple echelons draws upon prior work in multi-echelon inventory systems, which is discussed next. One of the first investigations in the area of multi-echelon distribution networks was Allen (1958) who attempted to optimally redistribute stock among several locations. Since then, numerous works extended this model (see Simpson 1959; Krishnan and Rao 1965; Das 1975; Hoadley and Heyman 1977). Another significant effort in this area was conducted by Clark and Scarf (1963) as it was the first study that attempted to generate and depict an optimal inventory policy in a multi-period, multi-echelon distribution model involving uncertain demand. Other research in this area has focused on the setting of optimal lot sizes and inventory safety stocks in a multi-echelon supply chain (Deuermeyer and Schwarz 1981; Eppen and Schrage 1981; Nahmias and Smith 1994).

Sinha and Matta (1991) and Rogers and Tsubakitani (1991) present modeling studies in this research domain. Both studies focused on two-echelon inventory systems employing periodic review under stochastic demand with fixed lead times. In Rogers and Tsubakitani (1991), the researchers concentrated on finding the optimal par values for the lower echelon such that the penalty costs were minimized. A budget value acted as a constraint of the maximum

inventory investment. The optimal par level is achieved by utilizing a critical ratio, which is adjusted by the Lagrange multiplier subject to the budget constraint. Sinha and Matta (1991) focused on minimizing the holding costs of multiple products at both echelon levels with the presence of penalty costs at the lower echelon. Similarly, the results demonstrated that the optimal par values for the lower echelon items were obtained using a critical ratio; however, the holding cost function provided a method for generating the optimal values for the upper echelon.

Nicholson et al. (2004) extend the work of Rogers and Tsubakitani (1991) and Sinha and Matta (1991) by considering a three-echelon inventory system. Specifically, this research concentrated on the healthcare sector and sought to compare an internally-managed three-echelon system to an outsourced two-echelon distribution system. Comparisons focused on inventory costs and service levels. The results suggest that outsourcing the targeted functions yielded lower inventory costs without sacrificing customer service. As mentioned previously, the use of periodic review par level servicing at the departmental level (i.e. at the individual care units) is a unique characteristic to hospital material management; however, it is important to note that the central pharmacy often operates in a similar manner utilizing another set of par values reflective of aggregate inventory requirements. Zhu et al. (2005) found similar results in their study by using numerical simulations and sensitivity analysis of two models. Like Nicholson et al. (2004), this work demonstrated cost savings with high service levels for the two-echelon distribution network where item demands were monitored by the distributor and delivered directly to the departments for use, as opposed to orders being routed through the CS as they would be in a three-echelon system.

Some models consider the case of lost sales. Nahmias and Smith (1994) examine a two-echelon supply chain where stockouts can penalize the retailer in cases where the customer is unwilling to wait for their order to be filled. The authors assume instantaneous deliveries from

the warehouse to the retailer which is often not the case in practice. Andersson and Melchior (2001) executed a similar study that allowed for excess demand to be handled using backorders. The supply chain in this work was comprised of one warehouse with multiple retail outlets being serviced. Demand here is independent Poisson processes, and lead times are considered constant. The heuristic developed by the authors provides a mechanism to evaluate this type of supply network on elements of cost and service level.

Other research examining the lost sales case is that of Hill et al. (2007), which looked at inventory control in a single-item, two-echelon system with a continuous review policy. Again, a central warehouse services several independent retailers and then has its stock replenished by an external supplier. The system operates such that any excess customer demand at the retailer can be filled from the warehouse provided the item is in stock; however, any items which are not in stock result in lost sales. Lead time for the retailer is equal to the transportation time required to move the item from the warehouse to the specific retail outlet.

The influence of order risk was examined by Seo et al. (2001) in a two-echelon distribution system. They claim that the service policies should reflect the availability of real-time stock information. Their model adjusts the reorder time on the basis of an approximated order risk, which is associated with orders that are filled immediately versus those that are delayed. Results show that this order risk policy performed well when warehouse lead time was short, where item demand was low, and where there were an intermediate number of retailers in the supply chain.

In 2003, Axsäter used an approximation technique to optimize inventory control in a two-echelon distribution network. Items displayed stochastic demand, and the system relied on a continuous review (R, Q) policy. In this situation holding costs at all locations and backorder costs at the retailer were assumed to be linear. Axsäter presents a simplified method for

estimating reorder points by using normal approximations for demand at both the retailer and the warehouse. Lee and Wu (2006) examined a simplified two-echelon supply chain system comprised of one supplier and one retailer. Here the retailer has a choice between two different restocking policies: traditional methods (such as an EOQ or periodic review approach) or a statistical process control (SPC) based method. The results show support for the SPC method in addressing inventory variation issues and in reducing order backlogs. Benefits are apparent in the areas of demand management and inventory control, which leads the authors to suggest this as alternative method for managing supply chain and inventory costs.

2.3 Practical Solutions for Inventory Management of Pharmaceuticals in Hospitals

The following section discusses some practical solutions to issues facing managers when dealing with prescription drugs. There is a description of some dilemmas hospital personnel face in filling prescribed medications and the alternative methods employed to satisfy drug orders. Each of these solutions satisfies various needs of management; however, new concerns also arise with their use. Finally, a brief overview of Multiple Criteria Decision Making is provided along with some approaches to decision support.

2.3.1 Current Management Trends and Operations in Pharmacy SCM

Hospitals have typically employed a variety of methods and policies to resolve pharmaceutical inventory management issues. A few of the more prominent solutions are discussed in this section to demonstrate the modern approaches seen in industry. Specifically, outsourcing, VMI, and information system (IS) based solutions are presented.

- **Outsourcing**

As described in the previous literature review, outsourcing has been widely used in the healthcare industry. Regardless of the specific product, entering into partnerships with suppliers and distributors for the purposes of combining services have generated benefits for the healthcare

providers (see Nicholson et al. 2004; Veral and Rosen 2001; Lunn 2000; Jarrett 1998; Li and Benton 1996, etc.). The magnitude of resources linked to pharmaceutical inventory and its management, the desire to shift or reduce pharmacy workloads, and the opportunity to refocus resources on patient care make this an appealing proposition for healthcare providers. However, as shown by Rivard-Royer et al. (2002), all parties must benefit from such arrangements to provide long-term gains.

- **VMI**

Another trend is the growing usage of VMI strategies (Kim 2005). This is a specific type of outsourcing in which pharmaceutical inventories located at various distribution locations (i.e. at the CUs) around the hospital are monitored by the supplier, in this case the pharmaceutical company or distributor, and replenished as needed. Currently, several hospitals employ a continuous review (s, S) inventory control policy. When demand for an item reaches a pre-determined minimum level (s), an order is automatically generated and transmitted directly to the supplier. The supplier, in turn, ships the amount necessary to refill the distribution centers to the maximum quantity (S). Depending on the specific circumstances, materials can be either sent to the pharmacy for re-packing and distribution or sent directly to the point-of-service, which bypasses the pharmacy entirely.

- **IT-based Inventory Management Solutions**

Information systems play a significant role in all of the aforementioned suggested approaches; however, they are perhaps even more critical in the next solution. Perini and Vermeulen Jr. (1994) reviewed a number of devices focused on the dispensation of medicines located around the hospital in the patient care unit (i.e. Lionville CDModule, Meditrol, Argus, MedStation™, Sure-Med, and Selectrac-Rx) with the purpose of replacing the traditional dosage carts used by pharmacies and to shift control of locally-stored pharmaceutical inventories and

controlled substances to caregivers at the point of use. Inventory stored in the CUs offer caregivers the opportunity to dispense medications quickly to patients; however, restocking these units can take extra time.

These medication-management machines are designed to offer financial and practical advantages over traditional operating procedures where inventories are stored in a central pharmacy and then distributed by dose carts as needed. Another benefit of using these local devices is the ability to quickly create, store, and access point-of-service patient information, which can also expedite the documentation requirements associated with drugs. The technology employed by these solutions enhances operating efficiency and facilitates customer care by lowering the risk of patients receiving incorrect medications. Regardless of the specific solution, these systems usually offer pharmaceutical administrators the ability to reduce inventory carrying and other costs, to improve billing and usage information, and to increase staff productivity by creating a highly-integrated, data-driven information flow.

2.3.2 Multiple Criteria Decision Making (MCDM)

The International Society on Multiple Criteria Decision Making (ISMCDM) has defined MCDM as “the study of methods and procedures by which concerns about multiple conflicting criteria can be formally incorporated into the management planning process” (ISMCDM 2008). Here “solving” a problem is associated with selecting the “best” alternative from a set of available and viable solutions. The best solution is the one that most closely satisfies managerial goals given the decision makers preferences in objectives.

Given the complexity of most business operations, this is an active area of research that serves as a foundation for decision support system development. In this field there are two types of problems: 1) multiple criteria evaluation problems and 2) multiple criteria mathematical programming (MCMP) problems. Multiple criteria evaluation is appropriate when there are a

finite number of alternatives that are explicitly known in the beginning of the solution process. For MCMP the number of alternatives is infinite and not countable, and these alternatives are usually determined using mathematical models. These alternative solutions are only implicitly known as well.

There are several methods employed to achieve optimization in MCDM. First, when there is a single decision maker (DM), a rating method can be used such that each criterion is rated on a scale of 1 to 10. The results are normalized to obtain weights for each criterion. Another common procedure is to use one of two ranking methods. The first ranking method is that of paired comparisons of criteria in which the decision maker is asked for preference information between various pairs of criteria. For example, decision makers are asked to identify if criterion A is preferred to criterion B, if B is preferred to A, or if they are indifferent in the choice. However, there could be a problem with the consistency of preferences. There is a method known as LINMAP developed by Srinivasan and Shocker (1973) that provides for the comparison of alternatives to determine the optimal weights. The process is designed to determine the optimal weights that will minimize the error or inconsistency in the decision maker's preference responses. Other methods involve various scaling methods such as simple scaling, linear scaling, vector scaling using linear programming norms, linear programming metrics, and using a combination of ideal solution and linear programming metrics.

Beyond these processes for establishing weights for the various criteria in problem optimization, there are several approaches for determining the optimal solutions of these problems. Methods that do not include any knowledge of the decision maker's preferences are global criterion and compromise programming (Yu and Zeleny 1975). Goal programming relies on pre-specified preferences and attempts to minimize the sum of the weighted deviations from the goals set for each criterion. Problems here would employ linear goal programming (LGP),

partitioning algorithms for goal programs (Arthur and Ravindran 1978, 1980), integer goal programming (Arthur and Ravindran 1980), nonlinear goal programming (Saber and Ravindran 1993, 1996), and intelligent search methods (Kuriger and Ravindran 2005).

CHAPTER 3: RESEARCH ENVIRONMENT AND METHODS

In this chapter, attention is given to the research problems and the methodologies employed to address these issues. The traditional supply and inventory control operations of hospitals around the world were presented earlier in this dissertation. Here an overview of the specific research environment is provided, as well as, some details about the IT-based, inventory management solution currently utilized by both this local hospital and many others. In addition, there are a number of quantitative and managerial challenges that are readily observed and expressed by hospital administrators. The focus of this research is to address these issues and provide quantitative models of varying complexity and differing data requirements that can be implemented for improving the operational, tactical, and strategic managerial decision making.

3.1 The Supply Chain and the Major Decisions of the Hospital Pharmacy

The basic structure of the supply network of the case hospital includes

- within the hospital
 - customers (doctors, nurses, patients),
 - local depots (*Pyxis MedStations*® at 86 different locations), and a
 - central depot (*Tallyst*® system at one location);
- outside the hospital
 - wholesaler (*Cardinal* GPO, one basic supplier) and
 - producers (around six major pharmaceutical companies selected by GPO).

The hospital applies advanced technology in controlling medication throughout the hospital.

The drugs are stored in the local depots (*Pyxis MedStations*®) in 86 different areas of the hospital. Each area has a different selection of drugs. The *Pyxis MedStation*® registers each transaction date and quantity of demand (withdrawal) and each delivery (refill) and the actual inventory level. It is connected to the central depot (*Tallyst*® system) through a computer network.

As the inventory level decreases to the reorder point (min par level) an automatic order is triggered by the local depot. The order quantity is determined by the order up to level (max par

level). The par levels can be selected and fixed for each drug. Currently, the par levels are based on fixed day-supplies suggested by the supplier GPO. These values are corrected occasionally by the local pharmacists using so-called “experiences”; however, no modeling or optimization is involved in setting these control values.

The demand for each drug is uncertain. The daily usage data is available for each drug and each local depot for the period of two years. In the drug supply a high service level is essential. In case of a shortage at a local depot (*Pyxis*®), an emergency delivery is necessary, and this emergency refill is very costly.

The central depot (*Tallyst*®) must satisfy the orders of the local depots within a day. One major goal of the hospital pharmacy is to minimize the number of refills (drugs per location) per day. If the number of refills per day is very large, it cannot be done in two shifts and to have overtime or an extra shift is difficult and costly. Shortage in the central depot is rare and in that case the wholesaler (GPO) refills within a day. The inventory holding cost factor is not a major concern for the hospital because the wholesaler is financing it. However, inventory holding cost is included later and in an effort to examine the effect of its consideration.

The physical volume (the total space) of the *Pyxis*® system is limited. It consists of drawers. Each drawer is subdivided by spacers that can be relocated so different cubicles are constructed and assigned to each drug. Different drugs cannot be stored in the same cubicle. The total room for the cubicles is fixed.

The main goals of the management are:

- provide a high service level for each drug,
- minimize the total number of expected refills (orders) per day for a *Pyxis*®, and
- use the limited space of a local depot (*Pyxis*®) in the best way by subdividing it to separate areas (cubicles) for each drug.

The decision variables are the reorder point (the min par level) and the order up level (max par level) for each drug. The average daily demand and the standard deviation of the daily demand

can be calculated from historical data. Also, we know the storage space requirement for a unit of each drug and the maximum storage space in a *Pyxis*®.

The **operational decision** problems occur on the item level: How to set the min and max par levels for each (250 to 300) drug in each one of the 86 *Pyxis MedStations*®?

- In setting the reorder point (min par level, s_i) there is a major tradeoff:
 - increase s_i since in case of shortage a high emergency refill cost occurs which requires the provision of a high service level;
 - decrease s_i since it needs additional buffer inventory that takes space from cycle stock and consequently more frequent orders and higher refilling cost arise; refilling cost rather the inventory holding cost is the primary concern for the hospital.
- In setting the order up level (max par level, S_i) the major tradeoff:
 - increase S_i to maximize cycle stock so that less frequent orders decrease the refilling cost;
 - decrease S_i because of the limited space for total inventory in a *Pyxis MedStation*®

There is also a connection between safety and cycle stock (s_i and S_i) for each drug, so it necessitates the joint consideration of s_i and S_i .

On the other hand, there is a tradeoff among the different drugs in a *Pyxis*® because of the total space limitation. Thus, the **tactical decision** problem occurs at the multi-item level:

How to allocate the space (by flexible drawer dividers) among the 250 to 300 drugs in each *Pyxis*®? What is the best allocation strategy for safety and cycle stock? How to set the s_i and S_i control parameters according to the allocation strategy? These questions indicate various tradeoffs to consider among the different drugs in a *Pyxis*®. Further requirements include:

- The limited space is subdivided to separate areas (cubicles) for each drug.
- The cubicles cannot be shared among drugs.
- The max inventory level (S_i) must fit into the assigned cubicle.

The major **strategic decision** problems include: What kind of tradeoffs are among refill workload, emergency workload, and variety of drugs offered (formulary)? What are their connections to the three key performance indicators: number of orders, the service level, and the available space?

In the subsequent portions we provide quantitative models, approximations and solutions starting with the operational decision problems and discuss the applicability and managerial implications of our models for tactical and strategic decisions in the hospital pharmacy.

3.2 Quantitative Models for the Hospital Inventory Management

This portion of the work presents three quantitative models examined in this investigation. In addition, a number of iterative processes are utilized to determine the optimal inventory control parameters given the goals of the individual models and the various constraints. The notations, models, and the solution processes are identified here.

3.2.1 Model 1: A General Multi-product (s, S) Model with Space Constraint and Its Approximation

The ultimate goal of the hospital pharmacy operation is to find the optimal values of the decision variables

- s_i : the reorder point (the min par level) and
- S_i : the reorder level (max par level or order up to level) for each drug i ($i = 1$ to n)

to minimize the total expected refilling (ordering), inventory holding and shortage cost under volume constraint of the local depots. The total space is subdivided into separated and dedicated storage areas for each drug, and they must be large enough to hold the max par level for each drug. The cost factors for item i are

K_i : cost of a refill (order),

$h_i = r c_i$: holding cost for a drug with value of c_i , and

p_i : shortage cost of an emergency refill that is independent of the size of the shortage.

The optimization problem can be formally expressed in

Model 1:

$$\text{Min} \quad \sum [K_i N_i(s_i, S_i) + h_i H_i(s_i, S_i) + p_i P_i(s_i, S_i)] \quad (1)$$

$$\text{s.t.} \quad \sum (v_i S_i) \leq M' \quad (2)$$

with the notation for each item

$N_i(s_i, S_i)$ = the expected number of orders per period,

$H_i(s_i, S_i)$ = the expected inventory per period,

$P_i(s_i, S_i)$ = the probability of shortage per period,

v_i = volume requirement for a unit,

M' = total volume of the space available for the n items.

Scarf (1963) expressed the above expected values, $N_i(s_i, S_i)$ and $H_i(s_i, S_i)$, using renewal functions. The probability of a shortage in a period has been derived by Schneider et al. (1995) using the steady state distribution of inventory on hand plus on order published in Iglehart (1963). Since these expressions use the renewal equation, it is only possible to get the exact solution for the single-item case with specific demand distributions. A further problem, as it was shown by Wagner et al. (1965), that the cost function, even for a single item, is not convex. Thus, following the traditional constrained optimization solution for Model 1 using the derivatives of the Lagrangian with respect to the parameters s_i and S_i , setting them equal to zero and solving the equations will not necessarily provide the optimum. However, the Roberts (1962) approximation based on the first derivatives of the Lagrangian produces nearly optimal solution for a single item cost function. Schneider and Rinks (1989) suggested an approximate solution for a constrained multi-item problem similar to Model 1, based on the Roberts (1962) approximation, and by employing a search algorithm they verify the approximate optimality of the derived policy. This procedure can also be applied as a benchmark in our case, but it is too cumbersome for our practical application.

There is a stream of publications handling hospital supply problems with some similarities to our case and another stream of papers handling similar multi-item constrained problems with no reference to hospital management. The publications in both streams closest to this situation are listed next.

Michelon et al. (1994) published a tabu search method to optimize the distribution of supplies in a hospital. Dellaert and van de Poel (1996) derived a simple inventory rule for joint ordering in a university hospital in the Netherlands. Banerjea-Brodeur et al. (1998) looked at an application of a routing model to match the different care units to be visited by a laundry department in a hospital. Vendor managed inventory (VMI) has been applied in healthcare since the nineties. An analysis and the hospital saving potentials of VMI are demonstrated in Kim (2005). Meijboom and Obel (2007) investigated supply chain coordination facing a pharmaceutical company with a multi-location and multi-stage operations structure. They concentrated on the organizational issues. Lapierre and Ruiz (2007) developed modeling approaches for improving healthcare inventory management by examining the impact of scheduling decisions on the coordination of supply activities while recognizing inventory capacities.

Ordering policies for multi-item inventory systems subject to multiple resource constraints considering deterministic demand were published in Güder and Zydiak (1999). A stochastic multi-item constrained model is discussed by Beyer et al. (2001) but only for the case of base stock policy. Ohno and Ishigaki (2001) examined a continuous review inventory system for multiple items with compound Poisson demands. Here the joint ordering was targeted but no space or budget constraints were considered. Minner and Silver (2005) analyzed the stochastic demand, continuous review lot-size coordination problem without safety stock consideration. In a recent paper, Minner and Silver (2007) analyze a replenishment decision problem where each replenishment has an associated setup cost and inventories are subject to holding costs. A second aspect of their analysis is that demands are random, here being modeled by a compound-Poisson demand process. This further complicates the analysis because safety stocks and cycle stocks share the limited warehouse space.

In summary, the published papers handle several aspects of this research case; however, they fail to consider jointly the challenge of multi-item and joint constraint with demand uncertainty or are too complex, time and data intensive for our practical application.

As such, another approach is taken to provide a faster approximate solution of Model 1. The model is simplified by applying straightforward first order approximation for the objective function (1) and the constraint (2). Consider

L = lead time (in our practical case it is one period), and use the additional notation for item i

$$D_i = S_i - s_i,$$

$$Q_i = \text{expected order quantity,}$$

$$d_i = \text{expected demand per period,}$$

$$\sigma_i = \text{standard deviation of the demand per period,}$$

u_i = *undershoot quantity*, expected inventory position below s_i when an order is placed. It can be approximated by the first two moments of the demand per period in the form (see Schneider 1981)

$$u_i \approx u_i(d_i, \sigma_i) = (d_i^2 + \sigma_i^2)/2d_i \quad (3)$$

Using this approximation, we can express the expected order quantity as function of d_i and σ_i :

$$Q_i \approx Q_i(d_i, \sigma_i) = D_i + (d_i^2 + \sigma_i^2)/2d_i \quad (4)$$

Thus we have the following simple approximate expressions as functions of d_i and σ_i :

$$N_i(s_i, S_i) \approx d_i / Q_i(d_i, \sigma_i) \quad (5)$$

$$H_i(s_i, S_i) \approx s_i - u_i(d_i, \sigma_i) - Ld_i + Q_i(d_i, \sigma_i)/2 \quad (6)$$

The probability of a shortage in a period can be approximated (see in Schneider et al., 1995)

$$P_i(s_i, S_i) \approx 1 - \int_{s_i}^{\infty} (x - s_i) f_i(x | L + 1) dx / Q_i \quad (7)$$

where

$f_i(x|L+1)$ is the demand density function for a period of length $L+1$.

The solution of Model 1 using approximations (4) to (7) is more straightforward, and it could be applied to check different practical scenarios in our case. However, the managerial problem is that the ordering and shortage cost factors are very difficult to provide. The technical

problem is that the large number of items ($n=250$ to 300 per local depot), the nonlinearity, and the stochastic demand make the solution challenging and time consuming.

The current control levels suggested by the distributor of the *Pyxis MedStations®* and by the pharmacy supplier (GPO) is a fixed day-supply, T_{\min} and T_{\max} policy, using $s_i = d_i * T_{\min}$ and $S_i = d_i * T_{\max}$, independently from the demand variability or storage space requirement. This simplistic policy results in frequent shortages and emergency refills for some drugs and also a large number of regular refills putting an overload and/or overtimes for the pharmacy staff. Additionally, storage space problems occur frequently. Based on experiences the pharmacists are frequently modifying the fixed day-supply policy, but there is a need for appropriate decision support in how to modify the s_i and S_i control parameters. To resolve those high priority problems, a simplified optimization model was formulated concentrating on the key goals.

The changing composition of the drugs stored (*formulary*) and the dynamic demand characteristics call for a fast solution on the daily operational level. The two different simplified models and simple approximate solutions we provide in the next two sections are also advantageous to provide efficient tactical decision support in managerial tradeoffs and in allocation strategies for safety and cycle stock. Further, for strategic decisions, the simplified models provide easy-to-handle tools. First, in Model 2 consideration is given to both ordering (refill) and holding cost under service level constraint. In the subsequent Model 3, the concentration is only on ordering (refill) cost minimization under service level constraint. In both models the space limit constraint is also included. The simple solutions enable using Excel spreadsheets that are familiar and easy to interpret by the pharmacists controlling the system.

3.2.2 Model 2: Optimal Allocation Based on Ordering and Holding Costs

In the inventory management literature the difficulty of providing the appropriate cost factors is well known, especially the shortage cost is hard to quantify. This is valid also in our

pharmacy case, so we follow the common practice and consider a service level constraint instead of shortage cost in the next two models. Since the shortage means an emergency refill in our case with a fixed cost (depending only on the number of shortage occasions per days and not on the amount of the shortage) it is appropriate to consider the so-called α service level which is the chance that there is no shortage in a period (day). Using this service level Model 1 can be modified and simplified into the following form.

Minimize the total refills (orders) cost plus the inventory holding cost for a *Pyxis*®,
subject to the constraints:

- the service level (chance of no shortage) for each drug is high (at least α),
- the total space needed for the maximum possible inventory level for all drugs is not more than the available total space of the *Pyxis MedStation*® (M').

Using the notation, expressions and approximations (3) to (6) from the previous section, we can formulate

Model 2:

$$\text{Min } \sum \left[K_i \frac{d_i}{Q_i} + h_i H_i(s_i, S_i) \right] \quad (8)$$

s.t.

$$\text{Prob (shortage for drug } i) \leq 1 - \alpha, \quad (i = 1 \text{ to } n) \quad (9)$$

$$\sum (v_i S_i) \leq M' \quad (10)$$

The solution of Model 2 is still quite complex because of the several variables, the nonlinearity and the stochastic constraints. To simplify the solution, we consider the two types of constraints, service level (9) and space (10) constraints, separately and also the two sets of decision variables (s_i and S_i) separately and solve the optimization Model 2 iteratively, using Power Approximation for handling the service level.

An iterative solution is applied based on two embedded iteration procedures for the optimization of Model 2. The specific Power Approximation formula derived in Schneider

(1978) provides a good approximation of the reorder points, s_i , providing the required service level α .

$$s_i = d_i(L_i + 1) + p(y_i)\sigma_{i,L_i+1} - \frac{\delta(\sigma_i^2/d_i - 1)(-1.95269 + 6.39059y_i)}{(1 + 21.17036y_i)} \quad (11)$$

with $\delta(x) = \max(x, 0)$ and $p(y_i)$ being a rational function of y_i , where y_i

$$y_i = \frac{(1-\alpha)Q_i}{\sqrt{\sigma_{i,L_i+1}^2}} \quad (12)$$

depends on the service level, α , and also on the Q_i values.

To initialize the iteration, we first set the value of the expected order quantity Q_i using the Economic Order Quantity (EOQ) formula, which is noted as Q_i' .

$$Q_i' = \sqrt{\frac{2d_iK_i}{h_i}} \quad (13)$$

Using the above Q_i' values and the fixed service level α we calculate the appropriate $s_i = s_i^{(0)}$ values from Power Approximation (11). The resulting decision variables provide the approximate optimal solution of Model 2 if the space constraint (10) is fulfilled. Using the notation of the previous section we get

$$S_i = s_i + D_i = s_i + Q_i - u_i \quad (14)$$

for the optimal parameters. In the case the approximate optimal par levels, s_i , S_i , ($i=1, \dots, n$) are provided by $s_i = s_i^{(0)}$, and (14) using the approximation (3) for the expected undershoot quantities, u_i .

If the space constraint (10) is not fulfilled, the above solution is not feasible. That means the equation

$$\sum (v_i Q_i) \leq M' - \sum [v_i (s_i - u_i)] \quad (15)$$

is not fulfilled, and there is a need to decrease the Q_i values so that the required storage space for order quantities $\sum (v_i Q_i)$ such that there is less than the remaining total free space for cycle stock

$$M = M(s_i) = M' - \sum [v_i (s_i - u_i)] \quad (16)$$

To find the optimal Q_i values that fit into the remaining space, M , defined by (16) we formulate the sub-problem of minimizing the ordering and cycle stock inventory holding cost under the remaining total free storage space. In this sub-problem, we fix the reorder points, $s_i = s_i^{(0)}$ and the resulting $M = M_0$ expressed in (16) using $s_i = s_i^{(0)}$.

Sub- problem 2A:

$$\text{Min} \quad \sum \left[K_i \frac{d_i}{Q_i} + h_i \frac{Q_i}{2} \right] \quad (17)$$

$$\text{s.t.} \quad \sum v_i Q_i \leq M \quad (18)$$

This sub-problem 2A cannot be solved directly, but the iterative solution procedure suggested by Ziegler (1982) can be applied.

To initialize the iteration, we use the Economic Order Quantities (EOQ), noted before by Q_i' , which also provides the upper bounds, $Q^{(u)}$, on the order quantities for the iteration.

The overall volume of using these Q values is

$$V' = \sum v_i Q_i' \quad (19)$$

Here we have the decision rule as described before, if $V' \leq M$, stop. Otherwise, go to step 1 of the iterative solution.

In the **first iteration step** we calculate the lower bound, $Q^{(l)}$, in the form Q_i'' , as

$$Q_i'' = \frac{M}{V'} Q_i' \quad (20)$$

and calculate values for λ_i , for $i = 1, \dots, n$, where

$$\lambda_i = \frac{d_i K_i}{v_i (Q_i'')^2} - \frac{h_i}{2v_i} \quad (21)$$

Once the values of λ_i have been calculated, set $\lambda' = \min \lambda_i$ and $\lambda'' = \max \lambda_i$.

In the **second iteration step**, average the min and max values as determined in step one to set the overall λ .

$$\lambda = \frac{\lambda' + \lambda''}{2} \quad (22)$$

In the **third iteration step**, we calculate a new Q_i using the λ provided in step two, which is noted as $Q_i(\lambda)$ for $i = 1, \dots, n$.

$$Q_i(\lambda) = \sqrt{\frac{d_i K}{\frac{h_i}{2} + \lambda v_i}} \quad (23)$$

and recalculate V using (19) and substituting the new $Q_i(\lambda)$ for the original Q_i . Next, employ the following decision rules.

If $V < M$, then set $\lambda'' = \lambda$ and $Q^{(u)} = Q_i(\lambda)$.

If $V > M$, then set $\lambda' = \lambda$ and $Q^{(l)} = Q_i(\lambda)$.

In the **fourth iteration step**, calculate the functions for the upper and lower bounds as

$$F(Q^{(u)}) = \sum \left[K_i \frac{d_i}{Q_i^{(u)}} + h_i \frac{Q_i^{(u)}}{2} \right] \quad (24)$$

$$F(Q^{(l)}) = \sum \left[K_i \frac{d_i}{Q_i^{(l)}} + h_i \frac{Q_i^{(l)}}{2} \right] \quad (25)$$

and use the stopping rule for the iteration

$$\frac{F(Q^{(u)}) - F(Q^{(l)})}{F(Q^{(l)})} \leq E \quad (26)$$

If the relative difference is determined to be less than or equal to the preset acceptable error, which was 0.01 in our case, stop. Otherwise, continue the iteration beginning at step two and repeat this process until convergence. Once the optimal Q_i values are obtained, move to the second stage of the iterative solution and use these Q_i values to adjust the reorder points and find

the s_i values providing the required service level, α , for each item. With the new $s_i = s_i^{(2)}$, we recalculate $M = M_2$ and solve the sub-problem 2A again with the iteration process above. The resulting Q_i values may be different than those determined in the prior step in which case new $s_i = s_i^{(3)}$ values are used for new iterations until the difference in s_i and Q_i is smaller than the preset accuracy limit ($E = 0.01$). The proof of the convergence of the above iterative procedure is in Ziegler (1982).

3.2.3 Model 3: Optimal Allocation Based on Ordering Cost

In this practical case, the major goal of the hospital pharmacy is to minimize the refill workload. Inventory holding cost is marginal and is not even considered currently in the *Pyxis*® database. This is motivation to simplify Model 2 and provide a simple, goal-oriented decision support tool for the pharmacy management. So, next consider the simplified constrained optimization problem.

Minimize the total number of expected refills (orders) per day for a *Pyxis*®, subject to the constraints:

- the service level (chance of no shortage) for each drug is high (at least α), and
- the total space needed for the maximum possible inventory level for all drugs is not more than the available total space of the *Pyxis MedStation*® (M').

Model 3:

$$\text{Min } \sum (d_i / Q_i) \quad (27)$$

s.t.

$$\text{Prob (shortage for drug } i) \leq 1 - \alpha, \quad (i = 1 \text{ to } n) \quad (28)$$

$$\sum (v_i S_i) \leq M' \quad (29)$$

Despite the objective function of Model 3 being simpler when compared to Model 2, we still have the problem of having the same large number of decision variables, as well as, the nonlinearity and stochastic constraints as before. As such, a similar iterative solution is applied,

but it proves to be faster and easier to interpret than optimization Model 2. Here we also consider the two constraints, service level (28) and space (29) constraints, separately and also the two sets of decision variables (s_i and S_i) separately and solve the optimization Model 3 iteratively, using the same Power Approximation as before for handling the service level. This method is very straightforward, intuitive and sheds light on the simple structure of the optimal allocation of the safety stock and cycle stock separately.

To **initialize the iteration**, set the reorder point

$$s_i^{(0)} = d_i * T_{\min}, \quad (30)$$

as it is suggested by the pharmacy supplier. Thus

$$M_0 = M_0(s_i^{(0)}) = M' - \sum [v_i (s_i^{(0)} - u_i)] \quad (31)$$

is the remaining total free storage space for order quantities.

To find the optimal Q_i values we formulate the sub-problem of minimizing the number of orders per day under the remaining total free storage space for cycle stock with fixed reorder points, $s_i^{(0)}$ and the resulting $M = M_0$ expressed in (31):

$$\text{Min } \sum (d_i / Q_i) \quad (32)$$

s.t.

$$\sum (v_i Q_i) \leq M \quad (33)$$

Proposition 1: The **optimal space allocation** for Q_i to minimize the expected number of orders is **proportional with the square root of the demand over volume rate**, and the optimal solution of (32) s.t. (33) is

$$Q_i^{(0)} = M/W * \sqrt{(d_i / v_i)} \quad (34)$$

with notation

$$W = \sum \sqrt{(v_i d_i)} \quad (35)$$

Proof: Considering the Kuhn-Tucker conditions for the Lagrange function of Model 2

$$L(\mathbf{x}, \lambda) = \sum (d_i / x_i) + \lambda [\sum (v_i x_i) - M] \quad (36)$$

for the optimal x_i^* and λ^*

$$x_i^* \partial L(x^*, \lambda^*) / \partial x_i = -d_i / x_i + \lambda^* v_i x_i = 0 \quad \text{for } i = 1, \dots, n \quad (37)$$

so if λ^* is known from (37) we get

$$x_i^* = \sqrt{(d_i / \lambda^* v_i)} \quad (38)$$

On the other hand, if any of x_i^* is known

$$\lambda^* = d_i / (v_i x_i^{*2}) \quad (39)$$

Since for the optimal solution the capacity constraint is active

$$\sum (v_i x_i^*) = M \quad (40)$$

Substituting (38) into equation (40) and using the notation

$$W = \sum \sqrt{(v_i d_i)} \quad (41)$$

the optimal value of λ^* can be expressed

$$\lambda^* = (W / M)^2 \quad (42)$$

and substituting (42) into (38) provides for $i = 1, \dots, n$ the optimal

$$x_i^* = \sqrt{(d_i / \lambda^* v_i)} = [M \sqrt{d_i}] / [W \sqrt{v_i}] = M/W \sqrt{(d_i/v_i)} \quad (43)$$

In the **first iteration step** adjust the reorder points and find the $s_i^{(1)}$ values that provide the required service level, α , for each item. Here the simple Power Approximation formula derived in Schneider (1978) expressed in (11) and (12) is employed.

The modified $s_i^{(1)}$ values will change the available space for cycle stock according to

$$M_1 = M_1(s_i^{(1)}) = M' - \sum [v_i (s_i^{(1)} - u_i)] \quad (44)$$

which provide the **next iteration** of

$$Q_i^{(1)} = M_1/W * \sqrt{(d_i/v_i)} \quad (45)$$

The iteration for $s_i^{(2)}$ results from Power Approximation (11) and (12) applying $Q_i = Q_i^{(1)}$.

Continue the iterations until convergence. According to formula (11), there is a minor effect of Q_i on s_i , thus the convergence is very rapid; by our experiences two-three iterations are sufficient to get within 0.1% range.

The approximate optimal control parameters for item i ($i = 1$ to n) are

- **min par level**, s_i , is the last iteration expressed in (32) and (33) ;
- **max par level**, S_i , is resulting from the last iteration (34) for M

$$S_i = s_i + D_i \quad (46)$$

using the approximation with expression (31) for W

$$D_i = \frac{M}{W} \sqrt{\frac{d_i}{v_i} - \frac{d_i^2 + \sigma_i^2}{2d_i}} \quad (47)$$

3.3 Comparison of Optimization Efforts for Model 2 and Model 3

In this section we examine the efforts required to achieve the optimal order quantities, Q_i , for the multi-item case using the sample of 70 items in a *Pyxis*®. First, Model 2 examples are presented to show the changes in iterations that occur as the optimal order quantities are reached. Second, an illustration of Model 3 is presented to demonstrate the simplicity of calculations and the quick nature of optimization using this approach. This is done to contrast these techniques, as well as, to show the steps and efforts necessary to complete the iterative processes.

3.3.1 Demonstration of Model 2

Model 2 involves a multi-iteration, multi-round process to achieve optimization. The specifics of the model and this process are presented in Chapter 3. Here we see the precise results obtained as the iterations progress. Model 2 required several rounds iterations with a number of iterations within each round. Specifically, 2 rounds of iterations were required with

11 iterations necessary in both rounds to achieve convergence. The results below reflect outcomes of final round of iterations, which ultimately provide the optimal Q_i values with the required accuracy.

To begin the iterative process a comparison must be made between the M value provided by Model 3 and the overall volume, V , required to house the items in the sample. As shown in Table 3-1, the space required was determined to be 17874.59 and exceeds our initial M^1 value of 4859.79, which prompted the start of the iterative process. With each step of the iteration, the V is adjusted by the Q_i values determined in the previous step in an effort to minimize the difference between the space needed and the space available, M . The magnitude of these corrections are very large early on in the process because of the tremendous discrepancy between V' and M_1 , but this volatility diminishes as optimization is achieved.

Table 3-1: Changes in Overall Volume

	Value	% Change
V'	17874.59	---
V_0	757.39	-2260.01%
V_1	1063.28	28.77%
V_2	1484.05	28.35%
V_3	2052.61	27.70%
V_4	2801.62	26.73%
V_5	3753.19	25.35%
V_6	4898.67	23.38%
V_7	4207.27	-16.43%
V_8	4511.35	6.74%
V_9	4692.29	3.86%
V_{10}	4791.93	2.08%
V_{11}	4844.36	1.08%

The values of V shown in Table 3-1 are changed by constantly adjusting the lambda, λ , values used in calculating the upper and lower bounds of Q_i . These values are available in Table 3-2.

Table 3-2: Values of Lambda

	Values of λ		
	λ'	λ''	λ
Initial	0.005	5.980	2.993
Iteration 1	0.005	2.993	1.499
Iteration 2	0.005	1.499	0.752
Iteration 3	0.005	0.752	0.379
Iteration 4	0.005	0.379	0.192
Iteration 5	0.005	0.192	0.099
Iteration 6	0.005	0.099	0.052
Iteration 7	0.052	0.099	0.075
Iteration 8	0.052	0.075	0.064
Iteration 9	0.052	0.064	0.058
Iteration 10	0.052	0.058	0.055
Iteration 11	0.052	0.055	0.054

As explained, the upper and lower bounds of Q_i are adjusted with each iterative step.

Table 3-3 summarizes the average percent changes in Q_i observed across all items in the sample.

In this case the upper bound of Q was corrected between 24% and 29% in each of the first five iterative steps. At that point the value of V , as shown in Table 3-1, prompted an adjustment of the lower bound by 23%. In steps 7 through 11, the corrections shifted back to the upper bound.

At that point, the iterations were halted as a result of the stopping rule.

Table 3-3: Average Percent Change in Q with Iteration

	$Q' = Q^U$	$Q'' = Q^L$
Step 0	---	---
Step 1	29%	0%
Step 2	28%	0%
Step 3	27%	0%
Step 4	26%	0%
Step 5	24%	0%
Step 6	0%	23%
Step 7	10%	0%
Step 8	6%	0%
Step 9	3%	0%
Step 10	2%	0%
Step 11	1%	0%

To further illustrate this process an example is provided at the item-level. The drug with the highest daily demand was selected to demonstrate the convergence to the optimal order quantity for that item. This is shown in Figure 3-1.

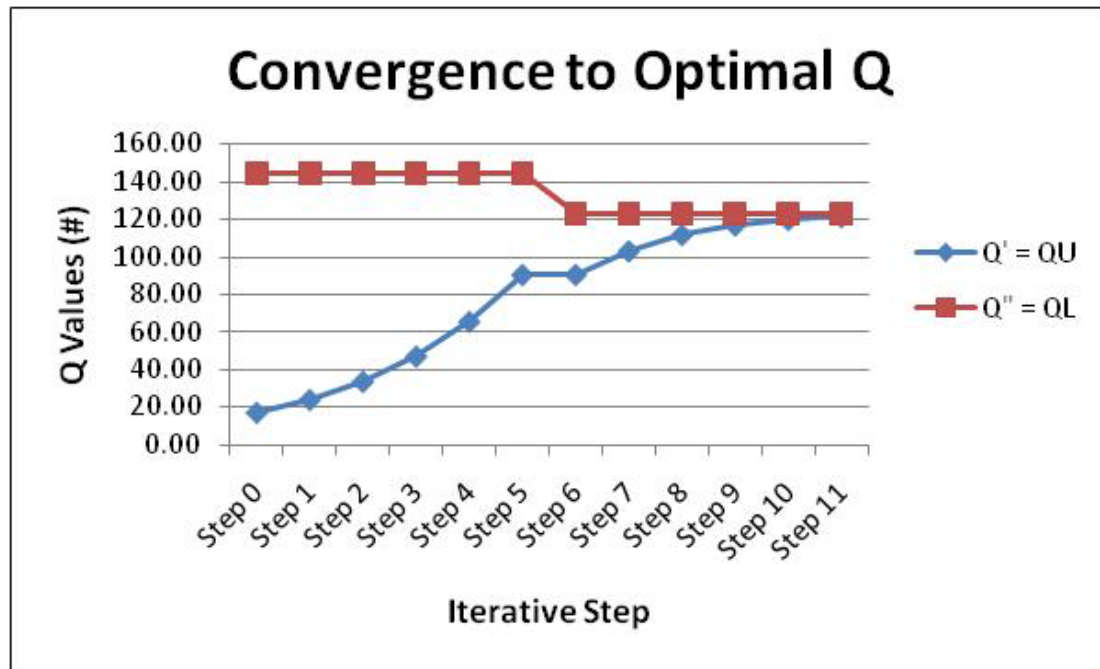


Figure 3-1: Convergence to the Optimal Q for a Sample Drug

The specific results for this drug are provided in Table 3-4. This table supplies both the upper and lower bounds of Q throughout the iterative process and the observed percentage of change resulting from each step. As expected, the pattern is similar to that presented in Table 3-3.

As described earlier in this chapter, the stopping rule for the iterations within each round is set such that the percent difference between the objective functions of the upper and lower bounds of Q must be below a preset error. Here the iterations were halted when the error was less than 1% (i.e. 0.01). Table 3-5 displays the results from the actual iterations in Round 2. As shown, the convergence is reached by individually adjusting the upper or lower bounds as

dictated by the procedure. Gradually, as the iteration evolves, these functions migrate until the difference is small enough to satisfy our stopping rule.

Table 3-4: Optimization of Q for a Sample Drug

	$Q' = Q^U$	$Q'' = Q^L$	Q^U % Change	Q^L % Change
Step 0	16.66	144.34	---	---
Step 1	23.53	144.34	29%	0%
Step 2	33.19	144.34	29%	0%
Step 3	46.67	144.34	29%	0%
Step 4	65.29	144.34	29%	0%
Step 5	90.41	144.34	28%	0%
Step 6	90.41	122.90	0%	-17%
Step 7	103.00	122.89	12%	0%
Step 8	111.64	122.89	8%	0%
Step 9	116.86	122.89	4%	0%
Step 10	119.77	122.89	2%	0%
Step 11	121.30	122.89	1%	0%

Table 3-5: Functions of Q for Model 2 Iterations

	$F(Q^U)$	$F(Q^L)$	Difference
Initial	2332.92	775.42	200.86%
Iteration 1	1684.32	775.42	117.21%
Iteration 2	1236.70	775.42	59.49%
Iteration 3	932.38	775.42	20.24%
Iteration 4	729.55	775.42	-5.92%
Iteration 5	597.80	775.42	-22.91%
Iteration 6	597.82	515.10	16.06%
Iteration 7	558.56	515.12	8.43%
Iteration 8	537.45	515.12	4.34%
Iteration 9	526.45	515.12	2.20%
Iteration 10	520.82	515.12	1.11%
Iteration 11	517.97	515.12	0.55%

This process is performed during each round of the iterative process. After the first round, the final Q_i ($Q_i = Q^L$) are used in the Power Approximation formula (11) to calculate the corresponding reorder points, s_i , for each item in the sample. These new s_i values allow for a

new M_1 value to be established, which initializes the next round of iterations. The values of M_1 used to initiate the model are presented in Table 3-6.

Table 3-6: Values of M for Iterative Rounds

	Round 1	Round 2	% Difference
M_1	4859.79	4860.14	0.01%

The rounds of iterations continue until the difference between Q_i and s_i values is small enough to meet our stopping rule of less than 1% difference. As mentioned previously, this specific example needed 2 rounds of iterations with each round requiring 11 iterations to reach convergence. Upon completion of Round 2, the resulting Q_i values are used once again in the Power Approximation formula to set to determine the corresponding s_i values for the sample items. Table 3-7 shows the calculated values of Q_i and s_i for the sample and supports the decision to stop the iterations after 2 rounds.

Table 3-7: Order Quantities and Reorder Points for Sample

	Iteration 1		Iteration 2		% Change	
	$Q_i^{(1)}$	$s_i^{(1)}$	$Q_i^{(2)}$	$s_i^{(2)}$	Q	s
Drug 1	122.89	59.95	122.89	59.90	0.00%	0.08%
Drug 2	122.62	34.23	122.62	34.21	0.00%	0.07%
Drug 3	120.03	26.00	120.03	25.98	0.00%	0.10%
Drug 4	51.11	25.99	51.11	25.97	0.00%	0.07%
Drug 5	71.48	17.86	71.48	17.85	0.00%	0.08%
Drug 6	66.34	15.82	66.34	15.81	0.00%	0.11%
Drug 65	24.95	2.96	24.95	2.96	0.00%	0.09%
Drug 66	28.75	2.19	28.75	2.18	0.00%	0.17%
Drug 67	35.88	6.87	35.88	6.85	0.00%	0.27%
Drug 68	18.92	5.40	18.92	5.40	0.00%	0.10%
Drug 69	18.77	4.48	18.77	4.47	0.00%	0.10%
Drug 70	30.68	1.72	30.68	1.72	0.00%	0.13%

0.00% 0.11% Average

3.3.2 Demonstration of Model 3

In contrast to the complexity of Model 2, a significant benefit of Model 3 is that it provides a much simpler and less cumbersome approach to optimizing the order quantities. A benefit of this approach is the need for relatively few inputs, which satisfies a major obstacle facing the hospital pharmacy. At present, the hospital and GPO were unable to provide any cost related data. It simply did not exist within the pharmacy database. In addition, something as basic as extracting accurate usage data for transactions at the Pyxis® units is a very arduous task. According to the pharmacy staff, usage data can only be extracted for a period of 6 days at a time. Pulling enough data for accurate analytical purposes is labor-intensive and taxes an already over-worked staff.

Once the model inputs are identified, the calculations are uncomplicated with a single, straightforward stopping rule. The model inputs include the average daily demand, the standard deviation of daily demand, and the unit size along with the current inventory control policy used by the hospital (shown in Tables 3-8 and 3-9). This information is used to initialize the iterative procedure.

Table 3-8: Fixed-days Supply Policy of Hospital

Tmin	Tmax
3	10

The hospital control settings (s , S) provide the initial values necessary to determine the space available for cycle stock, M_0 , given the reorder points. From this, the starting values for Q_i are established. These order quantities are then used in the first iterative step to modify the s_i values for the sample items, which creates a new value of M , M_1 . A comparison is then made between M_0 and M_1 . According to our stopping rule, the iterations continue until the change in M values from one step to the next is less than 1%. The changes in M values are shown in Table

3-10. Using this approach, convergence is usually reached quickly and only required 2 iterations in this optimization example.

Table 3-9: Inputs for Model 3

Drug	Average	Sigma	Size (v_i)
Drug 1	16.63	13.10	2
Drug 2	10.54	8.50	1
Drug 3	8.29	6.97	1
Drug 4	7.60	5.54	5
Drug 5	5.28	4.81	1.5
Drug 6	4.76	4.30	2
Drug 65	0.70	1.24	1
Drug 66	0.69	1.03	1.5
Drug 67	0.68	2.33	1
Drug 68	0.68	1.67	2
Drug 69	0.67	1.49	2
Drug 70	0.66	0.85	1

Table 3-10: Percent Change in Space Available to Cycle Stock (M)

	Initial	Iteration 1	Iteration 2
M	5357.58	4904.59	4859.79
% Change	---	9.24%	0.92%

Once the final values of s_i and Q_i are found, the difference between the reorder point and the order up to level, D_i , can be set according to the formula (47) and used to calculate the S_i values for the items, where $S_i = s_i + D_i$. The values of s_i and Q_i from the iterations are shown in Table 3-11 along with the final par values as determined by this approach.

Table 3-11: Optimal Values from Model 3

	Initial		Iteration 1		Iteration 2		Optimal Values		
Drug	$s_i^{(0)}$	$Q_i^{(0)}$	$s_i^{(1)}$	$Q_i^{(1)}$	$s_i^{(2)}$	$Q_i^{(2)}$	D_i	s_i	S_i
Drug 1	49.90	117.08	60.59	107.19	61.86	106.21	92.73	61.86	154.59
Drug 2	31.62	131.80	33.53	120.66	34.36	119.55	110.86	34.36	145.22
Drug 3	24.87	116.90	26.18	107.02	26.87	106.04	98.97	26.87	125.84
Drug 4	22.81	50.06	26.09	45.83	26.58	45.41	39.59	26.58	66.17
Drug 5	15.84	76.17	17.50	69.73	17.98	69.10	64.27	17.98	82.25
Drug 6	14.29	62.65	16.08	57.35	16.49	56.83	52.51	16.49	69.00
Drug 65	2.11	34.04	2.48	31.16	2.62	30.88	29.42	2.62	32.04
Drug 66	2.08	27.63	2.23	25.29	2.32	25.06	23.96	2.32	26.28
Drug 67	2.05	33.57	7.20	30.74	7.66	30.45	26.13	7.66	33.79
Drug 68	2.05	23.74	4.76	21.73	5.01	21.53	19.16	5.01	24.17
Drug 69	2.02	23.55	3.96	21.56	4.16	21.36	19.38	4.16	23.54
Drug 70	1.99	33.04	1.66	30.24	1.73	29.97	29.09	1.73	30.83

3.4 Accuracy of the Approximations

We examine the accuracy of our approximations for the three key performance indicators:

- the expected total number of orders (daily refills),
- the maximum space requirement for the total cycle stock, and
- the average service level.

We compare our approximations based on Model 3 with the result of using simulations of daily transactions. We applied various parameter settings and in the simulation we used the real demand observed at a particular *Pyxis MedStation*® of the case hospital for a year.

For illustration, in Table 3-12, we summarize our results based on the same case example we used in the previous part of this Section for the selected 70 drugs in the particular *Pyxis*® with the highest demand rate. We examine the performance characteristics – calculated and simulated – for the three inventory control policies: the supplier suggested (GPO), the one modified by the hospital (HM), and our approximate optimization Model 3 (OM). The maximal

space available (M) is set to be the same for each policy, which is equal to the volume that is currently used by the HM policy for the total cycle stock.

Table 3-12: Accuracy of the Approximations - Comparison of the Calculated and Simulated Key Performance Indicators

Simulation Results			
Inventory Policy	Refills	Max Space	SL
GPO	6.20	5845.75	99.95%
HM	5.86	5898.50	99.98%
OM	4.52	5691.50	99.98%

Model Predictions using our Approximation			
Inventory Policy	Refills	Max Space	SL
GPO	6.03	5860.75	99.89%
HM	5.74	5931.50	99.84%
OM	4.47	5921.50	99.94%

Percent Difference			
Inventory Policy	Refills	Max Space	SL
GPO	-2.86%	0.26%	-0.05%
HM	-2.05%	0.56%	-0.14%
OM	-1.12%	3.88%	-0.05%

As the above illustration in Table 3-12 shows the percent errors are below the 4% margin with significantly lower errors on the measure of average service level. Overall, these results effectively demonstrate the accuracy of our approximations. However, it is important to note that we observed that below 99% there is a tendency of underestimating the average service level for low demand rate. We discuss the reason for this phenomenon in the next paragraph. The daily usage rate is in the 16.63 to 0.66 range for the 70 items we considered. 35% of the items are below the 1 unit daily usage rate. As our detailed investigations revealed, these low-usage items are the main sources of the approximation errors. Disregarding them, the approximation error decreases below 1.2% that is well acceptable for our practical situation.

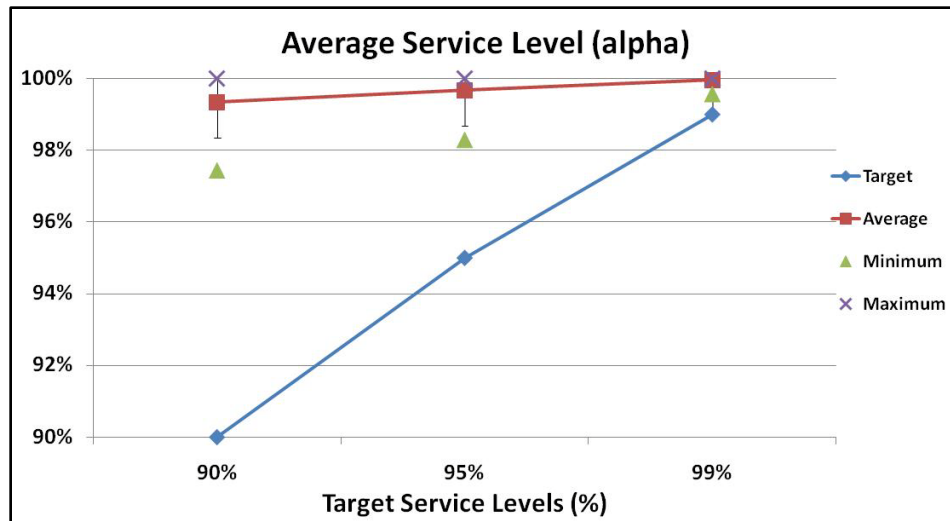


Figure 3-2: Approximation of Target Service Level

Figure 3-2 shows the average service level simulated for the 70 items for different target service levels. While the accuracy of the average service level approximation we achieved using simulation is good for the 99% target service level and above, there is a large error at the lower average service levels. To explain this phenomenon we need to examine service at the item level. This observed error can be explained by the absence of shortages for many of the low usage rate items. 76% of the low-usage items showed no shortage during a year period. The remaining 24% of these items typically had one shortage occasion and displayed high demand variability with all shortage items having a standard deviation of daily demand that was 2 to 3 times the amount of average daily demand for the item (this is the so-called “lumpy” demand). Correcting the error at the lower average service levels would allow for an increase in stockouts and more accurate service level estimate. However, this is impractical in our case given the expense of emergency refills and sensitivity of patient care. On one hand we can conclude that low volume items and “lumpy” demand items need better service level approximation, but on the other hand this is not so important for our practical case because their total safety stock contribution is small.

CHAPTER 4: ANALYSIS AND MANAGERIAL INTERPRETATION

In this chapter the focus is on describing the decision support tool developed for this project and the managerial interpretation of the analysis performed. To facilitate this research and to make this endeavor more applicable and beneficial for the stakeholders at the participating hospital, a great deal of consideration was given to their current operations and the manner in which inventory data is utilized. First, the rationale for the decision support tool and software selection is given. Second, comparisons are made between the efforts to achieve optimization using Models 2 and 3. Third, a comparison is made to evaluate the estimated inventory costs of employing the current hospital policy, Model 2 results, and the Model 3 control values. Finally, the operational, tactical, and strategic implications of the findings are explored and used to illustrate the practical value of this work. To that end, a number of managerial tradeoffs are considered along with comparisons amongst allocation strategies.

4.1 Application for Managerial Decision Support

For this project a modeling application and simulation were developed using MS Excel. There are a number of reasons this software was chosen. First, the demand and usage **data** is available for extraction and manipulation in a file format compatible with this program. The IT-based solution currently employed by the hospital to monitor and control pharmaceutical inventory works quite well with this software. Second, **pharmacy administrators** are very familiar with this application, as well as, with the MS Office Suite. MS Excel is used extensively by the staff and is one of the most commonly used spreadsheet applications around the world. As such, this was a logical application to utilize for the program and subsequent analysis.

Data from the identified *Pyxis MedStation*® is extracted at the transaction level, which is then manipulated into daily usage values. Once the data is in this form, the average daily demand and the standard deviation of daily demand is calculated for input into the quantitative models. The formulae and iterative processes (as described in Chapter 3) are incorporated into the application such that changes in control parameters are readily available for review throughout the procedure. An added benefit of having the daily usage data for every item in a local depot is the ability to verify the accuracy and utility of the calculated par values. In addition, now that the application has been tested and the accuracy established, the iterations of the models can be automated in MS Excel by setting a predetermined stopping value (i.e. 0.01) within the program when the difference between iterations is small. This is ideal for managers that have limited amounts of time to devote to optimizing operating settings and that have little interest in the steps necessary to achieve the final values.

Ideally, this application would be incorporated into the workings of the pharmacy, which is a relatively easy task, due to the utility of the program and the ease of its use. Furthermore, to achieve a greater potential impact on the critical performance indicators, mechanisms for updating inventory control parameters are easily added. For example, forecasting techniques, such as exponential smoothing or moving averages, might prove useful in monitoring product demand and adjusting the formulary to take advantage of the tradeoffs explained here. Also, the continuous review of inventory at any given *Pyxis MedStation*® and across all of these machines allows for real-time evaluation of the control values and facilitates swift changes and adjustments to settings as necessary.

4.2 Levels of Decision Support

This section identifies the manner in which the simplified approach of Models 2 and 3 supports decision making at multiple levels. First, the operational decisions are discussed.

Second, the tactical considerations are presented along with the utility of this decision support tool in analyzing managerial tradeoffs. Third, a breakdown of the strategic implications is provided.

4.2.1 Operational Decision Support

At this level of decision making, the focus is on the management of individual items. The high service level requirement dictates a high reorder point, s_i , be used to maintain healthcare standards and to avoid expensive emergency refills. Additionally, the order up level, S_i , for each item must be reduced to accommodate the other products in the *Pyxis*® given the space constraints of the storage unit. The reduced space for cycle stock generates a need for additional daily refills, which results in higher refilling costs and workloads for the pharmacy. Any changes at the item level can impact the operations and workloads associated with the local depot. Managers needed help in evaluating their current practices and in improving these procedures.

The decision support tool developed for this research project serves as a model for managers. It allows them to examine changes in the formulary or item usage, to evaluate options for modifying the control parameters, and to choose the par values that best fit hospital and management criteria. In addition, it allows for quick, simple analysis of the managerial tradeoffs associated with the pharmacy and storage unit capacities. Greater details on this issue are provided later in this chapter.

- **Cost Comparison of Allocation Strategies**

As described above, two methods for determining the optimal par levels and order quantities in multi-item, single-location settings under constraints have been explored. Here comparisons are made between the current hospital inventory policy (HM) and the alternative approaches of Model 2 and Model 3. This is followed by comparisons between the two

alternative approaches. As a reminder, the hospital currently uses a modification of the fixed day-supply policy suggested by the GPO. Model 2 is designed to find the optimal allocation of space across all items being considered by minimizing the sum of holding and ordering costs. While Model 2 focused on the issue of holding and refill costs, Model 3 was established to satisfy an exact desire of the hospital pharmacy to minimize the daily refill load without consideration of holding costs. Specifically, Model 3 minimizes the total number of expected refills (orders) per day for a *Pyxis*®, subject to the service level and storage capacity constraints.

Although accurate cost data was unavailable from the hospital, unit prices were obtained using a well-known, online pharmaceutical vendor. Despite not having exact holding cost values for the sample drugs, surrogate values were used for comparative purposes and to better understand the cost implications of these policies. Figure 4-1 illustrates the costs as calculated using actual product prices. Here the cost implications of such policies are easily observed.

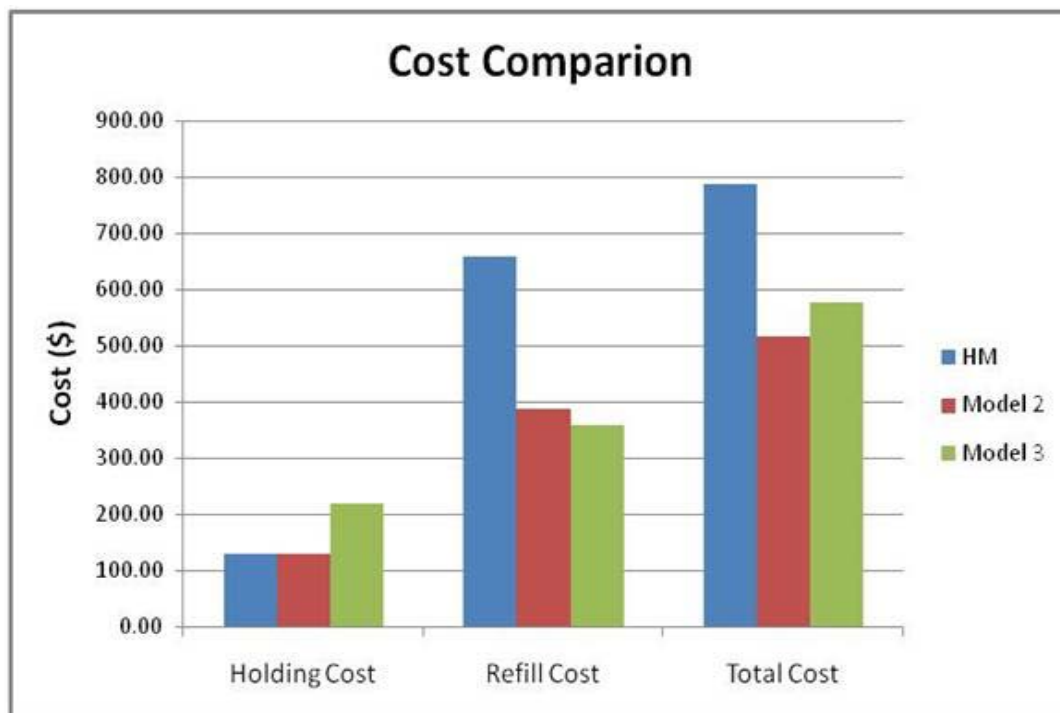


Figure 4-1: Cost Comparison for Allocation Methods

As shown in Figure 4-1, the holding cost, refill cost, and total cost of refill and holding are substantially different for the three policies. Holding costs are nearly identical for HM and Model 2 with the Model 3 policy resulting in holding costs around 40% higher than the other strategies. Refill costs are substantially higher for the HM policy than for either Model 2 or Model 3 with the refilling cost being 71.1% and 83.9% higher respectively. These higher refill costs result in a much higher total cost for the HM policy and is evidenced by a 52.8% higher cost than Model 2 and 36.4% higher cost than Model 3. These differences are summarized in Table 4-1.

Table 4-1: Percent Differences in Model Costs to Hospital Policy

	Percent Difference		
	Holding Cost	Refill Cost	Total Cost
Model 2	1.3%	-71.1%	-52.8%
Model 3	41.4%	-83.9%	-36.4%

In continuing with these comparisons, it is useful to examine the differences between the two approaches suggested as alternatives to the HM policy. Again, the two models are evaluated on the basis of holding cost, refill cost, and total cost of holding and refill. The results are available in Table 4-2.

Table 4-2: Cost Comparison of Model 2 and Model 3

	Percent Difference		
	Holding Cost	Refill Cost	Total Cost
Model 3	40.6%	-7.5%	10.7%

Model 2 provides 10.7% lower total cost of refill and holding with much of that due to the 40.6% lower holding cost realized by the model. Again, this is understandable given the cost-focus of this approach. The inclusion of prices allows for allocation to be based on item

cost and ensures that higher costing items are kept in smaller quantities, which enables the savings identified previously. On the other hand, Model 3 requires a 7.5% lower refill cost, which supports the desires of hospital administrators.

It is important to reiterate that neither the hospital nor the GPO could produce accurate cost data to support this research. As such, the cost analyses are performed primarily to serve three purposes. First, when holding and ordering costs are unknown, Model 3 provides a simplified technique for approximating the optimal order quantities, Q , that minimizes the number of refills. It is likely that many organizations operate without accurate cost information similar to our case hospital, so Model 3 offers an opportunity to assess policies and possibly improve upon them. Second, as with this pharmaceutical case, holding cost was not a primary concern for the pharmacy. Model 3 addresses their need to reduce refill activities, thereby decreasing workloads, while continuing to offer high service levels for caregivers administering patient treatments. This is not to say that costs are unimportant to pharmacy management, but it is not the main objective. Third, this analysis clearly demonstrates the significance of having accurate cost data to improve the cost performance of the supply chain and decision making. The comparisons with Model 2 reveal the relationship of the holding costs, h_i , to setting the optimal order quantities, Q_i , for all items. When holding costs are high, Q_i values are set lower to avoid elevated carrying costs. Conversely, items with lower holding costs can be held in higher quantities with small penalty. In cases where good cost data is available, the expected refill size Q_i is proportional to the rate of ordering cost, K_i , over holding cost, h_i .

- **Additional Considerations for Improved Operations**

It may be unrealistic for practitioners to re-run the approximation methods every time a change is proposed in the formulary. The demand for drugs changes on a daily basis, and items are added and removed from the formulary frequently. It may be too demanding to run the

iteration procedure each time a change occurs. Thus, some suggestions are offered as support for improving the day-to-day operations of the pharmacy. After an initial run of Model 3 to identify the reorder point and set the optimal order quantities, the pharmacy can employ an abbreviated technique since some of the variables in this equation will remain relatively constant during a short period of time. The optimal s_i values are provided by the Power Approximation (11) and set to satisfy the service level requirement. Using the final values from the initial run for the space available for cycle stock (see Table 3-10 for values of M), and our calculated W of 131.97 as determined by formula (41), we can provide a quick approximation of Q_i for any item according to formula (45). As explained previously, the optimal space allocation for Q_i to minimize the expected number of orders is proportional with the square root of the demand over volume rate. Knowing the appropriate s_i and Q_i values, the order up to level can be set according to $S_i = s_i + Q_i - u_i$. It is important to note that this is not the exact optimal solution; however, it will provide a good estimate of the solution until the next optimization run for the *Pyxis*® is made by the pharmacy.

Similarly, we propose a fast, simple approximation technique using the initial optimized values of Model 2. Using the final value of λ (see Table 3-2) from the initial optimization run and the formula (23) for Q_i , a good estimate of the optimal Q_i value can be generated. Since the reordering costs remain fairly constant over short periods of time and an appropriate holding cost is known, this formula can be applied by simply inputting the proper values of average daily demand and the unit size requirement. Again, this does not provide the exact optimal solution, but the simplified nature of this approach makes it a good alternative until another optimization run is made for all items in the *Pyxis*®. It allows pharmacy workers to make quick approximations of the optimal order quantity for an item any time a new drug is added to the formulary or when there is significant change in the average usage of an item.

Another important relationship to recognize is the influence that the rate of variance in daily demand to average daily demand (σ^2/d) has on inventory policy. The current hospital policy of a modified, fixed-days demand approach means that the reorder points for all items in the Pyxis® are set on average to be 3 days of expected demand. Understanding the influence of variance in daily demand and incorporating the σ^2/d ratio into the inventory policy can improve the operations. When this rate is large with the variance of daily demand being 2-3 times or more than that of the average daily demand, the pharmacy may consider modifying the policy according to the Power Approximation (11) and set a higher reorder point and lower the order up to level (i.e. use a 4, 6 policy not 3, 10). This higher reorder point allows the pharmacy to avoid stockouts and emergency refills and offers a mechanism for detecting atypical usage patterns. In addition, the lower order up to level enables the pharmacy to avoid keeping unnecessarily large inventory of low usage items. On the other hand, when the rate is lower with the variance of daily demand being equal to or much smaller than the average daily demand, then the hospital may consider lowering the reorder point and set the a higher order up to level (i.e. use a 2, 12 policy not 3, 10). Since orders are filled within 1 day by both the pharmacy and the drug supplier, replenishing inventory should not be a problem. Thus, the additional space allocated to an increased cycle stock limits the refill occasions for these items.

Both of the simple rules above offer improvements to current hospital pharmaceutical management practices. In addition, according to pharmacy information, technicians have limited access to usage data and only have the ability to extract 1 week's worth of usage data at a time. Since data availability and worker capacity is limited, employing this abbreviated technique and understanding the influence of demand variability on inventory policy can greatly enhance pharmacy practices at the operational level. Models 2 and 3 demonstrates the ability to address both the managerial goals of the pharmacy and to offer significant quantitative support for

workers charged with daily tasks in the pharmacy. The pharmacy can make optimization runs less frequently (i.e. every month or quarter) or only when substantial changes in the formulary or item demands have occurred.

4.2.2 Tactical Decision Support

In this section discussion shifts to “What If” analysis and the managerial implications of the findings demonstrated previously. The benefits and ability of Model 3 to outperform both GPO and current hospital practices has already been established in the previous chapter. Now, we demonstrate what happens if we make various changes to the current operating procedures and conditions.

- **Safety Stock and Cycle Stock Allocation Strategies**

Another important practical significance of Model 3 is to provide simple approximation to the optimal safety stock and cycle stock allocation strategy. There is also a relationship between the allocation strategy and operational control: how to select the near-optimal min and max par levels (s and S). This is shown below.

The safety stock is determined by the choice of the reorder point, s . The reorder point, s , is the sum of expected demand during the lead time plus the safety stock. The lead time is the refill time, which is one day in our case. According to the Power Approximation (11), the appropriate reorder point selection, providing the required α service level, depends also on the Q value. However, this influence is marginal compared to the effect of the α and demand parameters (mean and variance). Based on this observation, we can separate the allocation strategy for the min par levels from the allocation of the max par levels and provide a simple approximate strategy for the allocation of s as a function of the demand variability.

Considering the demand variability provides a significant improvement in the consistent allocation of safety stock compared to the simplistic fixed day-supply strategy suggested by the supplier (GPO) and also to the modified allocations based on local pharmacy experiences. We summarize the results of the comparisons next starting with the service level comparison.

Table 4-3: Policy Comparison with Constant Space Utilization (M)

Inventory Control Policy	Avg. Service Level	Service Level Range	Avg. daily Refills
GPO Suggested (GPO)	99%	7.15%	5.56
Hospital Modified (HM)	99%	5.14%	5.74
Our Model 3 (OM)	99%	0.44%	4.70

In Table 4-3, we examine the performance of the three inventory control policies (**GPO Suggested, Hospital Modified, and Our Model 3**) when the space availability (M) is set to be the same for all approaches, equal to the value that is currently used by the hospital (HM) policy. First, we evaluate the three approaches on the issue of service level. As shown above, all three policies perform very well on the average service level criteria with Our Model 3 (OM) outperforming the others in the consistency of the service level, measured by the service level range (max – min service level) achieved across all items in the *Pyxis®* unit. With respect to the number of refills required per day, the OM method outperforms both of the other approaches, which is a primary goal of our project.

Table 4-4: Policy Comparison with Constant Service Level (SL)

Inventory Control Policy	Space Used	Service Level Range	Avg. daily Refills
GPO Suggested (GPO)	99%	3.94%	6.03
Hospital Modified (HM)	100%	5.14%	5.74
Our Model 3 (OM)	82%	0.44%	5.68

Next, we compare the policies when a fixed average service level of 99% is set. Table 4-4 above presents the findings. In this case we notice that while the GPO and HM policies require essentially the same amount of storage space to achieve the required 99% service level the OM policy needs only 82% of that space to meet the same requirement. In addition, the OM policy offers a much more consistent level of service across the items found in the *Pyxis*®. The range in service level is less than half of a percent (0.44%) compared to 3.94% and 5.14% for the GPO and HM policies respectively. Further, employing the OM suggested par values resulted in slightly lower numbers of refills than the GPO or HM policy, which is noteworthy given the substantial difference in the amount of space used for inventory in this approach, under this service level constraint. The additional space available for use with the OM policy allows for greater flexibility in formulary changes and pharmaceutical management. As such we can increase the space allocation for cycle stocks to use the full capacity of the *Pyxis*®. In doing so, we exceed the service level requirement and can further reduce the expected number of daily refills in the *Pyxis*®. These results are summarized in Table 4-5 below.

Table 4-5: Policy Comparison with Constant Service Level and Increased Space

Inventory Control Policy	Avg. Service Level	Service Level Range	Avg. daily Refills
GPO Suggested (GPO)	99%	3.94%	5.56
Hospital Modified (HM)	99%	5.14%	5.74
Our Model 3 (OM)	99%	0.44%	4.70

Finally, we examine the changes in performance indicators if we set all of the average number of daily refills for each competing policy, equal to the refill number achieved by the current HM policy. We see in Table 4-6 that the OM policy uses less space (82%) than the GPO (99%) or HM (100%) inventory policies. All three policies perform well on the measure of average service level with all methods exceeding the 92% mark; however, the HM and OM

policies demonstrate the ability to deliver exceptional service by surpassing the 99% level. As shown previously, the OM policy continues to offer a more consistent service level at the item level than either of the other two management policies.

Table 4-6: Policy Comparison with Constant Number of Daily Refills (N)

Inventory Control Policy	Space Used	Avg. Service Level	Service Level Range
GPO Suggested (GPO)	99%	92.00%	27.60%
Hospital Modified (HM)	100%	99.84%	5.14%
Our Model 3 (OM)	82%	99.93%	0.44%

One of the main results from the practical point of view is that the optimal allocation strategy of the space for the order quantities (cycle stock) of the items is proportional with the square root of the demand over space rate. Comparing with different allocation schemes (like proportionally with demand, or volume) it is interesting to verify the value of the right space allocation in reducing the total number of expected orders per day. We have compared five different allocation strategies for several examples. Table 4-7 summarizes the average percent increases in the total number of refills applying an allocation rule that is different from the optimal one.

Table 4-7: Comparison of the Different Space Allocation

The expected refill size Q_i is proportional to	Percent increase in total # of orders per day
SQRT(d_i/v_i) – the optimal	0%
Demand rate, d_i	10%
Unit space requirement, v_i	400%
$d_i * v_i$	177%
d_i/v_i	38%

- **Changes in Holding Costs**

In this section we examine the influence the holding cost has in determining the optimal order quantity for *Pyxis*® items when Model 2 is used as the allocation method. The allocation depends on the cost rate of K_i / h_i where $h_i = r c_i$ and c_i is the unit price for an item. Specifically, the inventory holding cost rate, r , used to set the holding costs for the formulary items is manipulated. We select different r values to observe the resulting changes in both the iterative procedure and the optimal order quantities generated. In the demonstration of Model 2 provided in Chapter 3, a daily holding cost rate of 0.002 ($r = 0.002$) was used. In this analysis we modify this rate to reflect increases or decreases in holding costs and discuss the outcomes.

In Table 4-8, a summary of the changes in the available space for cycle stock, V , is presented. Here we show the starting values of V as calculated using formula (19) and the resulting final value of V achieved as a result of the second round of iterations. First, one can see that smaller rates, which result in smaller holding cost, have a greater starting value of V . For example, $r_1 = 0.001$ starts with a $V' = 25278.49$ and is significantly larger than V' of either r_2 ($r_2 = 0.002$) or r_3 ($r_3 = 0.003$), which are 17874.59 and 14594.55 respectively. However, the final values of V reached at the conclusion of the iterative procedure are nearly identical for all three rates. This provides evidence of the convergence to the value of the available space for cycle stock and the optimal solution achieved by this allocation strategy. Another notable observation is that the use of r_3 yielded convergence in fewer steps (10) than either of r_1 or r_2 , which required one additional iterative step to yield optimal values.

Table 4-8: Comparison of Space Available for Cycle Stock (V) at Varying Holding Costs

	V'	V^{final}	Iterations
$r_1 = 0.001$	25278.49	4817.43	11
$r_2 = 0.002$	17874.59	4844.36	11
$r_3 = 0.003$	14594.55	4867.37	10

Next, we summarize the percent change that occurs from the initial value of V' to the value of V provided by the final iteration. These are available in Table 4-8.

Table 4-9: Percent Change of Space Available for Cycle Stock (V) at Varying Holding Costs

	V'	V^{final}	% Change
$r_1 = 0.001$	25278.49	4817.43	80.94%
$r_2 = 0.002$	17874.59	4844.36	72.90%
$r_3 = 0.003$	14594.55	4867.37	66.65%

As demonstrated by Table 4-9, the holding cost rate influences the amount of change needed to reach the final value of space available for cycle stock. With an extreme value of r_1 , the difference between the initial and final values of V was nearly 81%. As the r value is increased, it appears that the initial amount of space needed is a better starting value for the iterative procedure and requires less correction to reach the optimal value. This is shown by the smaller percentages of change for r_2 (72.90%) and r_3 (66.65%).

The demonstration provided in Chapter 3 used a rate of $r_2 = 0.002$ to determine the holding costs of drugs. Here we examine the impact of increasing or decreasing this rate has on the values of V . In Table 4-9 the comparison is made between r_2 and the 2 other holding cost rates of $r_1 = 0.001$ and $r_3 = 0.003$.

Table 4-10: Impact of Changing Holding Costs on Available Space (V)

	Percent Difference (%)	
	V'	V^{final}
$r_1 = 0.001$	29.29%	0.56%
$r_3 = 0.003$	-22.47%	0.47%

As evidenced by Table 4-10, changes in the holding cost rate and holding cost will influence the initial estimate of space needed for cycle stock. If the value of r is decreased from 0.002 to 0.001, these results indicate a difference of 29.29% between the starting values of V'

with the value associated with r_1 being that much larger than the corresponding value of r_2 . In addition, if the holding cost rate is increased from 0.002 to 0.003, the initial value of V' for r_3 is 22.47% smaller than that of r_2 . Again, this supports the assertion that the higher holding cost rates provide starting values of V' that are closer to the actual space requirement of cycle stock. The above results also support the ability of this allocation technique to converge on the optimal solution regardless of the holding cost rate and subsequent holding costs. The final values of V are almost identical for all three rates, which is evidenced by the small differences of less than 0.56% across the three values.

Next, we demonstrate the changes in the optimal order quantity resulting from the varying inventory holding cost rates. As explained previously, the hospital pharmacy and the GPO were both unable to provide unit prices or accurate holding cost data. Unit prices were obtained from a well-known, online pharmaceutical vendor. Table 4-11 presents an example of the prices used in this analysis.

Table 4-11: Optimal Order Quantities (Q_i) at Differing Holding Costs

Drug	Price c_i	Q Values with Different r		
		$r = 0.001$	$r = 0.002$	$r = 0.003$
Drug 1	\$ 5.90	116.04	122.89	126.75
Drug 2	\$ 17.97	123.35	122.62	119.10
Drug 3	\$ 5.43	114.72	120.03	122.25
Drug 4	\$ 30.38	49.00	51.11	51.89
Drug 5	\$ 25.17	71.59	71.48	69.67
Drug 6	\$ 3.96	62.34	66.34	68.80
Drug 65	\$ 60.76	27.84	24.95	22.53
Drug 66	\$ 5.90	27.28	28.75	29.49
Drug 67	\$ 1.00	33.54	35.88	37.42
Drug 68	\$ 86.81	20.42	18.92	17.44
Drug 69	\$ 86.81	20.26	18.77	17.30
Drug 70	\$ 18.23	30.89	30.68	29.77

Using the above unit prices, we were able to study the changes that occurred in Q_i values at the three holding cost rates. Table 4-11 shows the impact holding costs have on the allocation of space within the Pyxis® as items of greater costs are kept in lower quantities. These findings demonstrate the relationship between holding costs and the optimal Q_i values. In general, as the holding cost rate used to determine the holding costs increases the resulting Q_i values will increase. Thus, there is a reduced penalty associated with carrying greater inventory. However, it is important to recognize that Q_i will not always increase with increases in r values, which is due to the influence of demand characteristics (i.e. average daily demand and standard deviation of daily demand) of individual items in setting the reorder points and ultimately calculating the optimal order quantities.

Next, we summarize the observed differences in optimal order quantities across the three levels of holding cost rate. Specifically, pairwise comparisons are made to show the overall differences (%) that result when this rate changes. In Table 4-12, the following measures are provided: average difference, absolute average difference, standard deviation of change, minimum difference, and maximum difference.

Table 4-12: Pairwise Comparisons of Percent Differences for Varying Holding Cost

	Q_i^1 and Q_i^2	Q_i^2 and Q_i^3	Q_i^1 and Q_i^3
Average Percent Difference	2.46%	3.34%	5.15%
Absolute Avg. Difference	6.92%	5.51%	11.66%
Standard Deviation of Change	6.61%	4.64%	10.20%
Minimum Difference	0.03%	0.15%	0.06%
Maximum Difference	24.86%	16.72%	37.42%

These results report the differences in optimal ordering values observed as we move from one level of holding cost to another. Since some Q_i values will increase and others will decrease as the holding cost rate is modified, it is useful to look at the overall average change

that occurs with shifts in rate. One can see from Table 4-12 that there is a 2.46% average increase in Q_i values across all items when the holding cost rate shifts from r_1 (0.001) to r_2 (0.002) with a slightly greater increase of 3.34% when the value changes from r_2 to r_3 (0.003). As expected, this difference is even greater when the disparity in rates is larger, which is evidenced by the r_1 to r_3 comparison that yielded a 5.15% increase in Q_i values. With respect to the absolute average difference, we see that the difference in optimal order quantities is 6.92% and 5.51% for the first pair-wise comparisons with the change being almost 12% when the rate increased from r_1 to r_3 . The move from r_2 to r_3 yielded the smallest standard deviation in change, which was followed by the r_1 to r_2 and finally r_1 to r_3 . The minimum percent changes were nearly the same for each pairwise comparison with each having items that exhibited less than 0.15% difference in Q_i values at the specified rates; however, this was not true for the maximum differences in Q_i . When the rate changes from r_2 to r_3 , the largest maximum change value occur was 16.72%, which was the lowest observed maximum change across the comparisons. Again, this was followed by the shift from r_1 to r_2 at 24.86% and finally r_1 to r_3 at 37.42%.

4.2.3 Strategic Decision Support

This research focused on healthcare SCM issues as they related to pharmaceutical inventory management within the hospital; however, there are a number of additional stakeholders interested in the product formulary. As previously established in the beginning of this work, these stakeholders all have their own objectives, which are often at odds. At the heart of this issue is tradeoff between product variety and economies of scale. Physicians value their prescribing autonomy and push pharmacy directors and hospital administrators to offer a wider selection of drugs. Pharmacy directors are constantly negotiating with the GPO over this same issue. According to pharmacy managers at the participating hospital, efforts are made to accommodate doctors and to offer greater variety, but product and operational costs are also a

concern. Unfortunately, the cost impacts of changes in the product formulary are not documented and remain essentially unknown to these parties. We estimate the influence of these costs using our models to provide valuable information for the hospital when negotiating with doctors or the GPO on issues related to the formulary and pharmaceutical inventory management.

A significant benefit of using this decision support tool is the allowance of quick evaluations of the managerial tradeoffs, which facilitates **strategic decision** making in the pharmacy. When suggestions are made that impact the number of workers or work shifts available in the pharmacy or when changes to the formulary are discussed, the pharmacy director can quickly analyze the issues based on our models and computation and identify the resulting changes in service levels, workloads, and operating costs.

- **Analysis and Interpretation of the Tradeoffs for the Hospital Inventory Management**

Besides the simple and fast computation, the practical importance of the simplified approximate Model 3 is the straightforward and efficient way of showing the tradeoffs in pharmaceutical supply management. It provides a simple and efficient strategic decision support tool to analyze the tradeoffs among the three key performance indicators:

- the service level (*emergency refill workload*),
- the available space (depending on the variety of drugs – *formulary*), and
- the number of orders (*refill workload*) per day.

Next we summarize the most important aspects of the tradeoffs.

The refill workload of a day for a *Pyxis MedStation®* is

N = the expected number of total orders (refills) per day.

The optimal N can be approximated by

$$N^* = \sum (d_i / Q_i) = W^2 / M. \quad (38)$$

The tradeoff between the number of orders and free storage space for a given service level can be expressed in the simple form

$$N M = W^2. \quad (39)$$

In this expression $W = \sum \sqrt{(v_i d_i)}$ is fixed, it depends only on the number of drugs (formulary) and on the volume and demand of drugs. The parameter $M = M' - \sum [v_i (s_i - u_i)]$ is the remaining free storage space for cycle stock. Since s_i depends on the service level, implicitly equation (39) also includes the service level tradeoff. M decreases with an increased service level requirement.

- **Managerial Tradeoffs: What-if and Sensitivity Analysis**

This section of the chapter identifies several key managerial tradeoffs and demonstrates the utility of this research in modeling the critical issues for management. Specifically, we examine the impacts of changing formulary, available space, and worker capacity on our primary performance measures. For a fixed service level the tradeoff curve has a hyperbola shape that is shifted to the right (higher space requirement) with increasing service level requirement. This property allows a simple visual tradeoff analysis, and a simple example is illustrated next.

In this research we use the example of a particular *Pyxis MedStation*® of the case hospital for illustration. All transactions (demand, refill, inventory position) and control parameters (s_i , S_i) for two years are available in Excel files. The number and composition of drugs (formulary) is changing from time to time. We use the same example as before for illustration and selected 70 drugs with highest usage rate out of the 214 drugs. These items make up 71% of the total usage and around 70% of the total volume of the *Pyxis*®. For available volume, M' , we took away the space used by the remaining low volume items that were disregarded. This sample was used to illustrate the relevant tradeoffs.

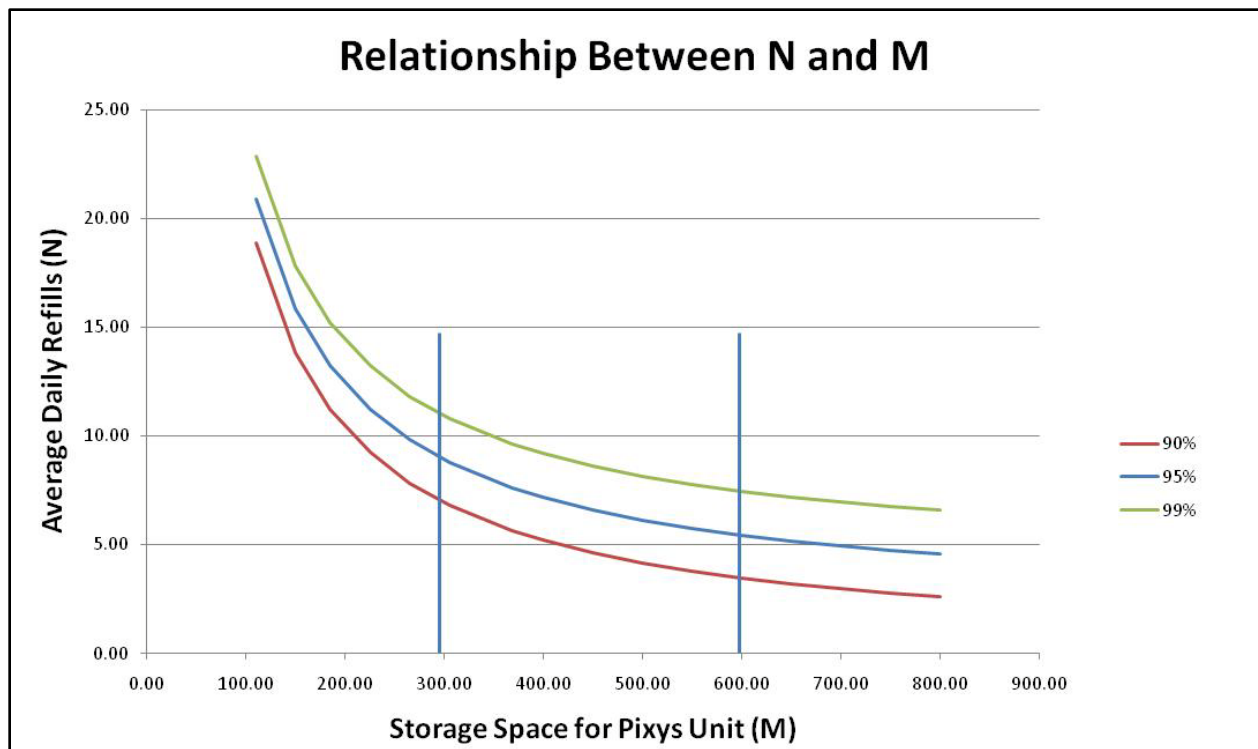


Figure 4-2: Performance Indicator Relationships and Tradeoffs

Figure 4-2 illustrates the relationship between available space for cycle stock, M , and average daily refills, N , at a given service level. Consider what happens when the available space increases at the 95% service level. As space availability increases, one can read the decrease in the average number of daily refills from the graphs. For example, if we double the space allocated for items from 300 to 600, the number of orders will decrease from 9 to 5. Understanding this relationship between space and refills allows us to analyze what will happen if we change service levels. As such, if we shift from 95% to 99% service level at the same space utilization, the graph demonstrates the expected increase in the refill requirements. Consider what happens at a fixed storage capacity level of 600. As the service level increases from 95% to 99%, the expected number of refills per day increases approximately by 25%.

The available space is directly connected to the formulary (the number of different drugs provided). Even if the total demand for the drugs doesn't increase, a bigger number of items

require a larger amount of safety stocks. The safety stock increase is proportional to the variability of demand. For lower level of demand, typically the σ/μ rate increases decreasing the available free space for cycle stock. For estimating a more accurate effect of increased formulary a more detailed comparison of the reorder points is required based on formula (32) and (33).

- **Changes to the Available Space and Product Formulary**

As established early in this work, there are a number of important stakeholder conflicts present throughout this supply network. The formulary is at the center of many of these disagreements and represents a substantial area of cost for the organization. Next we investigate the effects of adding or removing items from a *Pyxis*®. The inclusion of extra items means that less space is available at the item level for cycle stock in the *Pyxis*®. As such, reducing the number of items stored in the *Pyxis*® will have the opposite effect as more space becomes available for cycle stock for individual items in the machine.

In Table 4-13 a simple demonstration of the formulary changes and the resulting influence on pharmacy workload is provided. Again, we start with the sample of 70 drugs found in a particular *Pyxis MedStation*® and modify the product mix to include or omit 20% of items in the local storage unit. To establish a reasonable idea of the impact such changes to the formulary will have on the number of expected refills (N), we consider both high usage and low demanded items for the situation where items are added. In contrast, we only consider the low usage items for circumstances where items are removed from the *Pyxis*®, which is practical given the small likelihood of high usage items being eliminated from the formulary. This allows pharmacy directors to gain valuable insight into the cost implications resulting from introducing new items to the local depot.

Table 4-13: Impact of Adding or Subtracting Items to Local Formulary

Changes in Formulary	Expected Number of Daily Refills (N)	% Difference
Baseline (70 items)	3.58	---
20% Additional High Usage Items	5.31	48.32%
20% Additional Low Usage Items	4.08	13.97%
20% Fewer Items	2.70	-24.58%

As shown above in Table 4-13, increasing or decreasing the number of items in the *Pyxis*® will influence the numbers of expected daily refills needed for the machine. It is important to recognize the impact these scenarios will have on the operational, tactical, and strategic decisions facing managers. Another key issue is the relationship average daily demand and demand types have on impacting this measure.

Regardless of the daily demand, adding items will raise the number of refills. First, consider the situation where low usage or “lumpy” demand items are added to the local depot. In this case one can observe approximately a 14% increase in the expected daily refills at the *Pyxis*®. This additional workload may seem relatively small; however, this is only for one machine. Considering the participating hospital has over 85 *Pyxis MedStations*® distributed around the facility in various CUs, this increased workload poses significant problems from both a cost and worker capacity perspective. Second, we examine the effect of adding high usage items with daily demand values similar to the top 20% of items currently housed in the *Pyxis*® unit. If such products are added to the formulary, results indicate an increase in expected daily refills of more than 48%. On the other hand, we noticed almost a 25% drop in refills when the bottom 20% of drugs in the product formulary were removed. This demonstrates the importance of both reasonably restricting the product formulary and evaluating the items in the *Pyxis*® on a frequent basis for possible reductions. Again, these results are significant for managers

attempting to understand the influence of product variety on pharmaceutical inventory control and management.

- **Changes to Worker Capacity**

In this context the number of refills that can be accomplished by pharmacists and technicians during an 8-hour shift is relatively fixed. Pharmacists provide oversight of the refilling process due to the sensitive nature of controlling pharmaceuticals and the need to verify the prescribed medications before distributing these treatments to the patients. Pharmacy technicians are responsible for preparing drug carts used in transporting items from the pharmacy to the Care Units (CUs) and in the actual restocking of the *Pyxis*®. As a result, any increases in the number of refills required at the CUs can only be satisfied through incremental increases in the number of work shifts. As the service level increases, one expects that smaller numbers of items require refills on a daily basis to prevent expensive stockout occasions. On the other hand, higher service level, and the resulting higher safety stock, takes away space from cycle stock increasing the expected number of regular refills per day. Table 4-14 provides a simple illustration of these relationships.

Table 4-14: Incremental Increases to Worker Capacity

Shifts	Refills	
	95% SL	99% SL
1	10	15
2	20	30

Knowing this relationship and the expected number of refills required at any given *Pyxis*® allows managers to better schedule human resources and ensure that the workload does not exceed worker capacity. By optimizing the allocation of space within the *Pyxis*® such that the number of expected refills is minimized, the hospital pharmacy has the ability to keep workloads at a controllable level and track changes over time. Control charts are useful in

monitoring workloads and in determining if the workloads are exceeding preset limits, which indicates that conditions have changed and require attention. If the total workload for the system is determined and the number of workers is known, managers can create a control chart using the maximum, minimum, and average workloads to determine if the system is exceeding worker capacity. If so, the hospital must add workers to satisfy that excess workload. As an example, demand and the composition of items in the formulary can change over time. Trends indicating workloads are approaching the pharmacy capacity limits indicate a need to reevaluate pharmaceutical inventory control values and possibly adjust the number of technicians or work shifts refilling the machines.

4.5 Summary of Findings

This chapter provided a description of the decision support tool, its design, and its utility. In addition to this, numerous illustrations were provided demonstrating the decision support capabilities of Model 2 and Model 3. With the consideration of holding and refill costs, Model 2 outperforms Model 3 in that it provides an allocation strategy which minimizes the sum of these two costs. However, Model 3 is superior when holding costs are unknown or ignored, as they are in our practical case. This model also excels in its simplicity and ease-of-use. Furthermore, several simplified approaches to implementing these models on a daily basis were presented as means of improving operational decisions when products are added to the formulary or when demand characteristics change for an individual item. After an initial optimization run, these techniques offer quick managerial decision support for estimating the close to optimal order quantities and the min and max par levels for daily operations. Also, the included what-if analyses provide invaluable information to administrators at the tactical and strategic levels of decision making.

CHAPTER 5: CONCLUSION

This chapter provides closing discussions of the outcomes of this work. First, the contributions of this research are identified. Then, the limitations are recognized along with several possible extensions of the current project. Finally, concluding remarks are made concerning the project as a whole.

5.1 Generalizability of Findings

This work is based on inventory control models that are commonly used in practice and taught in academic settings. In addition, the case hospital, its dilemmas, and its current management practices are believed to be commonplace amongst other such healthcare facilities. The basic inventory problem considered in this research addressed the management desire to reduce workload (emergency and daily refilling occasions) while considering a high service level requirements and limited space availability, which are common inventory control constraints and goals of managers regardless of industry. Models 2 and 3 are adaptable to any such environments. Although the product characteristics make pharmaceuticals interesting to study, the methods employed in this work are easily applied to any other product where similar management constraints are present. For example, consider grocery stores that have large numbers of items to consider with varying product characteristics, limited storage capacity for these items, and substantial restocking activities that require considerable efforts. Here the workload requirements and costs of emergency and daily refilling may be major concerns for management, possibly even above inventory holding cost. In addition, this research allows for an easy interpretation of the operational, tactical, and strategic tradeoffs when inventory holding cost is also important and an optimal balance between holding and refill costs are sought. As such, the results of this research are highly generalizable, and the situations in which Models 2 and 3 can be applied are nearly limitless.

5.2 Contributions

This project resulted in a number of theoretical and practical contributions that have furthered the existing body of knowledge in healthcare supply chain management. The primary goal of this work was to improve the current pharmacy *inventory management* policy and to offer managerial support with the developed decision support tool. This has the potential of being an important step toward improving the healthcare supply chain.

5.2.1 Contributions - Theoretical

This dissertation provides several key theoretical contributions. Three quantitative models are presented that allow for the optimal setting of inventory control parameters (s , S) given a multi-item, multi-location inventory management environment under multiple constraints (i.e. service level, available space, and workload). Previous research in this area handle several aspects of this research case; however, they fail to jointly consider the challenge of multi-item and joint constraint with demand uncertainty or are too complex, time and data intensive for our practical application. This project addresses those shortcomings and accomplishes the following:

1. provides an extensive review of the relevant managerial and quantitative literature as it currently exists,
2. presents three quantitative models for determining the optimal min and max par values (reorder point and order up to level) and allocating space to multiple items under multiple constraints,
3. proposes two models (Models 2 and 3) and iterative procedures that both satisfy the aforementioned constraints and offer simplified, practical alternatives to more complicated optimization approaches,
4. applies these models and demonstrates their utility and performance using actual pharmaceutical usage data, and

5. supports the inclusion of key demand characteristics (i.e. rate of daily demand variance to average daily usage, holding cost rate, etc.) in the optimization process.

The quantitative models and Excel spreadsheets prepared are providing further *managerial support* for pharmacists to analyze tradeoffs between service level and cycle stock, test implications on cost savings and effects of parameters, and test a variety of parameter settings. Furthermore, the tools facilitate the management of *worker capacity*. Based on refill capacity requirements, pharmacy directors can manage the addition of pharmacists or overtime and the addition of another shift of pharmacy technicians responsible for filling the *Pyxis MedStations®* around the hospital.

5.2.2 Contributions – Practical

This work is of utmost practical relevance as it addresses real-world dilemmas and concerns of hospital administrators and pharmacy managers. The magnitude of the healthcare industry, ever-increasing healthcare costs, and role of pharmaceuticals within this industry demonstrate the importance of continued research in this area. In addition, the stakeholders, products, and policies create a unique research opportunity, and this investigation provides detailed study of these issues. Specifically, this dissertation offers the following contributions:

1. It achieves the primary objective of the project and offers improvements to the current inventory management practices at the local hospital;
2. It provides a decision support tool that allows for optimization of pharmaceutical inventory control at the local depots and that addresses managerial concerns at the operational, tactical, and strategic levels of decision making;
3. It illustrates the managerial tradeoffs associated with changes in formulary, service level, and space availability, as well as, offers quick, simple techniques for estimating

optimal min and max par levels on a daily basis when such changes occur and complete optimization of the system is impractical;

4. It shows the influence of holding and refill costs on optimizing inventory control parameters and demonstrates the benefit of including such costs in inventory policy comparisons.

Furthermore, for the *operational inventory decision*, the approaches offered provide the *min and max par levels* that control the automated ordering system. These parameters are based on near-optimal allocation policies of cycle stock and safety stock under storage space constraint. As proved, the suggested selection of the control parameters s_i and S_i

- provide consistent service level,
- allocate the safety stock to decrease the workload of emergency refilling, and
- allocate the cycle stock space decreasing the workload of daily refilling.

For the *tactical and strategic decisions*, the presented Models 2 and 3 can be applied as a simple visual decision support tool to analyze the tradeoffs among the refill workload, the emergency workload, and the variety of drugs offered. This work illuminates the relationship of these tradeoffs to the three key performance indicators at a local care unit: the expected number of daily refills, the service level, and the storage space utilization.

5.3 Limitations

As with any complicated area of study, one must consider the limitations of the investigation. Here it was necessary to restrict the scope of the project to allow for appropriate comparisons. Within pharmaceutical products one can easily observe great variety in the type, shape, and purpose of individual drugs. In addition, these variations often necessitate special handling and storage consideration both in the central pharmacy and in the local depots. To facilitate the evaluation of the research models and comparisons amongst allocation strategies,

this study concentrated on non-controlled substances that were readily available for examination and that could be stored using a consistent layout within a *Pyxis*® unit. All of the items in the sample could be stored using a matrix layout that uses dividers to separate drugs in the machine's drawers. Since the hospital has discretion in the setup of the *Pyxis*®, this is not a major limitation of this study and is a reasonable approach to analyzing this research problem.

Further study is necessary to examine other drug types, specifically controlled substances, and the various storage restrictions and requirements of these items. There are a number of drawer layouts and storage options available to the pharmacy, and the greatest variation in storage methods is employed with these controlled substances. Unfortunately, this may prove very difficult given the legal and ethical guidelines for handling such drugs. In addition, the specific issue of perishability was largely ignored for this study; however, this issue is somewhat covered with the impact of formulary changes on optimal space allocation within the *Pyxis*®.

Finally, the absence of a demonstration of Model 1 with optimal solution is a limitation of this study. The solution of Model 1 using approximations (4) to (7) is more straightforward, and it could be applied to check different practical scenarios in this research case. However, the managerial problem is that the ordering and shortage cost factors are very difficult to provide. As stated previously, the hospital pharmacy was unable to produce any specific cost data to support this research activity and does not include these costs in current policies. The technical problem is that the large number of items ($n = 250$ to 300 per local depot), the nonlinearity, and the stochastic demand make the solution challenging and time consuming. Given the pharmacy objectives and the practical requirements, this was not a feasible solution for this case.

However, to address this limitation, actual usage data was used to construct a simulation of daily transactions at the local depot for all 70 items included in the sample used for analytical

purposes. Using the min and max par levels for the GPO suggested policy (GPO), the hospital modified (HM) inventory policy, and our Model 3 (OM) policy and the daily transaction data for one year, this simulation tested the accuracy of model predictions by showing the reduction of inventory with use, indicating the amount of shortages (stockouts) when they occurred, and the amount and timing of refill occasions. In addition, the simulation calculated the average inventory levels for each item given the three policies. As evidenced in Chapter 3, the differences between model predictions and simulation results are very low and support the accuracy of this approach.

5.4 Future Research Directions

There are plenty of extension possibilities. Some of them are technical, quantitative in nature, others are managerial extensions. The main technical improvements include examining the effect of special demand types and the consideration of multiple objectives in which Multiple Criteria Decision Making (MCDM) tools may be applied. Specifically, more research is necessary to examine the effects of low volume demand, “lumpy” demand, and auto-correlated demand when subsequent days have a high demand applying a treatment followed by a longer period without demand.

Some of the most important managerial extensions include examining the effect of demand uncertainties on workload. Specifically, it is important to determine the uncertainty of the workload by analytic estimation or by simulation and to determine if there is enough worker capacity with certain reliability. Then, the question becomes if capacity is not enough, how many workers (or additional shifts) to add to satisfy that excess workload?

Another significant extension of this research is the opportunity to provide more specified quantitative support for negotiations between pharmacy administrators and medical doctors by analyzing the effect of extending formulary and the cost vs. product variety tradeoff. The current

research effort and these recommended extensions will provide further insight into stakeholder preferences and acceptable tradeoffs.

5.5 Concluding Remarks

This dissertation was introduced with a “real world” scenario of an ER supply problem that with variations in details will possibly be experienced at some time by individuals who read this work. A broad view of characteristics that make healthcare supply chain management a very intriguing area of study has been presented. The healthcare industry operates in a unique manner in that it has a number of special constraints all being enforced at once. Specifically, the focus is on maintaining a high level of service while restraining costs, as opposed to reducing them. In traditional supply chains, these variables are manipulated to achieve the optimal economic operating setting. However, in the healthcare industry, tradeoffs are not as easily achieved. Furthermore, medicines are special products as noted by Almarsdóttir and Traulsen (2005), which make pharmaceutical inventory management within the hospital a prime topic for study.

The significance of the healthcare industry is demonstrated by the provided cost breakdown and by conveying the importance of affordable, quality care to the described stakeholders. As such, works like the current project are valuable from both the practical and academic perspectives. The case is made for additional studies in this area, and an overview of the current endeavor and its objectives is given. A review of current managerial and quantitative modeling literature in this specific area is presented. It is important to recognize that the need for continued research in this domain is warranted. Many of the proposed inventory control models have yet to be tested in a healthcare setting or have not been evaluated under conditions of varying demand types (i.e. intermittent or auto-correlated demand). Outsourcing and VMI in some form are used extensively to alleviate strains on pharmacy resources and material management issues; however, greater study is needed to truly understand the impact of such

activities throughout the supply network. Information technology plays a significant role in determining the success of these solutions, and the case hospital applies advanced technology in controlling medication throughout the hospital. The drugs are stored in the local depots (*Pyxis MedStations*®) in 86 different areas of the hospital with each area having a different selection of drugs. The *Pyxis MedStation*® registers each transaction date and quantity of demand (withdrawal) and each delivery (refill) and the actual inventory level. It is connected to the central depot (*Tallyst*® system) through a computer network. It seems clear that investments in these resources will continue in the future as hospitals increase their reliance on the information created and controlled by these machines.

The findings presented within this dissertation have a profound reach and have the ability to impact anyone connected to healthcare. These results suggest alternative methods for allocating space for inventory within the local depots around the hospital and provide needed tools for managerial decision making at all levels. The proposed models deliver simplified, quick quantitative approaches that allow for setting the optimal reorder points and order up to levels for items in a *Pyxis*® unit, as well as, provide managers a mechanism for demonstrating key managerial tradeoffs and negotiating with other stakeholders in the supply network.

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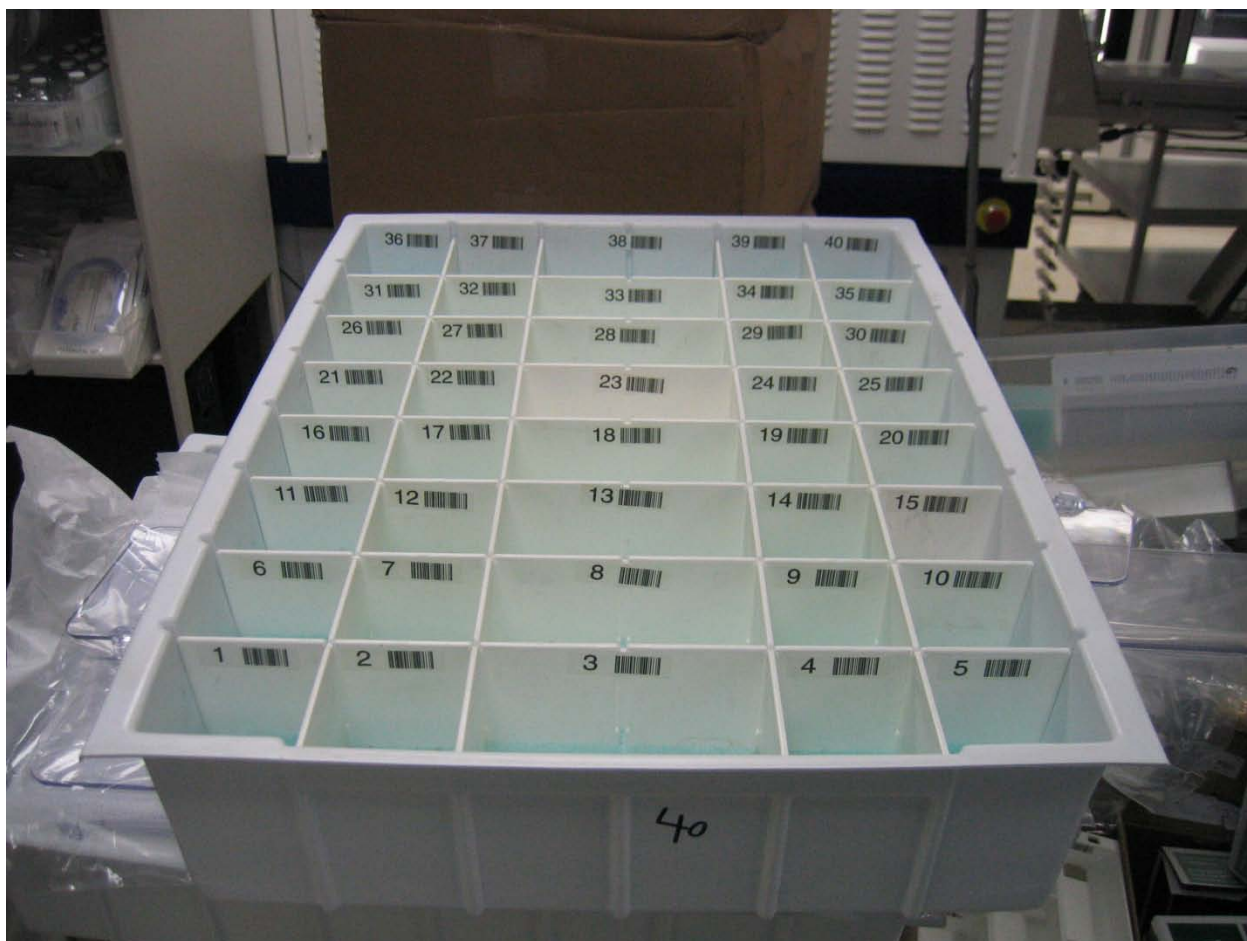
APPENDIX A: PYXIS MEDSTATION® AND MATRIX DRAWER



Pyxis MedStation® 3500

6-drawer main*

22.8" W x 27" D x 55" H



Example of a *Pyxis*® matrix drawer that uses plastic dividers to create a variety of storage configurations. This particular matrix is setup to house 40 different products; however, the maximum number of separate cubicles is 48. Dividers can be added/removed to accommodate different numbers of items with varying sizes and shapes.

APPENDIX B: POWER APPROXIMATION

For the Power Approximation formula (11) the rational function $p(y_i)$ is defined as

$$p(y_i) = \frac{a_0 + a_1 w + a_2 w^2 + a_3 w^3}{b_0 + b_1 w + b_2 w^2 + b_3 w^3 + b_4 w^4}$$

with notation

$$w = \sqrt{\ln (25/y_i^2)}$$

and with given constants:

$$a_0 = -5.3925569$$

$$a_1 = 5.6211054$$

$$a_2 = -3.8836830$$

$$a_3 = 1.0897299$$

$$b_0 = 1.0000$$

$$b_1 = -0.72496485$$

$$b_2 = 0.507326622$$

$$b_3 = 0.0669136868$$

$$b_4 = -0.00329129114$$

APPENDIX C: MODEL 2 CALCULATIONS FOR REORDER POINT AND OPTIMAL Q

	Formulae:	K	100
	$h_i = rc_i$	r	0.002
	$M_i = M^i \cdot \sum [v_i(s_i^{(i)} - u_i)]$	M_i	4860.14
Step 0:	$Q^i = v(2d_iK/h_i)$		
	$V^i = \sum v_i Q_i^i$		
Step 1:	$Q_i^{(1)} = (M^2 / V^i) * Q_i^i$	$V = \sum v_i Q_i$	
	$\lambda_i = d_iK/v_i(Q_i^i)^2 - h_i/2v_i$		
	$\lambda^i = \min \lambda_i ; \lambda^u = \max \lambda_i$		
	$\lambda = (\lambda^i + \lambda^u)/2$		
Step 2:			
Step 3:	$Q_i(\lambda) = v(2d_iK/(h_i/2 + \lambda v_i))$		
	$V^i = \sum v_i Q_i(\lambda)$		
	If $V < M$, then $\lambda^u = \lambda$ and $Q^u = Q_i(\lambda)$		
	If $V > M$, then $\lambda^i = \lambda$ and $Q^i = Q_i(\lambda)$		
Step 4:	$F(Q^u) = \sum [K(d_i/Q_i^u) + h_i(Q_i^u/2)]$		
	$F(Q^i) = \sum [K(d_i/Q_i^i) + h_i(Q_i^i/2)]$		
	$F(Q^u) - F(Q^i) / F(Q^i) \leq \epsilon$		

Step 2	λ^i	λ^u	λ_i
Initial	0.005	5.980	2.993
Iteration 1	0.005	2.993	1.499
Iteration 2	0.005	1.499	0.752
Iteration 3	0.005	0.752	0.379
Iteration 4	0.005	0.379	0.192
Iteration 5	0.005	0.192	0.099
Iteration 6	0.005	0.099	0.052
Iteration 7	0.052	0.099	0.075
Iteration 8	0.052	0.075	0.064
Iteration 9	0.052	0.064	0.058
Iteration 10	0.052	0.058	0.055
Iteration 11	0.052	0.055	0.054

Values												
F(Q)	Initial	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7	Iteration 8	Iteration 9	Iteration 10	Iteration 11
F(Q ^u)	2332.92	1684.32	1236.70	932.38	729.55	597.80	597.82	558.56	537.45	526.45	520.82	517.97
F(Q ⁱ)	775.42	775.42	775.42	775.42	775.42	775.42	775.42	515.12	515.12	515.12	515.12	515.12
Difference	200.86%	117.21%	59.49%	20.24%	-5.92%	-22.91%	16.06%	8.43%	4.34%	2.20%	1.11%	0.55%

Drug	Average	Sigma	Size (v _i)	K	Price c _i	h _i	Step 0			Step 1			Step 3						Step 4		
							Q _i ¹ = Q ^u	vQ _i ¹	Q _i ¹ = Q ⁱ	d _i K/v _i (Q _i ¹) ²	h _i /2v _i	λ _i	d _i K	h _i /2	λv _i	Q _i (λ)	v _i Q _i (λ) _i	Q ^u	Q ⁱ	F(Q ^u)	F(Q ⁱ)
ZOFR2	16.63	13.10	2	100	6	0.0118	530.86	1061.72	144.34	0.040	0.003	0.04	1663.49	0.01	0.11	121.30	242.61	121.30	122.89	14.43	14.26
ACET3UD	10.54	8.50	1	100	18	0.0359	242.19	242.19	65.85	0.243	0.018	0.23	1053.95	0.02	0.05	121.37	121.37	121.37	122.62	10.86	10.80
SENOKOTS	8.29	6.97	1	100	5	0.0109	390.93	390.93	106.30	0.073	0.005	0.07	829.16	0.01	0.05	118.55	118.55	118.55	120.03	7.64	7.56
H100U10ML	7.60	5.54	5	100	30	0.0608	158.18	790.92	43.01	0.082	0.006	0.08	760.22	0.03	0.27	50.49	252.43	50.49	51.11	16.59	16.43
PROM25I	5.28	4.81	1.5	100	25	0.0503	144.83	217.25	39.38	0.227	0.017	0.21	528.07	0.03	0.08	70.74	106.10	70.74	71.48	9.25	9.19
KDUR20	4.76	4.30	2	100	4	0.0079	346.63	693.26	94.25	0.027	0.002	0.02	476.29	0.00	0.11	65.47	130.94	65.47	66.34	7.53	7.44
DIPH50I	4.13	3.88	1.5	100	16	0.0328	158.57	237.86	43.12	0.148	0.011	0.14	412.53	0.02	0.08	65.29	97.94	65.29	66.04	7.39	7.33
DEX4I	3.99	3.95	1.5	100	15	0.0298	163.73	245.59	44.52	0.134	0.010	0.12	398.91	0.01	0.08	64.72	97.08	64.72	65.47	7.13	7.07
NEXI40C	3.84	5.36	2	100	8	0.0156	221.84	443.68	60.32	0.053	0.004	0.05	384.47	0.01	0.11	57.83	115.66	57.83	58.57	7.10	7.02
NEUR300	3.73	4.60	1	100	115	0.2292	57.08	57.08	15.52	1.550	0.115	1.44	373.30	0.11	0.05	47.12	47.12	47.12	47.32	13.32	13.31
NYSTSUSP5ML	3.00	4.15	2	100	115	0.2292	51.19	102.38	13.92	0.775	0.057	0.72	300.27	0.11	0.11	36.80	73.60	36.80	37.04	12.38	12.35
ZOFR7	2.97	3.14	1.5	100	20	0.0399	121.91	182.87	33.15	0.180	0.013	0.17	296.73	0.02	0.08	54.38	81.58	54.38	54.98	6.54	6.49
R10V	2.65	2.92	2	100	11	0.0227	153.06	306.12	41.62	0.077	0.006	0.07	265.40	0.01	0.11	47.33	94.66	47.33	47.92	6.14	6.08
SODB650T	0.68	1.67	2	100	87	0.1736	28.07	56.14	7.63	0.587	0.043	0.54	68.39	0.09	0.11	18.78	37.56	18.78	18.92	5.27	5.26
SUCRALUD	0.67	1.49	2	100	87	0.1736	27.84	55.69	7.57	0.587	0.043	0.54	67.30	0.09	0.11	18.63	37.26	18.63	18.77	5.23	5.22
DIG125UD	0.66	0.85	1	100	18	0.0365	60.27	60.27	16.39	0.247	0.018	0.23	66.21	0.02	0.05	30.37	30.37	30.37	30.68	2.73	2.72
Sum							17874.59						4844.36							517.97	515.12

Here we start with the inputs of average daily demand, standard deviation of daily demand (Sigma), the unit size (V_i), and the unit price (c_i) for each item in the sample. To begin, we calculate the expected order quantity (Q_i) using the Economic Order Quantity (EOQ) formula (13) and use the notation of Q_i¹. Next, we determine the corresponding reorder point value (s_i) using the Power Approximation (11). If the space constraint (10) is fulfilled, we set the order up to level (S_i) using (14). If the space constraint (10) is not fulfilled, we must decrease the Q_i values to satisfy this constraint. To accomplish this we must find the values of Q_i that fit into the available space, M, defined by (16) using the initial values of s_i = s_i⁽⁰⁾. We set Q_i¹ as the upper bounds, Q⁽¹⁾, on the order quantities for the iteration and determine the overall volume needed for these values (V¹) using (19). In the first iterative step we set the lower bounds, Q^(L), according to (20) and calculate values for lambda (λ) using (21). In the second iterative step we determine the overall λ value by averaging the min and max lambda values according to (22). In the third step, we calculate a new Q_i value, which is noted as Q_i(λ) using (23) and employ our decision rules. In the fourth step of the iterative process, calculate the functions for the upper and lower bounds according to (24) and (25) and employ the stopping rule (26). If the relative difference is less than or equal to the preset acceptable error, which was 0.01 in this case, stop. Otherwise, continue the iterations beginning at step two and repeat until convergence. Using the optimal Q_i values as determined by this process to recalculate the reorder points (s_i) using (11). With the new s_i = s_i⁽²⁾ values, recalculate M = M² and solve sub problem 2A (17) again. The resulting Q_i values may be different than those determined in the prior step in which case new s_i = s_i⁽³⁾ values are used for new iterations until the difference between s_i and Q_i is smaller than the preset accuracy limit (E = 0.01). For further explanation of this process, reference section 3.2.1 in the text.

APPENDIX D: MODEL 3 CALCULATIONS FOR REORDER POINT AND OPTIMAL Q

Tmin	Tmax												
	3	10											
*M' = Hospital M'													
Step 0: Initial Values													
M' = T _{max} Σ(v _i d _i)	5931.50												
M ₀ = M' - Σ[v _i (s _i -u _i)]	5357.58												
W = Σv(v _i d _i)	131.97												
V ₀ = M ₀ ² / 2W ²	824.10												
Iterative Process	Iteration 1	Iteration 2											
M _k = M' - Σ[v _i (s _i -u _i)]	4904.59	4859.79	M ₀	M ₁		M ₂							
Difference		0.009	5357.58	4904.59		4859.79							
			% Change	---		9.24%		0.92%					

APPENDIX E: MODEL 2 CALCULATIONS FOR SENSITIVITY ANALYSIS

[illegible]

APPENDIX F: MODEL 3 CALCULATION FOR SENSITIVITY ANALYSIS

Tmin	Tmax	SL											
	3	10	0.99										
*M' = Hospital M'													
Step 0: Initial Values													
M' = T _{max} Σ(v _i d _i)		4200.00											
M ₀ = M' - Σ[v _i (s _i -u _i)]		3271.80											
W = ΣV(v _i d _i)		78.82											
V ₀ = M ₀ ² / 2W ²		861.49											
Iterative Process		Iteration 1	Iteration 2										
Σ[v _i (s _i -u _i)		1101.51	1118.74										
M _k = M' - Σ[v _i (s _i -u _i)]		3098.49	3081.26	M ₀	M ₁				M ₂				
Difference			-0.006	3271.80	3098.49				3081.26				
				% Change	---				-5.59%				
									0.56%				
Drug	Average	Sigma	Size (v _i)	u _i	Step 0		Step 1		Step 2		Step 3		
					s _i ⁽⁰⁾	Q _i ⁽⁰⁾	s _i ⁽¹⁾	Q _i ⁽¹⁾	s _i ⁽²⁾	Q _i ⁽²⁾	D _i	s _i	S _i
DRUG 1	10.00	10.00	5	10.00	30.00	58.70	47.08	55.59	47.70	55.28	45.28	47.70	92.99
DRUG 2	10.00	10.00	5	10.00	30.00	58.70	47.08	55.59	47.70	55.28	45.28	47.70	92.99
DRUG 3	10.00	10.00	2	10.00	30.00	92.82	41.65	87.90	42.30	87.41	77.41	42.30	119.71
DRUG 4	10.00	10.00	2	10.00	30.00	92.82	41.65	87.90	42.30	87.41	77.41	42.30	119.71
DRUG 5	10.00	4.00	5	5.80	30.00	58.70	25.23	55.59	25.42	55.28	49.48	25.42	74.90
DRUG 6	10.00	4.00	5	5.80	30.00	58.70	25.23	55.59	25.42	55.28	49.48	25.42	74.90
DRUG 7	10.00	4.00	2	5.80	30.00	92.82	23.61	87.90	23.81	87.41	81.61	23.81	105.42
DRUG 8	10.00	4.00	2	5.80	30.00	92.82	23.61	87.90	23.81	87.41	81.61	23.81	105.42
DRUG 9	5.00	5.00	5	5.00	15.00	41.51	21.14	39.31	21.45	39.09	34.09	21.45	55.54
DRUG 10	5.00	5.00	5	5.00	15.00	41.51	21.14	39.31	21.45	39.09	34.09	21.45	55.54
DRUG 11	5.00	5.00	2	5.00	15.00	65.63	18.50	62.15	18.81	61.81	56.81	18.81	75.62
DRUG 12	5.00	5.00	2	5.00	15.00	65.63	18.50	62.15	18.81	61.81	56.81	18.81	75.62
DRUG 13	5.00	2.00	5	2.90	15.00	41.51	11.93	39.31	12.03	39.09	36.19	12.03	48.22
DRUG 14	5.00	2.00	5	2.90	15.00	41.51	11.93	39.31	12.03	39.09	36.19	12.03	48.22
DRUG 15	5.00	2.00	2	2.90	15.00	65.63	11.12	62.15	11.22	61.81	58.91	11.22	70.13
DRUG 16	5.00	2.00	2	2.90	15.00	65.63	11.12	62.15	11.22	61.81	58.91	11.22	70.13

Here dummy values are used in sensitivity analysis. The calculations are identical to those used with the actual pharmacy data, which are described in Appendix D. This analysis was done to demonstrate the influence of the various product characteristics on the determination of the optimal control parameters and order quantities.

VITA

John Michael Woosley was born in Memphis, Tennessee, to Dwight and Barbara Woosley; however, his family moved to Baton Rouge, Louisiana, soon after his birth. He graduated from Redemptorist High School in 1993 and received his Bachelor of Science, majoring in kinesiology, from Louisiana State University (LSU) in 1997. As an undergraduate, John was a student-athlete and a 3-time varsity letter winner for the LSU Track and Field program. While still competing for LSU, John began his graduate studies in the Kinesiology Department with a concentration in motor behavior. He earned a Master of Science from this program in 2000.

Upon the completion of his studies in kinesiology, John shifted his focus and started his second Master of Science program in the Information Systems and Decision Sciences (ISDS) Department at LSU, which he completed in 2002. In the fall of that same year, he began the doctoral program in ISDS. While still working on his dissertation, John accepted a position as an Assistant Coach with the LSU Track and Field program. He held this position for three years before returning to ISDS to complete his doctoral program.

John has accepted a position at Southeastern Louisiana University in Hammond, Louisiana. He and his fiancé are scheduled to marry in the summer of 2009, and they plan to stay in Louisiana as they start their lives together. In addition to his academic career, John continues to work with local high school track and field athletes on a volunteer basis.