Workflow Analysis, Scheduling, and Chance Constraint Models in Community Pharmacy Operations

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Community pharmacy networks provide most of the US population's prescribed medication. However, failing to pick up the medication or using it improperly can lead to problems such as medication non-adherence and medication misuse. This research focuses on improving community pharmacy chain network services by proposing a change in the role pharmacists play in these networks. A key task pharmacists perform which is a critical step in the medication dispensing process is verifying that the medication filled is the one prescribed and that it does not conflict with other medications the patient is taking. This dissertation proposes that pharmacists provide important counseling services (i.e. PDPC services) to patients inside community pharmacies. We discuss how adding PDPC services changes the workflow of a community pharmacy and discuss strategies to overcome obstacles preventing pharmacists from providing PDPC services.

We use a Discrete Event Simulation (DES) model to simulate a local community pharmacy as well as a community pharmacy chain network to evaluate strategies that can be used to either improve the workflow process internally (internal strategies) or provide an external resource that can be used to provide support to the pharmacy (external strategies). The internal strategies studied are adding a staff member, predicting prescription pick up times, and providing short duration PDPC services in busy hours. The external strategies studied are utilizing a central fill to dispense part of the pharmacy's demand and adding PDPC kiosks to provide PDPC services inside the pharmacy. The effect of each strategy and the extent of its benefits are studied and highlighted in chapters 2 & 3.

The central fill location problem was modeled as a chance constraint stochastic P-median capacitated facility location problem. Three extensions to the location model are added and discussed in detail. Several lower bounds were provided to the problem and an efficient solution method was used to solve the problem. Finally the model was applied to a community

pharmacy chain network in PA in a case study. The results showed that ignoring the highest demand scenarios can save the community pharmacy chain network from having to add an additional central fill.

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Preface

The completion of this work would not have been possible without the constant support and help of Dr. Bryan Norman. During the last five years I have learned several lessons by watching how Dr. Norman tackled problems and issues both in an academic environment and a non-academic one. Dr. Norman has taught me many things but perhaps the most valuable lesson was the perfect balance between patience and decisiveness. He has made me a better researcher, a better husband, a better father, and a better person in general. I honestly do not think that I possess the proper writing skills to truly describe how grateful I am to have been his student. When I had my first child three months before my proposal, you showed nothing but support and gave me a magnificent collections of baby books. These books happened to be your children's favorites and soon became Ahmed's favorite books as well. I asked one of your first PhD students about you and she told me that you were as compassionate then as you are now. I can only hope that I learned enough from the weekly meetings we had as they are truly irreplaceable. Thank you Dr. Norman for helping me during my times of need and pushing me when I needed it.

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Most importantly, I would like to express tremendous gratitude to my parents, Ghassan & Asmahan, my brothers, Abed & Ahmed, and my unofficial brother Alaa. It has been six years since I last saw you but the ten thousand miles distance only makes me love you even more. I still remember the last hug I gave each one of you and I hope to see you soon and make new memories. Mom, thank you for encouraging me to pursue my graduate studies - I cannot begin to imagine how hard it was to see your first child travel to another country but you are without a doubt one of the strongest and most passionate people I have ever met. Thank you for all the love and support you have given me.

1.0 Introduction

Over the past decade electronic prescriptions (eRx) have became the standard method for healthcare providers to prescribe necessary medication for a community member. The introduction of eRx impacted the workflow in community pharmacies; these pharmacies are a vital part of the healthcare system and are essential to the development of the overall quality of life in any community. community pharmacy chain networks provide most of the US population's prescribed medication as they are widespread and available in almost all communities. This research is motivated by the role the community pharmacy plays in improving healthcare. We study the workflow of community pharmacies and how eRx could be utilized to improve the overall patient experience. The proposed idea of this dissertation is to use pharmacists in community pharmacies to provide more Pharmacist Delivered Patient Care (PDPC) services such as Patient Counseling (PC), Medication Therapy Management (MTM), Disease Management (DM), and Vaccination Immunization services.

It is important to note that MTM is a comprehensive service that includes PC and DM. MTM is one of the longest PDPC services that became popular after The Medicare Prescription Drug, Improvement, and Modernization (MMA 2003) Act was introduced in 2003. Additionally, the implementation of Medicare Part D in 2006 demanded that insurance plans offered to 20 million Medicare users had to include MTM services. Currently, MTM services are typically offered by community pharmacies to beneficiaries of medicare part D plans. Hence, the amount of MTM Services offered by a community pharmacy is limited to the number of medicare part D beneficiaries. This study focuses on adding PDPC services which is a more generic term that includes reimbursable services such as MTM but also includes simple PC services to any customer (e.g., answering questions about over the counter medications).

Prescription abandonment, medication misuse and misunderstanding are primary factors impacting medication adherence. The consequences of medication non-adherence can be severe both in terms of lives and costs. Providing PDPC services is an effective method to improve medication adherence. The benefits of adding more PDPC services in a community pharmacy can be discussed from the pharmacy's perspective, customer's/patient's perspective, and the community as a whole. To the community pharmacy, adding more PDPC services is a potential new source of revenue that is not generated from dispensing medications. The average revenue generated from performing MTM services is $2 per minute [26]. Thus, a 30 minute MTM session generates an average revenue of $60. An earlier study showed that the average generated revenue from an MTM service (of shorter duration) is $9. The two studies showed generated income from MTM services as reimbursements from medicare part D plans, but that potential income does not have to be limited to part D plans. As more PDPC services are offered, customers/patients are less likely to be readmitted into hospitals, recover faster, and are healthier in general which reduces the cost of maintaining their health [26][7]. This is an incentive for all insurance companies to adopt a similar approach. Not to mention that a community pharmacy that provides PDPC services is more attractive to customers than one that does not.

As mentioned earlier, the health of community pharmacy customers benefits greatly from PDPC services. According to the Nashville project [11] PDPC services caused cardiovascular medication use to increase more than 300% (i.e better medication adherence) and actual cardiovascular medical costs decreased by 45%. Additionally cardiovascular medical cost decreased from 30.6% of total health care costs to 19%. According to the same study, PDPC services improved the quality of life for patients with cardiovascular diseases by 6 Quality-adjusted life years (QALYs). Finally, the benefits of providing more PDPC services on the community can be seen both in terms of lower healthcare costs as well as better public health. PDPC services helps patient focus on adhering to their medication which in terms reduces the costs patients spend on redundant medication. In fact, according to a 7 year analysis of the effect of MTM services, the average estimated cost avoidance per patient was $93 [7]. MTM also was shown to improve medication adherence by 4.6% among outpatients with chronic illnesses which can also be thought of as a cost avoidance of 4.6 billion dollars since medication non-adherence costs the US health care system $100 billion per year[8].

Adding more PDPC services in the community pharmacy can be challenging since pharmacists are busy dispensing eRX which makes them highly utilized. This research focuses on evaluating strategies that can be used to either improve the workflow process internally (internal strategies) or provide an external resource that can be used to provide support to the pharmacy (external strategies). A discrete event simulation model was built to evaluate the effectiveness of both classes of strategies. Four different internal strategies are evaluated starting with adding an extra staff member, using precise pick up information models, using imprecise pick up information models (with and without prediction errors), and dynamically changing the PDPC service duration. We show that pick up information models can be beneficial but only if the prediction error is not too high (we show that less than 87% prediction accuracy for the community pharmacy evaluated in this study is not beneficial). Adding a pharmacist and using dynamic PDPC both improve performance measures when the system is trying to provide a high level of PDPC service. In addition, three main external resource sharing strategies were evaluated: providing PDPC services using kiosks that connect to a PDPC center, using an automated CF to help dispense prescriptions, and offloading part of the dispensing process to nearby pharmacies. The results show the benefits and costs for each strategy. Kiosks are shown to provide PDPC services that help the pharmacy attain high levels of PDPC services, a CF is used to reduce the dispensing load but does not offer any PDPC support except redirecting existing pharmacist time to PDPC which proves to be beneficial to some extent.

Finally the problem of locating a CF that can support multiple pharmacies under stochastic demands was studied. The problem is modeled as a joint Chance Constrained P-median Capacitated Facility Location Problem. Several models were proposed that included the cost of dispensing eRx inside the CF, the cost of dispensing prescriptions inside the local pharmacy, proposing a distance constraint between the pharmacy and the CF, and limiting the amount of prescriptions dispensed inside the local pharmacy. The general model proved to be hard and a Benders decomposition solution procedure was proposed to improve the efficiency of the solution time. The model and solution methodology are used in a case study to improve patient care provided by a pharmacy chain network. The resulting network is a more capable community pharmacy chain network that is robust to stochastic demands and provides higher levels of patient care. The case study showed that ignoring the highest 10% of demand scenarios in a community pharmacy chain network saved the network from building an extra CF.

The organization of this dissertation is as follows. Chapter 2 evaluates the effectiveness of internal strategies on the community pharmacy's workflow. Chapter 3 discuses the value of using network type resources to improve PDPC services across the network. Chapter 4 considers the problem of locating a CF for a community pharmacy chain network and models the location problem as a large scale discrete optimization problem with a chance constraint and an expected dispensing cost in the objective function. Finally, Chapter 5 shows the main conclusions of this dissertation.

2.0 Evaluating Pharmacy Operating Policies to Enhance Pharmacist-Patient Interaction

Community pharmacies are a vital part of the healthcare system and this research is motivated by the role the community pharmacy plays in enhancing the quality of healthcare. We study community pharmacy workflow to offer more Pharmacist Delivered Patient Care services such as patient counseling, disease management, and medication therapy management. A discrete event simulation model is built to evaluate intervention strategies designed to handle the increase in workload caused by increasing Pharmacist Delivered Patient Care services. The intervention strategies evaluated are referred to as internal strategies as they focus on the use of resources within a particular pharmacy location. Three main internal strategies are evaluated. The first is adding staff, the second is using prescription pick up information, and finally offering dynamic PDPC service durations. The results show that different levels of prediction pick up information have different degrees of benefit and that in some cases, if the prediction pick up information only has limited accuracy, then it may be worse than having no pick up information.

2.1 Introduction

Patient safety and medication adherence are critical challenges in healthcare environments and these have led to numerous interventions in order to improve safe and effective use of medication. One effective intervention is providing patient counseling, disease management, Medication Therapy Management (MTM), and clinical services (i.e. immunization and vaccination services) to patients. These services are pharmacist-to-patient interactions also known as Pharmacist Delivered Patient Services (PDPC) that can be performed in a community pharmacy. Patient counseling is a product oriented service provided by the pharmacist which insures that patients are aware of how to use a specific product. Disease management programs provide patients with the necessary tools required to manage a specific disease [50]. Medication Therapy Management is defined by the pharmacy profession as a distinct service or group of services that optimize therapeutic outcomes for individual patients that are independent of, but can occur in conjunction with, the provision of a drug product [10]. MTM is a more comprehensive service that is inclusive of patient counseling and disease management services and is more focused on improving medication adherence for patients [7].

This study is focused on enhancing community pharmacy operations and workflow. The enhanced workflow is used to free up pharmacy resources to provide high levels of PDPC services at community pharmacies in order to improve patients' understanding of their health conditions and medications. The key challenge is that PDPC can only be provided by a pharmacist and the pharmacist is responsible for the oversight of critical tasks in the medication dispensing process. Providing higher levels of PDPC services while maintaining acceptable workflow performance measures requires the addition of more pharmacist capacity. However, pharmacists are expensive resources, for example the average annual salary for a pharmacist in the state of Pennsylvania is $113,630 [23]. Hiring a pharmacist to handle higher levels of PDPC is one of the strategies that is evaluated in this study but it is an expensive solution when applied to a network of community pharmacies that contains hundreds of locations. Additionally, the capabilities of the current pharmacists are not fully utilized if the main task the pharmacists are performing is medication dispensing. Therefore, a simulation model was built to simulate a community pharmacy and evaluate different intervention strategies that affect pharmacist utilization as well as pharmacy workflow. These strategies are evaluated with the objectives of minimizing customer waiting time, maximizing the number of customers serviced, and providing as much PDPC as possible. A number of important variables are taken into account including customer arrival patterns, staff schedules, prescription abandonment, and prescription pick up information.

The organization of the remainder of this paper is as follows. Section two provides an introduction and a literature review followed by a discussion of the motivation, objectives, and pharmacy processes. The fourth section shows the discrete event simulation used to model a pharmacy's operations. The fifth section is a detailed analysis of the simulation results. Finally, the last section provides conclusions based on model results.

2.2 Literature Review

We start this section with a brief discussion of different types of pharmacies in terms of differences in workflow, types of patients, types of medications, and the services provided. We then proceed to articulate a general discussion on the effects of technology on general pharmacy operations and then focus on the operations of a community pharmacy. This is followed by a literature review of prescription abandonment effects on both pharmacy operations. Additionally, we provide a detailed description of various discrete event simulation models in the literature for different pharmacy types. Finally, we highlight the main differences between this research and the existing literature.

2.2.1 Pharmacy Operations

There are three main types of pharmacies: inpatient, outpatient and community or retail. In an inpatient pharmacy, prescriptions are often referred to as medication orders, and the information required for these orders differs from that required for outpatient prescriptions. Inpatient pharmacy customers are residents of the hospital. Their medications are administered by nurses and can be changed frequently by physicians. The methods of delivery include using IV drugs that need a lot of preparation with a fair amount of calculation, mixing, and checking. Outpatient pharmacy patients take their medications and leave which means that the patient is in control of picking up the medication as well as administering it. Patients receive multiple days' supply and they come back for refills as needed[30]. Outpatient pharmacies are similar to retail/community pharmacies in terms of workflow but they do have subtle differences. Hospital-owned outpatient pharmacies retain a clear advantage over traditional retailers through their access to the patient's electronic health record and they carry a wider range of medications. A hospital pharmacy is more likely to be involved in teaching pharmacy, and other types of, students and to be engaged in clinical trials. On the other hand, pharmacists in community pharmacies provide counseling for Over The Counter (OTC) medications as well as regular prescriptions and deal with insurance companies and Medicare more extensively[30].

Community pharmacies account for a large share of all outpatient drugs dispensed to patients in the US. According to the National Association of Chain Drug Stores (NACDS), in 2016, 9-out-of-10 Americans lived within 5 miles of a community pharmacy[58]. Also, more than 17.7 billion electronic transactions were conducted by community pharmacies[70]. It is clear that community pharmacies play an important role in the healthcare system.

During the last decade, activities and operations in pharmacies have changed significantly. One of the primary drivers of this is the increasing use of Health Information Technology (HIT). Electronic prescriptions (eRx) are one HIT innovation that has changed pharmacy practice[59]. Today, eRx are an integral part of the pharmacy workflow. According to the 2018 National Progress Report over 258 million patients (more than 79% of the US population) received at least one eRx and 73% of all prescriptions were electronically prescribed[70].

eRx have changed the community pharmacy's workflow as eRx can be filled prior to the arrival of patients which provides patients with shorter waiting time but also create a noticeable increase in prescription abandonment (patients not actually filling/picking up their prescription)[9]. Patients arriving to the pharmacy with a paper prescription are unlikely to abandon their medication. Prior to eRx, patients intending to abandon their prescription would simply ignore the prescription and would never get it filled which has no effect on the pharmacy's workflow. As eRx use has grown, eRx abandonment has become a significant issue for pharmacy workflow since abandoned eRx require resources to fill, store, and then restock them. Additionally, higher prescription abandonment is indicative of medication non-adherence by patients which is a patient safety concern. Additionally, Odukoya and Chui [59] suggest that using eRx can create significant pharmacy workflow changes which, in some instances leads to inaccurate filling of prescriptions.

In addition to the new technological impacts on pharmacy operations, the role of pharmacists in patient care has also been changing over time. Primary care providers include doctors, nurses, dentists, and pharmacists, but for far too long pharmacists have been viewed as merely medication dispensers [27]. In recent years there has been a realization that community pharmacists can play a major role in educating patients about safe and effective use of medications. For example, when MTM services educate patients on the nature of their condition they may reduce adverse drug events and improve patients' medication adherence [36]. The impact of pharmacist counseling services in a community pharmacy is highlighted throughout the literature. In one case study, pharmacist intervention was shown to rectify medication errors in most cases and reduce costly rehospitalization and emergency department visits [28]. Unfortunately, at the present time many community pharmacists are too busy filling, verifying and validating prescriptions to allow time to provide PDPC services for patients. This can negatively impact patients' ability to appropriately adhere to their treatment regimen.

2.2.2 Pharmacy Simulation Analysis

In this research we use a Discrete Event Simulation (DES) to assess community pharmacy operations taking into account the effects of using eRx and incorporating PDPC into the workflow. It is important to note that DES has been used to assess pharmacy operations in the past. Moreover, community pharmacies and outpatient pharmacies have very similar workflow, and therefore, we review literature for both.

Using DES to evaluate policies, systems and workflow in a hospital pharmacy (inpatient and outpatient) is common in the literature. In fact, Law (2011)[40], suggests that simulation is most useful if there is complexity in the real system, or interdependence between system controls or if it is difficult or impossible to predict certain changes. Literature regarding pharmacy simulation studies can be classified according to different pharmacy types.

While pharmacists are in charge of dispensing medications, overseeing pharmacy workflow, and maintaining medication inventory stock, the main role of a pharmacist is dependent on the type and size of a pharmacy. For example, in a small pharmacy the pharmacist would be in charge of most of the dispensing process whereas in a bigger pharmacy the pharmacist would focus on drug review. Spry (2005)[69], studied the different types of drug orders in an inpatient pharmacy and studied the effects on pharmacist and technician utilization. The paper also simulated different pharmacy staff schedules and analyzed their effect on pharmacy workflow. Reynolds (2011)[61], evaluated the impact of several factors including prescription workload, staffing levels, staff skill-mix, and utilization of the dispensaries' automatic dispensing robots. The study was based on two London hospitals. The main objectives were to minimize the mean prescription turnaround time and maximize the percentage of prescriptions completed within 45 minutes. The paper findings were used to support business cases for staffing changes.

Abel (2013)[1], performed a simulation analysis on an inpatient pharmacy with the objective of improving cycle time. Mukherjee (1991)[56], used DES for hospital pharmacy management with the goal of minimizing drug delivery times to patients within the hospital. Mohammadi (2012)[53], focused on the quality of service in an inpatient hospital pharmacy in Malaysia. The main objective of the study was to emulate the currently working system in order to find intelligent schedules that can reduce patient waiting time, dispense medications faster, and reduce queue lengths. Bahadori (2014)[6], applied DES to an outpatient pharmacy in Tehran. An *M/M/1* queue is used as the base model. The paper focused on optimizing waiting time, system utilization, and the number of pharmacists needed. Lu (2012)[46], performed a simulation study on a large community hospital pharmacy to evaluate medication preparation and delivery times.

One of the earliest DES for outpatient pharmacies is presented by Vemuri [75] with the objective of reducing patient waiting time. Vemuri used a fixed factorial designed experiment (12 configurations). Different levels of the number of technicians, typists, and pharmacists were considered in the factorial experiment. In Valluri(2007)[74], the costs of mail order prescriptions versus community pharmacy prescriptions is evaluated using a simulation model. The study data is taken from a Medicaid population for chronic prescriptions. The study showed that a 5% increase in drug utilization and a 5% decrease in drug cost were found when mail order prescriptions were used. Vila-Parrish (2008)[77], presented a simulation model for managing the inventory of perishable drugs for inpatient services. Vila-Parrish used an MDP model to model drug demand as a function of patient condition, the model was used to provide appropriate levels of drug inventory. Due to the fact that the number of states increased as a function of the number of patients, the MDP becomes computationally intractable and simulation is used to provide realistic results.

Mohebbi (2010)[54], claimed that pharmaceutical expenditures are regarded as the biggest contributor to rising health care costs across the nation. The author suggested that the main reasons for such high costs are problems in allocating resources, inventory control, pharmacy workflow, and automation for the dispensing process. Finally, the paper also emphasize the lack of community pharmacy DES in the literature.

Mei (2013)[34], analyzed the effects of staffing and dispensing automation on customer waiting time in a community pharmacy. The retail pharmacy studied in the paper used a small dispensing robot capable of handling 500-550 prescriptions per day. The retail pharmacy in Mei's paper studied three types of prescriptions: walk-in, phone/fax in, or eRx. The paper showed that unexpected phone calls, walk-in patients, and employee tardiness are big contributors to higher patient waiting times. The paper also suggested that in order to achieve acceptable levels of patient waiting time a bigger robot is required.

Zhang (2014)[82], presented a simulation study done for Kroger which uses an (s,S) policy to manage their inventory. The main goal is to reduce stockouts and overstocking of inventory. Furthermore, the paper discussed a stochastic inventory optimization problem and adopted simulation-based algorithms and a local search heuristic to provide approximate solutions.

Dan (2016)[18], used a DES model on an outpatient pharmacy aiming to improve its queuing system efficiency. The study used a queuing simulation approach to evaluate the effect of a single queue multiple window and a multiple queue multiple window system in the pharmacy. It is important to note that the number of prescriptions handled by an outpatient pharmacy in China is around ten thousand prescriptions on a busy Monday which is a much higher dispensing load than the average community pharmacy in the USA not to mention the differences in the dispensing process especially with regard to reviewing drugs.

As described above, previous DES models for inpatient pharmacies focused on improving staff utilization[69], evaluating the impact of adding staff personal with different skill levels[61], or improving cycle time[1]. Furthermore, DES models applied to outpatient pharmacies focused on prescription pick up waiting time[75], evaluating the cost of mailed prescriptions[74], and improving system queuing efficiency[18].

Pharmacy workflow intervention strategies can be classified into internal and external strategies. An internal intervention strategy is one that does not involve external resources in the dispensing process. For example, using an automated CF pharmacy to dispense eRx then ship them directly to the pharmacy is an external intervention strategy, but hiring an additional staff member is an internal one. Our DES model is mainly designed to assess internal strategies. To the best of our knowledge, our work is the first in evaluating the effect of using several internal strategies such as different work scheduling policies, staff schedules, prioritizing work using pick up time prediction models to examine the feasibility of providing more PDPC services in a community pharmacy, and offering dynamic PDPC service durations that are changed in real time as the pharmacy gets busier. Additionally we evaluate differences between being able to perfectly predict customer pick up times (full information), and partially predicting pick up times (partial information). We also test different levels of confidence (prediction accuracy) in predicting pick up information by assuming that part of the pick up predictions are inaccurate.

2.3 Problem Motivation, Definition, and Objectives

The main objective of this section is to provide a more detailed discussion for the motivation of the problem, establish a clear problem definition, discuss solution methods, and finally clarify and define the overall study objectives.

2.3.1 Problem Motivation

Community pharmacies play a vital role in patient safety. That role includes providing necessary medications to patients and also providing PDPC services. Community pharmacies have been experiencing tremendous growth in eRx volume in the past decade which has a significant effect on pharmacy workflow and has provided a noticeable growth in prescription abandonment. The following figure shows the growth of eRx in the last decade which was obtained from the e-prescribing system Surescripts (a national health care network[70]). This figure does not include all eRx nationwide but is representative of the tremendous growth in the use of eRx in the last decade.

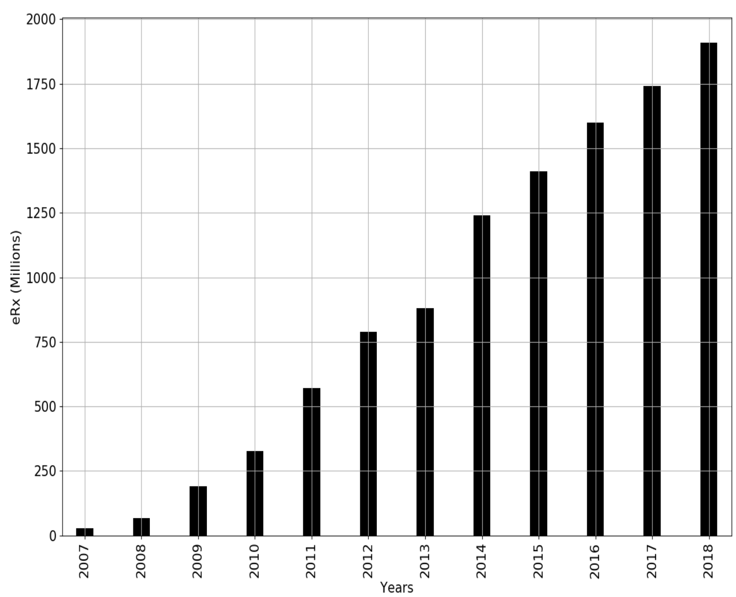

Figure 2.1: eRx Growth

The increase in the use of eRx has led to a significant increase in the rate of prescription abandonment. Research has found that there are four major reasons for prescription abandonment of eRx: cost, pharmacy behavior, patient age, and drug class [65]. The literature suggests that an eRx is 65% more likely to be abandoned [65] than a paper or faxed prescription. It is important to note that pharmacies are able to track abandonment for eRx much easier than for printed or faxed prescriptions. The issue of prescription abandonment is a public health concern and has direct impact on patient safety since it has a direct impact on medication non-adherence. Not adhering to proper medication usage results in higher patient health risks as it accounts for 10% of older adult hospitalizations and higher health care costs (it costs the US healthcare system around $100 billion annually[76]). As described by the World Health Organization (WHO), medication adherence is a multidimensional phenomenon which can be divided into five factors: social and economic factors, health care system factors, condition related factors, therapy related factors, and patient related factors. Each one of these factors is essential to the adherence process, some of these factors are personal, others are social. PDPC services could be provided by a pharmacist at a community pharmacy which will address several of these factors, and help improve adherence to their medications. For instance, some medications, such as antidepressants, must be taken for a while before they affect patients so a patient may think that they have no effect and as a result the patient stops taking the medication but in an PDPC session he/she would understand how the medication works and therefore be more likely to adhere to it [71]. Additionally, some patients might be reluctant to take their medication due to a side effect that they believe they cannot control [38]. Both examples could have been avoided by providing PDPC services for the patient, which motivates improving patient safety by providing more PDPC services at community pharmacies.

2.3.2 Problem Definition

Pharmacists are an essential resource in the pharmacy workflow due to the fact that they perform essential tasks in the dispensing process. Figure 2.2 shows the different processes performed in a community pharmacy and the staff members that can perform these tasks.

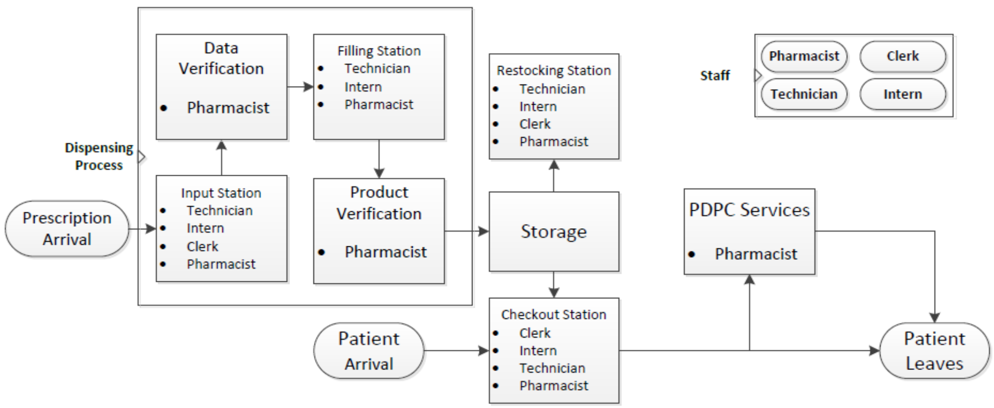

Figure 2.2: Pharmacy Workflow

The community pharmacy in this study operates under the assumption that all the prescriptions are eRx. Figure 2.2 shows a serial pharmacy workflow process. It begins at the input station which consists of tasks including: inputting eRx information into the system, verifying the eRx information for accuracy, reviewing the patient's profile and checking insurance. Then the prescription is filled in the filling station and reviewed by a pharmacist to make sure there is no conflict with current medications and that there are no errors in the prescription. The last station for customers is the PDPC service station and the objective of this study is to permit the community pharmacy to provide as much PDPC as possible. A DES model is built to model community pharmacy operations taking into consideration the following performance measures:

- Average customer waiting time
- Average staff utilization
- Percentage of satisfied customers (customers serviced within 45 minutes)

2.4 Simulation Model

The model developed in this paper is used as an evaluation tool to understand the pharmacy workflow and measure the impact of the intervention strategies suggested in this paper. The first part of this section describes the input data, the arrival process, and the pharmacy workflow. The second part of this section explains the relationships between customer and prescription arrivals. This process plays a major role in how prescription abandonment is modeled. The final part of this section describes customer and prescription workflow inside a community pharmacy. $Simio^{TM}$ was used to simulate all pharmacy operations.

2.4.1 Input Data

Input data for the proposed model can be classified into three categories: customer data, prescription data, and service data. customer data includes the arrival times of customers, the number of eRx per customer, and whether or not the customer needs PDPC. Prescription data includes the arrival time to the pharmacy, customer information (e.g., customer identification number, number of eRx for that customer), and pick up information. Service data includes pharmacy processing times for the various stations. All data were obtained through collaborating with the University of Pittsburgh's School of Pharmacy.

2.4.1.1 Customer Data There are two main data elements regarding customers - the pick up day distribution and the pick up time distribution. The pick up day distribution has three possible cases: same day pick up, later day pick up, and abandoned. The customer pick up day distribution is an essential part of the arrival process, as it contains information about prescription abandonment. Same day pick up represents the portion of customers that pick up their eRx on the same day, later day pick up represents the portion of customers picking up their prescription within 14 days, and abandonment represents the portion of customers abandoning their prescriptions. Prescription abandonment amongst insured customers has been studied well in the literature and a common estimate for prescription abandonment is approximately 4%[65]. The same study showed this number is three times higher for first time prescriptions, but most importantly this number was estimated for the insured population in a community pharmacy, however the actual portion of abandonment can be much higher for the general population. More recent studies showed that the abandonment rate can be as high as 24%[24]. The abandonment rate used in this study is 10% which represent a representative rate of abandonment across a full spectrum of customers. We assume that 40% of eRx are picked up on the same day and 50% are picked up on a later day.

The pick up time distribution, shown in Figure 2.3, characterizes customers' arrivals during working hours in a given day. A key assumption is that most customers pick up their eRx before work, during the lunch hour, or after work. This data was based on discussions with community pharmacy experts and staff and an independent community pharmacy database. The exact minute of arrival is sampled uniformly within each hour.

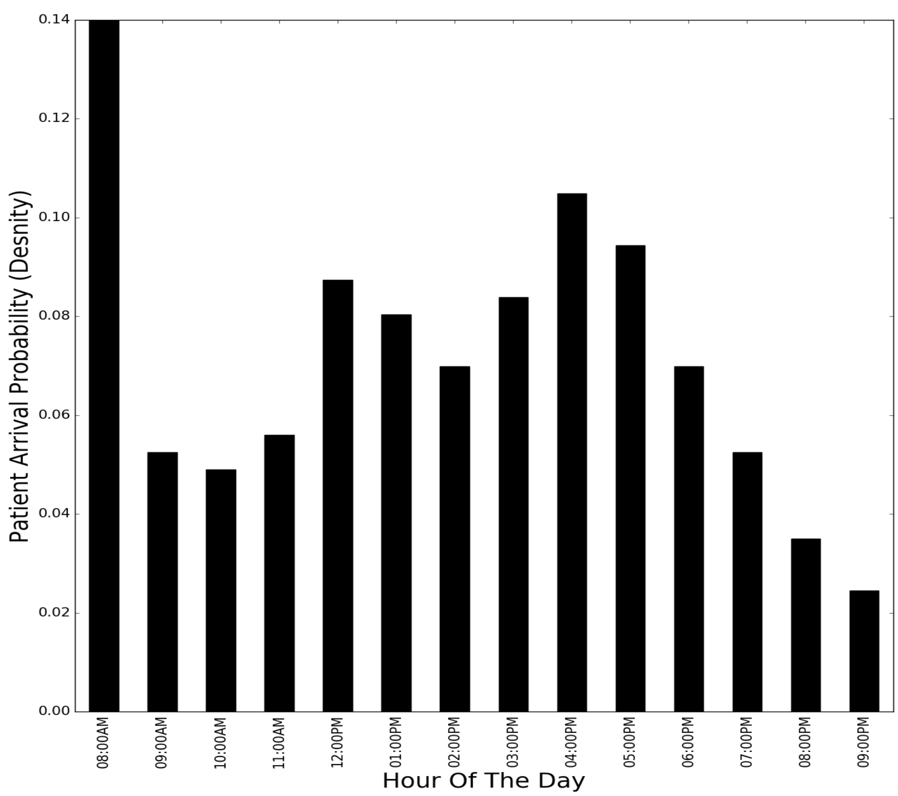

Figure 2.3: Arrival Hour Distribution

2.4.1.2 Prescription Data Prescription data can be classified into two categories. The first is hourly prescription arrival rates. The second is customer information which includes customer ID number and the number of eRx the customer plans to pick up. It is assumed that prescriptions orders are electronically sent to the pharmacy at the moment of creation. Consequently, one or more eRx for the same customer are received in the pharmacy at the same time. In this model, we assume that on average, each customer has two eRx to pick up that are linked together and are either picked up or abandoned. Additionally, the number of eRx per customer is assumed to follow the distribution in Figure 2.4. The eRx arrival process is assumed to be a Non-Homogenous Poisson Process (NHPP) with the rates shown in Figure 2.5. Further details about the arrival process are discussed in the arrival process section.

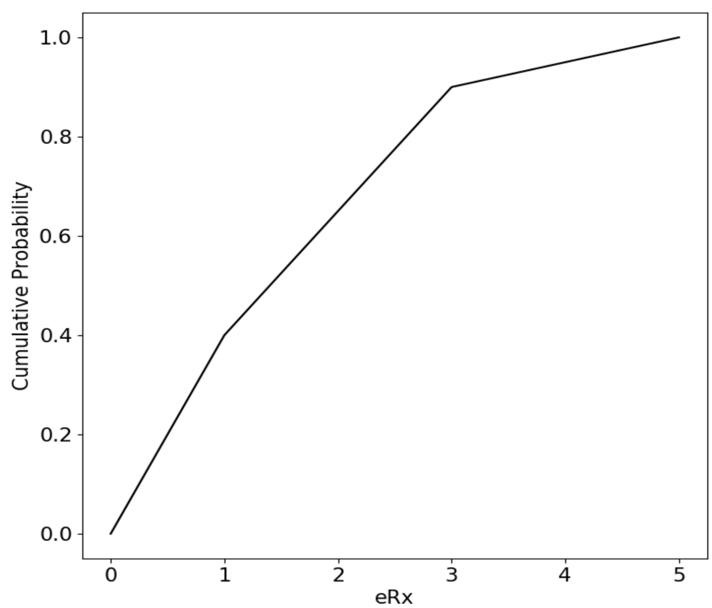

Figure 2.4: Number of eRx Per customer

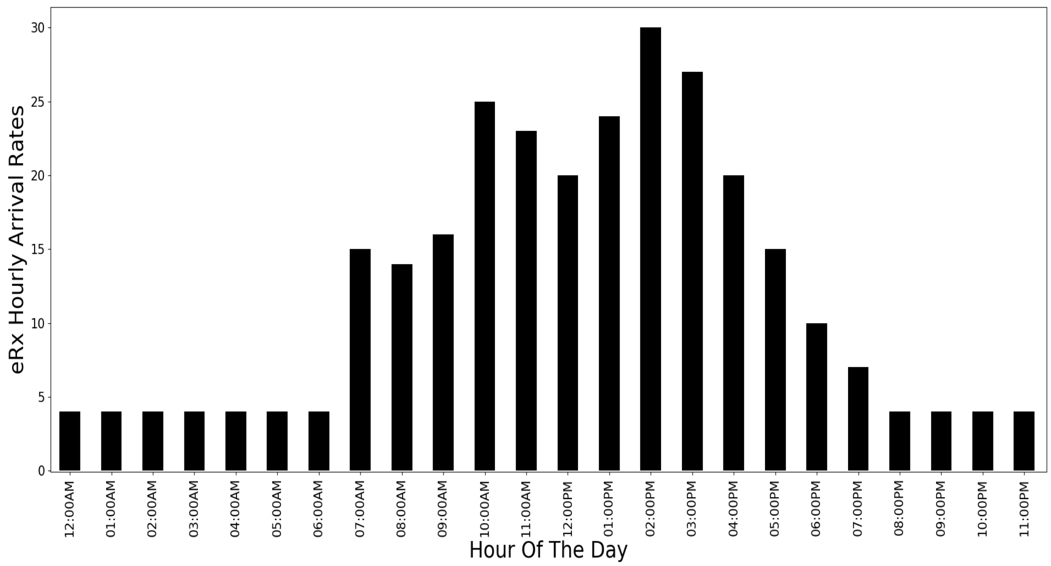

Figure 2.5: Medication Order Rates

2.4.1.3 Service Durations The last part of the input data are the service durations for the input station, filling station, drug review station, restocking station, checkout station, and PDPC station. Service duration data was obtained through meetings with pharmacy student interns who observed and performed some of these tasks, pharmacy experts from a large regional grocery store chain, and work that was presented by Banner Health [33]. Service durations are assumed to follow a triangular distribution with an expected time in minutes shown in Table 2.1.

Table 2.1: Expected Service Duration (Minutes)

Input	Filling	Verify Product	Verify Data	Checkout	Restock	PDPC Services
1.5	1.9	1.5	2.5	3	2	10

2.4.2 Arrival Process

In most community pharmacies, arrival processes can be split into customer arrival, and prescription arrival. The customer arrival process describes the interarrival time for customers to pick up their medication. The prescription arrival process indicates the time a prescription is electronically delivered to the pharmacy. Customers only arrive during pharmacy operating hours as seen in Figure 2.3. Prescriptions, on the other hand, could be delivered any time during the day. Customer arrival and prescription arrival to the pharmacy are highly correlated. Figure 2.6 shows the process initiated when an eRx first arrives.

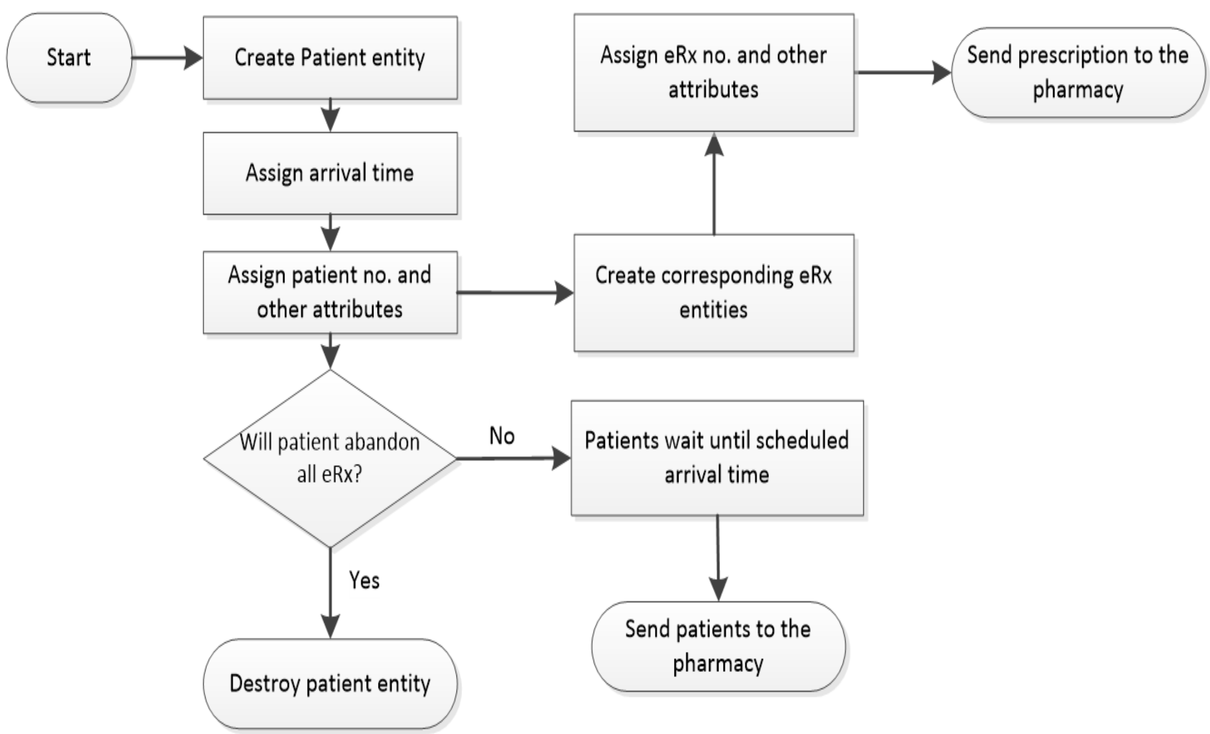

Figure 2.6: Arrival Process

The process shown in Figure 2.6 is executed according to a NHPP with the rates shown in Figure 2.5. Consequently, the NHPP triggers two main arrival events. First, a customer entity is created in the model and assigned an arrival time. Then, the corresponding number of eRx, sampled from Figure 2.4, are created. All eRx entities are immediately sent to the pharmacy (as eRx are in practice).

Actual customer arrivals are defined by the day a customer decides to pick up his/her prescriptions and the exact time of day for an arrival which were discussed in the Data section. As a result, on the first simulation day only customers who decided to pick up their prescriptions on the same day will be candidate arrivals to the pharmacy. Consequently, the first two simulation weeks will have different customer arrival rates each day but after 14 days, the number of days needed to restock a prescription, the simulation will have a constant average customer arrival rate for each simulation day. A warmup period of 14 days is used to nullify the effect of these initial conditions.

2.4.3 Workflow and Priority Rules

The pharmacy workflow shown in Figure 2.2 is a serial process. Our analysis focuses on three pharmacy resources - pharmacists, technicians, and clerks - that are capable of working on different subsets of the pharmacy operation. The pharmacist has the ability to work at all stations and the clerk can work at the smallest number of stations.

The simulation model considers three different levels of prescription pick up information: prescriptions with unknown pick up time meaning that the pharmacy has no information about when the customer will arrive for pick up, prescriptions with known pick up day (Imprecise Information), and prescriptions with full knowledge of pick up time (Precise Information). We also look at different levels of accuracy for imprecise information where the pharmacy's prediction model provides an $\alpha\%$ accurate prediction.

These different levels of information are assessed in order to determine the value of having more or less information regarding customer pick up. Different community pharmacies are investigating different mechanisms for obtaining better information regarding customer pick up and by exploring these different levels of information, our simulation model can help determine the benefits and value of having this information so that it can be weighed against the cost and effort required to obtain that pick up information.

Processing eRx in the pharmacy depends on the priority of the eRx. The simulation model can also assess the impact of using different priority rules. As a rule of thumb, if a customer is waiting in the pharmacy then his/her prescriptions are considered high priority work. Otherwise, prescriptions are filled according to different priority rules such as FIFO or other more complicated rules based on estimated pick up time (if information is available).

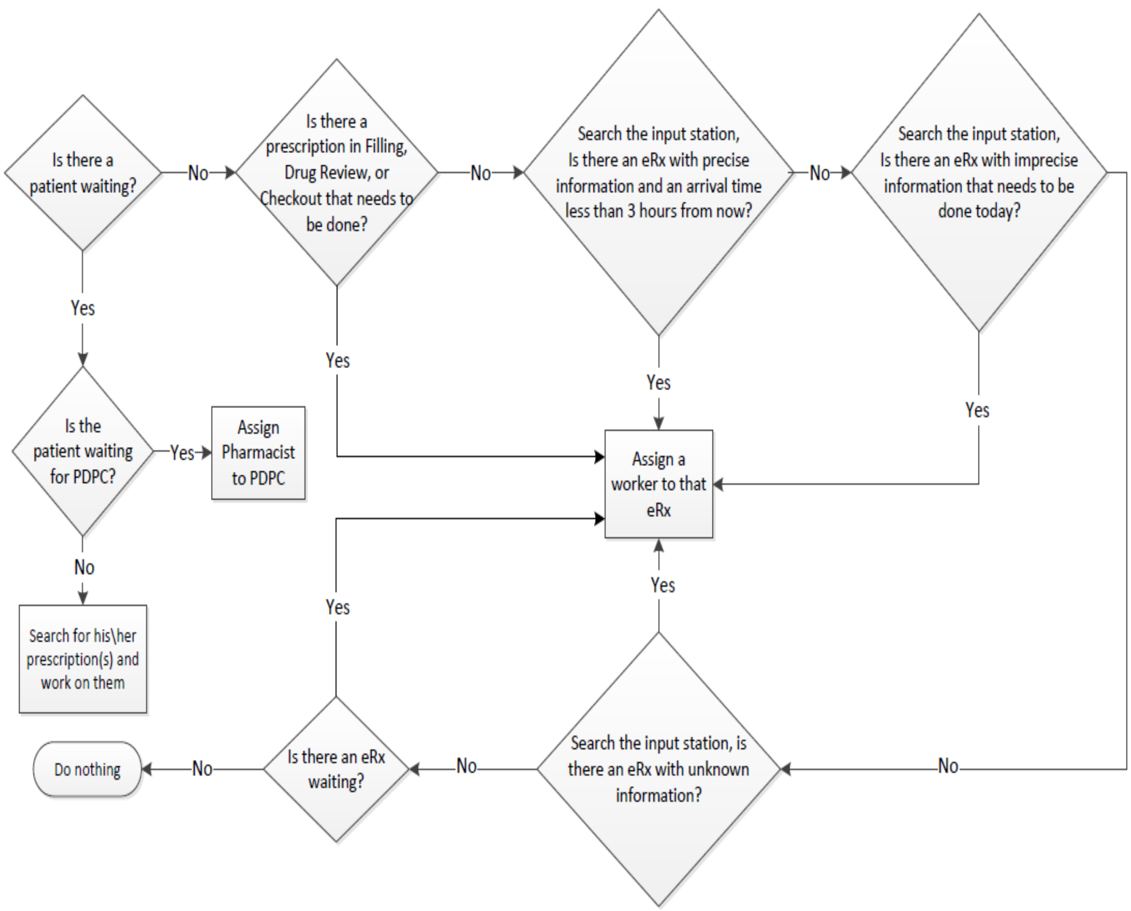

Figure 2.7: Example Priority Rule Scheme

Figure 2.7 shows an example priority rule scheme that is implemented in the simulation model. The process starts when a staff member finishes his/her work and is looking for the next task to do. Figure 2.7 shows how priority is assigned from the lowest to highest in a pharmacy. For example, for a pharmacist the highest priority is assigned to customers waiting in PDPC, the second highest priority goes to an eRx with an urgent predicted pick up date (using precise and imprecise information), and then to an eRx with unknown pick up information, finally the lowest priority is assigned to an eRx with a less urgent predicted pick up time (less urgent indicates later in the day or a later day).

2.5 Results and Analysis

In this section, the simulation model is used to evaluate different intervention strategies designed to relieve the pharmacy's workload and deliver better customer service by providing more PDPC services. This section is organized as follows: the first part of this section discusses the effect of providing more PDPC services on pharmacy workflow performance measures (staff utilization, customer waiting time, etc.), the second part shows the effect of adding an extra pharmacist or an extra technician or both, the third subsection investigates the value of using precise pick up information, the fourth subsection studies the feasibility of using imprecise pick up information, the final subsection evaluates using dynamic PDPC services. The default staff schedule used to generate the simulation results includes two clerks, two technicians, and three pharmacists. The service durations and arrival process data are shown in Section 2.4.1 and will remain the default parameters for the rest of this study.

2.5.1 The Effects of Providing Various Levels of PDPC Services

The simulation model was used to evaluate workflow effects of introducing increased levels of PDPC services. Table 2.2 shows eleven different experiments starting from no PDPC services provided in case 1, and increasing the levels of PDPC services up to a 100% in case 11. While in practice, no community pharmacy would likely reach 100%, it is desirable to achieve higher levels of PDPC services as it enhances customer safety and possibly generates a new stream of income as the pharmacy can potentially be reimbursed for performing these services [22]. The main pharmacy workflow performance measures include staff utilization, customer waiting time, and the percent of unsatisfied customers for both check out and PDPC. Customers are considered unsatisfied at check out if they have to wait for 45 minutes, at which point it is assumed they immediately renege the queue. We assume that the maximum allowable number of customers waiting in the PDPC queue is equal to 3. Unsatisfied PDPC customers are checked out customers that requested (or were offered) a PDPC service but could not get one because the PDPC queue was full or the waiting time to get PDPC was more than 10 minutes.

Table 2.2: PDPC Services Effect

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
0	0%	1	0	1%	0%	0%	69	63
1	10%	1	1	1%	1%	10%	76	67
2	20%	2	2	4%	3%	19%	84	71
3	30%	4	3	7%	8%	25%	89	74
4	40%	6	4	10%	14%	31%	94	77
5	50%	7	4	13%	20%	35%	97	78
6	60%	10	5	18%	24%	37%	99	80
7	70%	13	5	24%	28%	39%	100	81
8	80%	17	5	30%	30%	39%	100	83
9	90%	20	5	36%	32%	39%	100	83
10	100%	23	5	42%	33%	39%	100	84

In Table 2.2, case 1 has ideal performance measures with a low percentage of unsatisfied customers, low customer average waiting time, and modest staff utilization. Cases 2 through 11 show an increase in pharmacist utilization as expected due to more PDPC services being provided. The technicians' (and the clerks') utilization follow a similar pattern. Normally, the more PDPC services are added to the pharmacy's workload, the higher the staff utilization gets. However, this is not always the case as technician utilization did not increase in cases 9 through 11 due to the very high pharmacist utilization and that pharmacists prioritize customers in the PDPC station over eRx waiting in drug review. This creates a bottleneck in the pharmacy workflow and a larger number of customers that are not serviced resulting in less work for the technicians and clerks. However, these cases would be avoided in practice because the waiting time and customers not served measures are unacceptably high.

2.5.2 Adding Extra Staff

One of the basic strategies to improve workflow in a community pharmacy is simply increasing staff levels to handle the increase in workload. The question is what staff member should the pharmacy hire? The answer is not straight forward. Clearly, hiring an extra full time pharmacist would have the highest impact on pharmacy workflow since a pharmacist can perform any task in the pharmacy, but adding an extra pharmacist can be expensive, especially if the community pharmacy chain network contains numerous pharmacies. In fact, according to The U.S. Bureau of Labor Statistics the average annual salary for an entry pharmacy technician is $31,750 which is less than half the annual salary for an entry level pharmacist [13].

Tables 2.3 and 2.4 show the effect of hiring an extra pharmacist and an extra technician on the community pharmacy of this study. Adding a pharmacist when there are no PDPC services, (case 1, Table 2.3), provides little to no value to the pharmacy as the pharmacy already has enough resources to handle the workload, the same can be said about adding an extra technician under the same workload (case 1, Table 2.4). The effect of adding a pharmacist can be seen as PDPC service levels increase, in fact a pharmacy with an extra pharmacist and 20% PDPC services, (case 3, Table 2.2), shows very similar average check out wait time to the base case pharmacy with no PDPC services (case 1, Table 2.2). A pharmacy with an extra technician can handle 20%-30% added PDPC services where a pharmacy with an extra pharmacist can handle 40%-50% more PDPC services while maintaining reasonably good service metrics.

Table 2.3: Adding a Pharmacist

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	1	0	1%	0%	0%	57	56
2	10%	1	0	1%	0%	10%	65	59
3	20%	1	1	1%	1%	20%	70	63
4	30%	2	2	3%	3%	28%	76	66
5	40%	3	2	6%	6%	35%	81	69
6	50%	5	3	8%	11%	41%	85	71
7	60%	5	4	10%	16%	46%	88	73
8	70%	6	4	11%	21%	50%	90	74
9	80%	6	4	12%	24%	53%	93	76
10	90%	7	5	13%	28%	56%	95	77
11	100%	8	5	14%	31%	59%	97	78

Table 2.4: Adding a Technician

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	0	0	1%	0%	0%	61	52
2	10%	1	1	1%	0%	10%	70	55
3	20%	2	2	3%	3%	19%	79	57
4	30%	4	3	7%	8%	26%	86	59
5	40%	5	4	10%	13%	31%	92	60
6	50%	7	4	13%	21%	35%	95	61
7	60%	9	5	16%	26%	37%	98	62
8	70%	11	5	21%	29%	39%	100	63
9	80%	15	5	28%	31%	40%	100	64
10	90%	18	5	33%	33%	40%	100	65
11	100%	21	5	39%	35%	40%	100	65

Improving the performance of a pharmacy by adding an extra staff member is costly and would likely only be cost effective if the number of community pharmacies in the network is small.

2.5.3 The Value of Predicting Pick Up Information

This section discusses intervention strategies designed to effectively prioritize eRx and improve pharmacy workflow. This can be done using models that are capable of providing customer pick up information. These models can vary from a machine learning model to using a mobile app to calling customers to get a better understanding of when eRx will be picked up. It is assumed that the community pharmacy chain network uses a model that can provide pick up times. This section provides an evaluation of how impactful prediction models can be on pharmacy workflow. Two different prediction models are evaluated in this study. The first prediction model provides precise pick up information for customers, which provides the pharmacy with accurate pick up times for each customer. The precise information prediction models are assumed to be accurate 100% of the time and are used as a benchmark to show the effect of the best possible prediction model. Section 2.5.3.2 provides a discussion on the value of using less accurate, but more practical, prediction models capable of predicting the day of pick up with some degree of accuracy, we call these models imprecise pick up information models.

2.5.3.1 Precise Pick Up Information In this section, five different levels of precise pick up information (0, 25%, 50%, 75%, and 100%) are tested for pharmacies with different levels of PDPC services. The same base staff schedule discussed in the previous sections (2 clerks, 2 technicians, and 3 pharmacists) was used to evaluate the effect of using precise pick up information. Table 2.5 shows the results of an experiment with 20 cases. Using precise information has different effects on pharmacy performance measures depending on the overall pharmacy workload. For example, the increase in precise information for case 1 through case 5 has little effect on customer satisfaction and average waiting time because the system is lightly loaded. However, there is a significant improvement in pharmacy staff utilization as the percent of precise information increases, primarily due to being able to predict abandoned eRx which eliminates unnecessary work.

Pharmacy workflow can be scheduled in a much more efficient way if pick up information is available for arriving eRx. The pharmacy assigns the highest priority to customers waiting, then eRx with pick up due times within 3 hours, and finally eRx with unknown pick up due times. All entities with the same priority level are treated in a FIFO manner as discussed in Section 2.4.3. Hence, knowledge of precise pick up information has two major effects on the pharmacy workflow. It reduces unnecessary work and prioritizes work in an effective manner. The effect of work reduction can be seen in all 20 cases as staff utilization decreases with higher levels of pick up information. However, work prioritizing seems to be more effective in cases where the pharmacy has a high workload. As a result, the effects of precise information become more noticeable with increased levels of PDPC services as seen in cases 16 through 20 with 60% PDPC services. The pharmacist is overutilized in the base case (case 16) which leads to poor pharmacy performance measures with high average waiting time and a poor customer satisfaction percentage as many customers leave the pharmacy unsatisfied. But with 100% precise pick up information it can be seen that there is a significant reduction in customer waiting time and customer dissatisfaction. Using a 100% precise pick up information model has two major effects on the pharmacy: abandoned prescriptions are filtered out in the input station, and prescriptions are scheduled to be filled according to the earliest due time.

Table 2.5: Precise Pick up Information Workflow Effects

Cases	PDPC (%)	Precise Information (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	0%	0.7	0	1%	0%	0%	69	63
2	0%	25%	0.7	0	1%	0%	0%	68	61
3	0%	50%	0.6	0	1%	0%	0%	66	59
4	0%	75%	0.5	0	1%	0%	0%	65	57
5	0%	100%	0.2	0	1%	0%	0%	63	55
6	20%	0%	2.5	1.7	4%	3%	19%	84	71
7	20%	25%	2.4	1.7	4%	3%	19%	83	68
8	20%	50%	2.4	1.8	4%	3%	19%	83	66
9	20%	75%	1.8	1.8	3%	3%	19%	81	64
10	20%	100%	0.6	1.9	1%	4%	19%	79	63
11	40%	0%	5.5	3.7	10%	14%	31%	94	77
12	40%	25%	5.4	3.7	10%	14%	31%	94	74
13	40%	50%	4.9	3.7	9%	15%	31%	93	71
14	40%	75%	4.2	3.8	8%	15%	31%	93	70
15	40%	100%	3.4	3.8	6%	15%	32%	91	68
16	60%	0%	10.0	4.7	18%	24%	37%	99	80
17	60%	25%	9.4	4.7	17%	24%	38%	99	77
18	60%	50%	9.4	4.7	17%	25%	38%	99	74
19	60%	75%	8.2	4.8	15%	26%	38%	99	73
20	60%	100%	6.0	4.8	10%	26%	40%	98	71

It is also important to note that the arrival process to the pharmacy, shown in Figure 2.3, is not uniform. Most customers arrive to the pharmacy in the three busy periods which is the main driver for customer satisfaction rates due to the fact that a large number of customers are required to be processed during those peak periods. Figure 2.3 shows that the four busiest hours of the day account for approximately 60% of the customers. This creates an uneven workload during the day that makes staff utilization harder to understand. For example, looking at case 15 in Table 2.5 the pharmacist utilization is 91%, which on the surface indicates that pharmacists are idle 9% of the time and can therefore afford to provide more PDPC. However, this is only true if the customer arrival rates were uniform. Because customer arrivals are not uniform through the day, in case 15 the pharmacist barely has enough time to handle 40% PDPC services due to overutilization during the busy periods of the day. Generally speaking, adding precise information to a pharmacy should improve the average check out waiting time, and this behavior can be seen in cases 1-5, 6-10, 11-15, and 16-20. It is important to note that PDPC satisfaction rates do not exhibit a noticeable change as more precise information is used. This is due to the fact PDPC services, unlike filling, can not be done ahead of time and stored as inventory.

2.5.3.2 Imprecise Pick Up Information The previous section presented a discussion of the value of using precise pick up information, but in reality obtaining precise pick up information is very difficult. Practical prediction models typically have some degree of accuracy and there are limitations to how much information can be gained. The next set of experiments assumes that the pharmacy has a more realistic prediction model capable of providing insights only on a customer's day of arrival. The predicted day of arrival would have a degree of accuracy of $(1 - \alpha)$ that indicates what percent of customers arrive on their predicted day. For example, if an imprecise data instance has a 90% level of accuracy, then 10% of the customers would come to the pharmacy on a different day than the one the pharmacy planned for. Imprecise pick up information essentially classifies eRx in the pharmacy as same day eRx and later day eRx. Same day eRx are expected to be picked up on the same day assuming that the predication is accurate. Later day eRx are expected to be picked up on a later day.

Community pharmacies typically finish filling all eRx that arrived during working hours by the end of that day. Work scheduling in the imprecise instance is similar to that of the precise pick up information instance. Waiting customers and their corresponding eRx get the highest priority, same day eRx are prioritized over eRx with unknown pick up dates, and the lowest priority is assigned to later day eRx. Note that an incorrect prediction can have a big impact on pharmacy workflow. Assume that α is the error percentage in the prediction model and the average customer arrival rate per hour is λ. We know that 40% of customers decide to pick up their eRx on the same day the eRx were sent to the pharmacy. This implies that 0.4λ is the arrival rate for customers that decided to pick up their eRx on the same day. This would also imply that $0.6\alpha\lambda$ is the number of customers arriving to the pharmacy with erroneous eRx prediction times (i.e, customers arriving to the pharmacy on a day the pharmacy did not plan for). As a result, there is a high probability that customers will arrive to the pharmacy to pick up eRx that are not ready. Consequently, wrong predictions have a big impact on customer waiting time and customer satisfaction especially due to the fact that 60% of customers arrive during peak periods. Table 2.6 shows the results of the first set of experiments for the imprecise information case with 100% prediction accuracy, different levels of imprecise information and different levels of PDPC services. The effects of imprecise information are very similar to the precise information with minor differences (cases 12-15, 17-20 have slightly lower waiting time in the precise case).

Table 2.6: Imprecise Pick up Information with 100% Accuracy

Cases	PDPC (%)	Imprecise Information (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	0%	0.7	0	1%	0%	0%	69	63
2	0%	25%	0.6	0	1%	0%	0%	68	61
3	0%	50%	0.6	0	1%	0%	0%	67	59
4	0%	75%	0.6	0	1%	0%	0%	65	57
5	0%	100%	0.6	0	1%	0%	0%	63	56
6	20%	0%	2.5	1.7	4%	3%	19%	84	71
7	20%	25%	2.5	1.7	4%	3%	19%	83	69
8	20%	50%	2.5	1.7	4%	3%	19%	82	67
9	20%	75%	2.2	1.8	3%	3%	19%	81	64
10	20%	100%	1.4	2.0	1%	4%	19%	79	64
11	40%	0%	5.5	3.7	10%	14%	31%	94	77
12	40%	25%	5.5	3.7	10%	14%	31%	94	74
13	40%	50%	5.4	3.7	9%	14%	31%	94	72
14	40%	75%	5.0	3.7	8%	15%	31%	93	69
15	40%	100%	4.3	3.8	7%	16%	31%	90	68
16	60%	0%	10.0	4.7	18%	24%	37%	99	80
17	60%	25%	9.7	4.7	17%	24%	37%	99	77
18	60%	50%	9.9	4.7	17%	24%	37%	100	75
19	60%	75%	9.1	4.7	16%	25%	38%	99	72
20	60%	100%	6.8	4.8	12%	26%	39%	97	71

The reason is that both cases correctly predict abandonment, and both cases prioritize eRx that will be picked up in the same day of arrival over eRx that will be picked up on a later day. The subtle difference between those two cases lies in prioritizing the same day eRx in the pharmacy. The use of precise pick up information prioritizes eRx according to the earliest due time (i.e. pick up time) versus the imprecise pick up information with 100% prediction accuracy model that prioritizes same day eRx in a FIFO manner. This subtle difference is not enough to create a significant improvement in favor of precise information. Note that the highest rate of eRx arrivals in one hour is 30 eRx. Both the precise and imprecise cases would assign a low priority for 18 eRx (on average) because they will be picked up on a later day and only 12 eRx on average are considered high priority because they will be picked up the same day.

The expected time required to complete the tasks (input station, filling station, product verification, and data verification) for all 12 eRx is 72 minutes. In truth, there is more than enough available staff to finish filling and reviewing all 12 eRx within one hour which is why the earliest due time rule is very similar to the FIFO rule. This explains why when there is no PDPC (in Table 2.5), the use of precise information, which uses the earliest due time rule to prioritize work, does not have a significant improvement over no pick up information which uses FIFO to prioritize work.

The next logical question is "How would the pharmacy's performance measures change if the prediction models had prediction error built into them?" Table 2.7 shows the same set of cases that are in Table 2.6 but with a 5% inaccurate prediction rate. All the bold cases show improvement in the pharmacy's performance measures compared to the case with no pick up information.

Table 2.7: Imprecise Pick up Information with 95% Accuracy

Cases	PDPC (%)	Imprecise Information (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	0%	0.7	0	1%	0%	0%	69	63
2	0%	25%	0.7	0	1%	0%	0%	68	61
3	0%	50%	0.7	0	1%	0%	0%	67	59
4	0%	75%	0.8	0	1%	0%	0%	65	58
5	0%	100%	0.9	0	1%	0%	0%	63	56
6	20%	0%	2.5	1.7	4%	3%	19%	84	71
7	20%	25%	2.8	1.7	4%	3%	19%	83	69
8	20%	50%	2.7	1.6	4%	2%	19%	83	67
9	20%	75%	2.2	1.6	3%	3%	19%	81	65
10	20%	100%	1.9	1.5	2%	4%	19%	79	64
11	40%	0%	5.5	3.7	10%	14%	31%	94	77
12	40%	25%	6.0	3.6	10%	14%	31%	94	74
13	40%	50%	5.7	3.6	10%	14%	31%	94	72
14	40%	75%	5.4	3.7	9%	15%	31%	93	70
15	40%	100%	4.9	3.7	8%	15%	31%	91	68
16	60%	0%	10.0	4.7	18%	24%	37%	99	80
17	60%	25%	10.2	4.6	18%	24%	37%	100	78
18	60%	50%	10.1	4.7	18%	25%	37%	100	75
19	60%	75%	8.8	4.7	16%	25%	38%	99	73
20	60%	100%	7.2	4.7	13%	25%	39%	97	72

The results in Table 2.7 provide different insights depending on the level of PDPC services provided by the pharmacy. In Cases 1 through 5 the pharmacy's performance measures are acceptable without pick up information. However, using imprecise pick up information with 95% accuracy shows a decline in these performance measures. This decline is mainly due to the 5% of customers that arrive to the pharmacy (likely in busy hours) only to find their eRx has been considered a later day eRx and given the lowest priority for filling. It is interesting that only a 5% inaccuracy rate is enough to offset the benefit of having pick up information for low levels of PDPC.

It was established in the precise information section that prediction models have two main effects on pharmacy workflow, the reduction in staff utilization due to abandonment prediction, and scheduling work in a more effective manner. The effects of prioritizing work in the pharmacy seems to take on more significance as more PDPC services are offered. A similar trend can be noticed with imprecise information with 95% accuracy. The benefits of using these imprecise prediction models can be noticed as the pharmacy gets busier and cannot handle the workload.

Cases 11 and 16 are examples where imprecise information can be helpful to the pharmacy. But it is clear that less accurate imprecise prediction models can result in worse performance. In fact, Table 2.8 shows the same experiment run with 80% prediction accuracy. This data supports the conclusion that 80% accurate imprecise pick up information is worse than having no pick up information at all for most cases. The purpose of prioritizing work using predicted pick up information is to make sure that when customers arrive at the pharmacy their eRx are ready to be picked up. But having a high value for the error percentage α leads to a significant amount of time being spent filling eRx with erroneous predicted pick up times. Furthermore, higher values of the error percentage α lead to more customers arriving at the pharmacy only to find their eRx are not filled.

Table 2.8: Imprecise Pick up Information with 80% Accuracy

Cases	PDPC (%)	Imprecise Information (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
1	0%	0%	0.7	0	1%	0%	0%	69	63
2	0%	25%	0.9	0	1%	0%	0%	68	61
3	0%	50%	1.2	0	2%	0%	0%	67	60
4	0%	75%	1.3	0	2%	0%	0%	66	58
5	0%	100%	1.8	0	3%	0%	0%	64	57
6	20%	0%	2.5	1.7	4%	3%	19%	84	71
7	20%	25%	2.8	1.8	4%	3%	19%	84	69
8	20%	50%	3.1	1.7	5%	3%	18%	83	68
9	20%	75%	3.1	1.8	5%	3%	18%	82	66
10	20%	100%	3.2	2.0	5%	4%	18%	81	65
11	40%	0%	5.5	3.7	10%	14%	31%	94	77
12	40%	25%	6.0	3.7	11%	14%	31%	94	75
13	40%	50%	6.1	3.6	10%	15%	31%	94	73
14	40%	75%	5.9	3.6	10%	14%	31%	93	70
15	40%	100%	6.1	3.6	10%	14%	31%	92	70
16	60%	0%	10.0	4.7	18%	24%	37%	99	80
17	60%	25%	10.4	4.6	19%	24%	37%	100	78
18	60%	50%	10.8	4.7	19%	24%	37%	100	76
19	60%	75%	10.5	4.8	18%	25%	37%	99	73
20	60%	100%	8.4	4.8	15%	26%	38%	98	73

The previous experiments showed that depending on the prediction accuracy level, a pharmacy that uses imprecise pick up information can perform better/worse than the base case (using FIFO, and no pick up information). This observation raises an important question. What level of prediction accuracy is equivalent in performance to that of the base case? The importance of this question arises from the fact that any predication rate higher than the cutoff point would be beneficial to the pharmacy. This cut off point can be different depending on different pharmacy inputs such as the arrival process, the prediction model, service durations, and eRx abandonment. It is also important because the level of effort and cost required to get different levels of accuracy can vary greatly.

Figure 2.8 provides an example where the effect of prediction accuracy is shown for a pharmacy with 30% PDPC services, imprecise pick up information with 100% accuracy and the same staff schedule used in the previous experiments. A pharmacy that has no pick up information has an average customer waiting time of 5 minutes. Figure 2.8 shows that using no pick up information is better than using imprecise pick up information with 86% accuracy. In fact, for this workload imprecise pick up information would need to have a prediction accuracy of at least 87% to be better than the no prediction model. Lower values of PDPC lead to a higher threshold and vise versa. Table 2.8 shows that for 60% PDPC the threshold could possibly be as low as 80%.

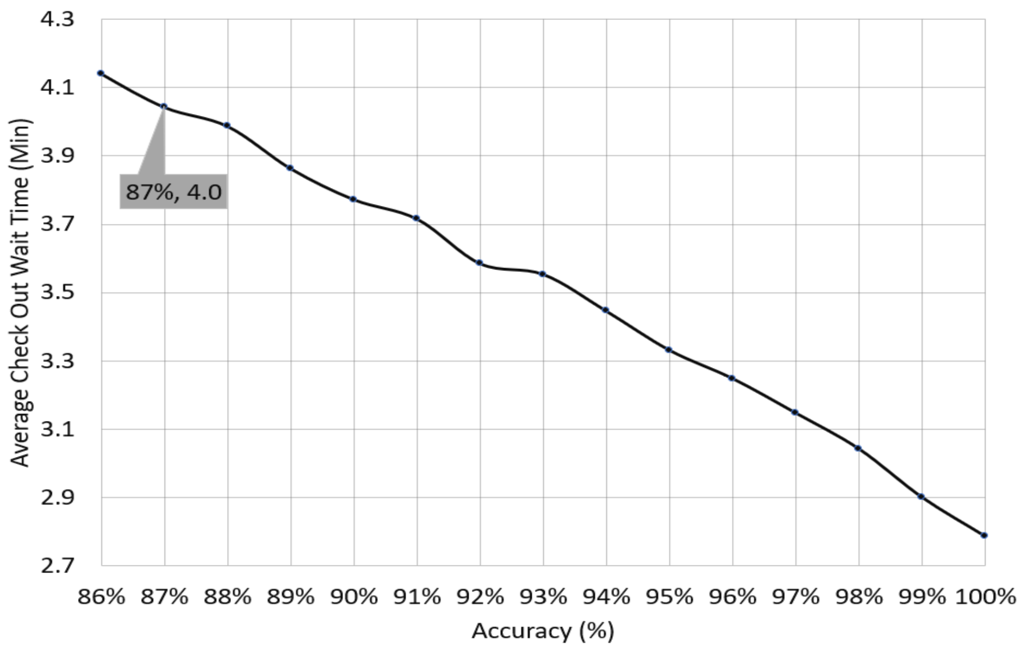

Figure 2.8: Imprecise Model Accuracy Effects on Average Waiting Time

All previous results assume that any customer seeking PDPC would receive the full duration of PDPC services regardless of how busy the pharmacy is. During rush hours, a high number of customers arrive to the pharmacy to pick up their eRx. Providing a full service of PDPC to all seeking customers is both time consuming and not feasible in most cases. The following section introduces another approach to handle PDPC service durations.

2.5.4 Dynamic PDPC Services

Introducing high levels of PDPC services to a community pharmacy requires providing PDPC services to customers during busy periods. This section evaluates the effect of offering 50% faster PDPC service during busy periods or at times when there are more than 3 customers waiting to get PDPC.

Figure 2.9 shows the effective level of PDPC services for the base staff, adding a pharmacist, adding a technician, using dynamic PDPC, and using dynamic PDPC with an extra pharmacist.

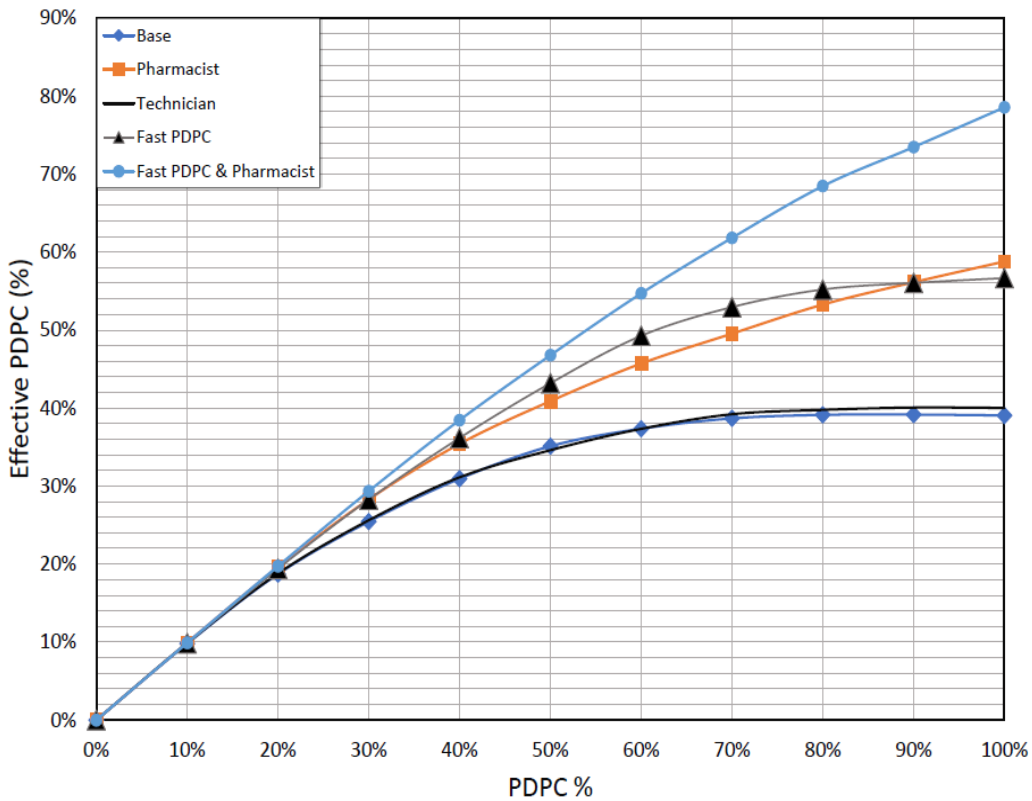

Figure 2.9: Effective PDPC (%)

Adding an extra technician does not have a significant influence on the effective level of PDPC services but adding a pharmacist does. An added pharmacist can effectively increase the level of PDPC services up to 54% while keeping the percent of unsatisfied customers low.

Adding a pharmacist and using dynamic PDPC services seem to have a similar effect on the effective rate of PDPC. This is due to the fact that dynamic PDPC provides 50% faster PDPC services (if the pharmacy is busy) which can match the number of satisfied PDPC customers of the extra pharmacist strategy. It may seem that providing dynamic PDPC is a superior strategy to adding an extra pharmacist; however, pharmacist utilization levels in the dynamic PDPC strategy are significantly greater than when adding a pharmacist as seen in the next set two experiments. Table 2.9 provides a comparison between four different scenarios combined with multiple levels of precise pick up information. The experiments shown in Table 2.9 are designed to illustrate how a combination of intervention strategies can be used to increase the effective level of PDPC when 60% of checked out customers are offered a PDPC service.

Table 2.9: 60% PDPC Service Offered

Strategies	Cases	Precise Information (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
Base Case	1	0%	10.0	4.7	18%	24%	37%	99	80
	2	25%	9.4	4.7	17%	24%	38%	99	77
	3	50%	9.4	4.7	17%	25%	38%	99	74
	4	75%	8.2	4.8	15%	26%	38%	99	73
	5	100%	6.0	4.8	10%	26%	40%	98	71
Dynamic PDPC	6	0%	6.6	3.1	12%	7%	49%	97	78
	7	25%	6.6	3.1	12%	7%	49%	97	75
	8	50%	5.8	3.2	11%	8%	50%	97	73
	9	75%	5.1	3.2	10%	8%	50%	96	71
	10	100%	3.8	3.3	7%	8%	51%	95	69
Extra Pharmacist	11	0%	5.4	3.7	10%	16%	46%	88	73
	12	25%	5.0	3.7	9%	16%	46%	87	71
	13	50%	4.6	3.7	9%	16%	46%	87	69
	14	75%	4.0	3.8	7%	16%	46%	86	67
	15	100%	3.6	3.8	7%	17%	47%	84	66
Dynamic PDPC & Extra Pharmacist	16	0%	3.4	1.9	6%	3%	55%	83	70
	17	25%	3.2	1.9	6%	3%	55%	83	68
	18	50%	3.0	1.9	6%	3%	55%	82	66
	19	75%	2.3	2.0	5%	3%	56%	81	64
	20	100%	1.2	2.1	3%	4%	56%	80	63

The results shown in Table 2.9 are generated when 60% of checked out customers are offered a PDPC service. The effective level of PDPC service indicates the portion of customers that finished a PDPC service. Case 1 shows that only 37% of customers had a PDPC service even though 60% of checked out customers sought such services. This is due to the fact that it is not possible to provide 60% PDPC for all customers without using an intervention strategy.

Cases 1-5, 6-10, 11,15, and 16-20 show that precise pick up information improves the performance of the implemented strategy specifically by enhancing the dispensing process (i.e. lowering check out wait time and the check out unsatisfied percent). However, using differing degrees of pick up information does not significantly affect the portion of customers that receive PDPC as explained earlier in Section 2.5.3.1 primarily due to the fact that PDPC services cannot be inventoried.

Dynamic PDPC services seem to have the highest impact on increasing the number of PDPC services offered. However, pharmacist utilization in cases 6-10 ranges between 95%-97% which is far from ideal. Adding a pharmacist (cases 11-15) shows lower effective PDPC rates but only by a difference of 3%-4%. Adding a pharmacist clearly has benefits over dynamic PDPC especially in terms of enhancing overall pharmacy performance measures while keeping resource utilization at an acceptable level, but it is a more expensive strategy that will provide the full duration of PDPC services to a lower number of customers.

If the overall goal is to maximize the effective PDPC rate in the community pharmacy, a combination of dynamic PDPC and adding a pharmacist provided an effective rate of 55%-56% when 60% of customers where offered PDPC. The reason that there is a 3%-4% difference between the service level required and the actual service rate is the fact that during busy periods the PDPC queue gets full and some customers renege.

2.6 Conclusions

This paper addresses issues associated with adding PDPC services and their impact on community pharmacy workflow. Adding PDPC increases overall workload in the pharmacy but most importantly it increases the workload of the pharmacist which is a bottleneck resource. Several internal strategies to increase pharmacist capacity were tested using a simulation model including adding an extra staff member or properly prioritizing eRx using different pick up information models. Adding a pharmacist, as opposed to a technician, is desirable if the pharmacy aims to increase PDPC services by more than 40%. For lower levels of PDPC services, an extra technician could be a cost efficient solution. In general, adding an extra staff member might be an effective strategy for an individual pharmacy, but would be very costly for a large community pharmacy chain network.

The simulation results indicate that if the goal is to have 20% PDPC services then strategies such as having information about prescription pick up times can be beneficial. Interestingly, the simulation results show that having precise pick up information is not significantly better than having imprecise pick up information if there is no prediction error. Both cases prioritize work according to predicted pick up information and both cases benefit greatly from being able to predict eRx abandonment. Prioritizing work based on predicted pick up times does not provide significant improvements over using a FIFO work scheduling rule when the overall staff utilization is low. This is mainly due to the ability of the pharmacy staff to finish filling eRx in a relatively short period of time - making prioritizing work according to the earliest due time less impactful.

The use of imprecise pick up information with prediction errors is shown to be beneficial for low levels of prediction error. Imprecise pick up information can be more influential when more PDPC is offered in the pharmacy. This reasoning stems from the fact that when the pharmacy is not very busy the FIFO rule seems to be an effective way to prioritize work in the pharmacy and the staff can afford to expend effort to fill an eRx that is due on a later day rather than on one due today. However, as the pharmacy becomes busier, for example when offering PDPC services, careful work scheduling inside the pharmacy, promoted by the use of pick up information models, show significant improvements over the FIFO system.

A key finding of this study is that imprecise information is only better than no pickup information if the day of pickup is known with high accuracy. In most cases, the accuracy must be at least 80% or else the system performance is worse than having no pickup information. The accuracy level needed depends mainly on the workload in the pharmacy and the portion of eRx that need to be finished in the same day.

Knowledge of pick up information (precise or imprecise) essentially improves the dispensing process by eliminating the need to work on abandoned prescriptions and identifying eRx that can be filled in less busy periods. This strategy essentially focuses on dispensing and stocking eRx before the customer arrives which improves customer wait time and the percent of unsatisfied customers. It is important to note that when it comes to offering more PDPC services, precise pick up information indirectly adds more pharmacist capacity by eliminating the need to work on abandoned prescriptions. But note that the added capacity is not sufficient to handle more than 20%-25% PDPC services.

The final strategy tested was dynamic PDPC services. The results show that using dynamic PDPC services provides higher effective PDPC rates than hiring an extra pharmacist. However, this comes at the price of higher check out wait times and higher rates of unsatisfied customers. The results showed that a combination of dynamic PDPC and hiring a pharmacist produces the highest effective PDPC rates.

In the final analysis, we explore different combinations of strategies to achieve a target PDPC level. The results show that to achieve high levels of PDPC, for example 60%, it is necessary to use a combination of strategies such as hiring an additional pharmacist, using Dynamic PDPC services during busy periods, and having some knowledge of pickup information.

An extension of this work would be to use a similar simulation model to evaluate external strategies such as using a CF or sharing pharmacy resources where less busy pharmacy resources are used to provide support for busier pharmacies. The right strategy to use, internal or external, depends on the size of the community pharmacy chain network, the size of an individual community pharmacy, and the level of PDPC services desired.

3.0 Expanding the Size of Clinical and Pharmacist-Patient Services in A Community Pharmacy Using External Resources

Patient safety and medication adherence are critical challenges in the healthcare environment. Prescription abandonment combined with medication misuse/misunderstanding directly impacts medication adherence. The consequences of medication non-adherence can be severe to the community both in terms of lives and costs. One effective method to improve medication adherence inside community pharmacies is providing Pharmacist Delivered Patient Care (PDPC) services such as Patient Counseling (PC), Medication Therapy Management (MTM), and Disease Management (DM). Adding more PDPC services in the community pharmacy can be challenging since pharmacists are an expensive resource that is highly utilized. This research focuses on evaluating resource sharing strategies in a community pharmacy chain network to provide a significant boost in PDPC services. The key challenge is providing the pharmacist with enough time to talk to customers without deteriorating the overall performance of the pharmacy. A discrete event simulation model is built to evaluate strategies that utilize an external resource to improve the local community pharmacy's workflow. Two external resource strategies are considered, providing PDPC services using kiosks that connect to a PDPC center, and using an automated central fill (CF) to help dispense prescriptions. The results show that using the CF was helpful to improve resource utilization as well as reduce customer waiting times. Although the CF was used to minimize the pharmacist dispensing time and redirect that time toward PDPC services, the amount of time redirected was only helpful for moderate levels of PDPC services. PDPC kiosks proved to be a much more effective approach to provide higher levels of PDPC services.

3.1 Introduction and Motivation

Community pharmacies play an important role in local communities by providing customers with the necessary medication to maintain and improve their health. However, dispensing medication is no longer the only reason customers visit community pharmacies. In fact community pharmacies are shifting from being merely a medication dispenser to more of a patient care service provider. These pharmacies are capable of providing important services such as medication therapy management, disease management, patient counseling, and various other services. Most of these services are Pharmacist Delivered Patient Care (PDPC) services that require attention and time of the pharmacist inside the community pharmacy. These services aim to enhance patients' health by improving the patient's understanding of their medication [60], improving medication adherence [12], reducing medication errors, improving medication abandonment, and helping patients organize their medication intake to achieve optimal results [60].

Shifting the role of community pharmacies from a dispensing focus to a PDPC service provider leads to a major redesign of the workflow inside the pharmacy. The pharmacy would now have two types of products to offer - one physical in the form of medication and the other is a service provided by a pharmacist. The process of dispensing medication has been developed and improved over the years especially as electronic prescriptions (eRx) became popular. However, the process in general remains serial in nature and can be partially performed by clerks and technicians, Section 3.3 provides more details about the dispensing process. At this point, pharmacies can dispense prescriptions before the arrival of customers then stock them to minimize customer check out waiting time. In theory, the customer does not have to be present to start the process of dispensing eRx but has to be present to start most PDPC services (unless it is done over the phone). Additionally, most PDPC services require a significant amount of pharmacist time which can interfere with the dispensing process. Different policies and strategies can be used to improve pharmacy workflow while committing to providing a non-trivial amount of PDPC. We classify these strategies into internal and external strategies. An internal strategy is one that only uses internal pharmacy resources to improve pharmacy workflow while an external strategy uses an external resource (e.g., a central filling facility) to improve pharmacy workflow and performance measures. We explore the benefits of using several internal strategies in a previous article [64] and Chapter 1. This study is focused on evaluating the effects of using numerous external strategies to improve the workflow inside the local community pharmacy.

There are two main strategies that are evaluated in this study and these outsource part of the workload one way or another. The first strategy, an automated filling facility centralized in a community pharmacy chain network is used to outsource the dispensing process. The CF provides a cost efficient way to satisfy demand while reducing dispensing burden on the pharmacy[5][14][67]. It also allows existing pharmacists to focus more on providing PDPC.

The second strategy is offering PDPC services using kiosks that can connect to a pharmacist via a video call. The pharmacist can provide PDPC services online and the kiosk can assist the customer by providing access to educational material as well as diagnostic tools. This paper evaluates the effectiveness of such kiosks, called PDPC kiosks, under the assumption that all PDPC services can be offered via video. The pharmacist that connects to the PDPC kiosks is present in a call center that we call PDPC center. This study tests several policies that use these PDPC kiosks differently. The first operating policy tests the effect of only using PDPC kiosks to provide PDPC services, the second operating policy evaluates using both local pharmacists and PDPC kiosks to offer PDPC services but the local pharmacists prioritize dispensing work, and the third operating policy evaluates providing shorter durations of PDPC services during peak service intervals by both the local pharmacists and the PDPC kiosks.

The remainder of the paper is organized as follows. Section 3.2 discusses relevant community pharmacy literature. Section 3.3 shows the formal problem definition and objectives. Section 3.4 shows the results of using different external strategies and operational policies. The last section 3.5 shows the main conclusions and recommendations.

3.2 Literature Review

The main role of the pharmacy is provide necessary medications to patients, but pharmacies differ in terms of the types of patients they service, the amount of medication they carry, and their workflow. The most popular pharmacies are: hospital pharmacies (i.e. inpatient & outpatient), mail order pharmacies, and community pharmacies [45]. This study is mainly focused on community pharmacies as they dispense a large share of all outpatient medication, and are widely spread around the US[58]. The role of community pharmacies and pharmacy workflow has been evolving over the past decade especially as electronic prescriptions became more popular[59][70]. We explore several strategies to provide PDPC services using an external resource. The first sub section shows relevant literature for the CF strategy. The second subsection shows the literature for using computer kiosks to provide PDPC services.

3.2.1 Central Fill (CF) Facility

In recent years, automation has played a greater role in dispensing medications. Automation can be used both locally (i.e. small robots in a pharmacy) and as a stand-alone pharmacy. Lauren [4] studied the impact of using automation locally in a community pharmacy. The study showed that automation improved the productivity of the pharmacist allowing more pharmacist interactions with patients. A mail order pharmacy is an example of using automation in dispensing medication and then the medications are mailed directly to customers. There have been several studies aimed at improving the efficiency of mail order pharmacies. Daoud [20] developed a discrete optimization model to minimize the total completion time for patients orders. The model can be classified as an order scheduling model that minimizes the completion time for medication orders and it proved to be a hard problem to solve. A genetic algorithm was developed and used to solve the problem. Wang [79] used a DES model to tackle the same problem and choose the best work schedule to minimize the total completion time for medication orders which essentially leads to mailing the medication faster.

The mail order pharmacy has no physical contact with patients which eliminates any potential to provide PDPC services. The CF studied in this paper is part of a community pharmacy chain network and dispenses directly to the community pharmacies. Spinks [68] argues that automatic dispensing systems have been successfully used locally in hospitals and retail pharmacies, but have not been used widely in community pharmacy chain networks. The study concludes that more work is required to evaluate the effectiveness of a hub and spoke community pharmacy chain network using a CF. The study also claims that the hub and spoke model can potentially disrupt the entire dispensing process in community pharmacies and dramatically change the role of each staff member. A British community pharmacy chain network (Boots), reported that it was evaluating the use of CFs in their network but no work was published on the results of this evaluation [5].

3.2.2 PDPC Kiosks

Providing patient services through kiosks has been gaining popularity during the last decade[32]. A kiosk is a computer based station, shown in Figure 3.1, that can be used in a healthcare setting to provide patients with important health information[39]. Kiosks are meant to be interactive and can be both self-service or act as a station for a health care specialist (or a pharmacist) to provide a service[39]. Chan [15] surveyed recent studies that used kiosks to deliver healthcare services to community members. The study found that touch screen interactive kiosks provided a low cost healthcare delivery device that proved to be highly effective in delivering important services to community members regardless of sex, age or education level.

Abraham [2] studied the value of using kiosks, like those shown in Figure 3.1, to a majority African American community. The kiosks were designed to be self managed by a community member and are capable of aiding in the detection of undiagnosed health conditions as well as providing healthcare services to patients with particular diagnosed conditions. The study showed that a majority of the population was satisfied by the services provided.

Figure 3.1: Example of a Community Kiosk

Kiosks have been used to improve medication reconciliation by automatically looking up medication history and checking for medication adherence issues. The process reduced nursing time needed to deal with medication reconciliation by 50% [41]. Lasky [39] provided a feasibility study to utilize kiosks in a Rhode Island community pharmacy. The kiosks provided educational information for patients' medications and were used as place for pharmacists to provide PDPC services. The study showed that using kiosks to display/print drug information, labeling, package inserts, and guides helped increase pharmacist PDPC productivity.

Blood pressure kiosks were deployed in a community pharmacy to identify patients with elevated blood pressure [31]. After identifying those patients, the kiosk would provide helpful information to improve their condition and pharmacists provided MTM (which can be billed for and generates revenue). The study evaluated the economic feasibility of using blood pressure kiosks and concluded that the kiosks are valuable to the pharmacy.

Kiosks have been used in the literature to provide self-service care for patients [31][39][2] and have been used as a venue for a local pharmacist to provide patients with a PDPC service [39]. This study also evaluated kiosks that provided PDPC services by contacting a pharmacist via video. It has been shown that pharmacists can provide MTM over the phone. In fact, the impact of pharmacist-provided telephone MTM for eligible patients has been shown to be effective [51]. The pharmacist is typically in a call center that belongs to the community network and provides PDPC services over the phone for patients across the community pharmacy chain network.

This study aims to investigate the effectiveness of using such kiosks inside the community pharmacy to provide PDPC services. The kiosks could operate in a self-service manner by providing educational material but the goal is to have them serve as a virtual venue for a pharmacist to provide PDPC services via a video call. We study the effect of offering more PDPC services using local pharmacists and kiosks and show that kiosks can be used to increase the level of PDPC provided inside community pharmacies.

3.3 Problem Definition and Objectives

This section provides a formal description of the challenges that a community pharmacy chain network faces when trying to provide more PDPC services. We discuss the motivation and objectives of the problem and then provide several strategies and intervention strategies that are studied further and evaluated in the next section. All the strategies discussed involve using a resource that is external to the local pharmacy. The external resource typically belongs to the community pharmacy chain network and provides support for multiple pharmacies. The main external resources analyzed in this study are using a CF to dispense eRx and using a PDPC center. Using external resources will change the local community pharmacy's workflow. Figure 3.2 shows the workflow including a CF. The strategies discussed in this section are evaluated using an extension of a simulation model developed in $Simio^{TM}$ and discussed in Section 2.4.

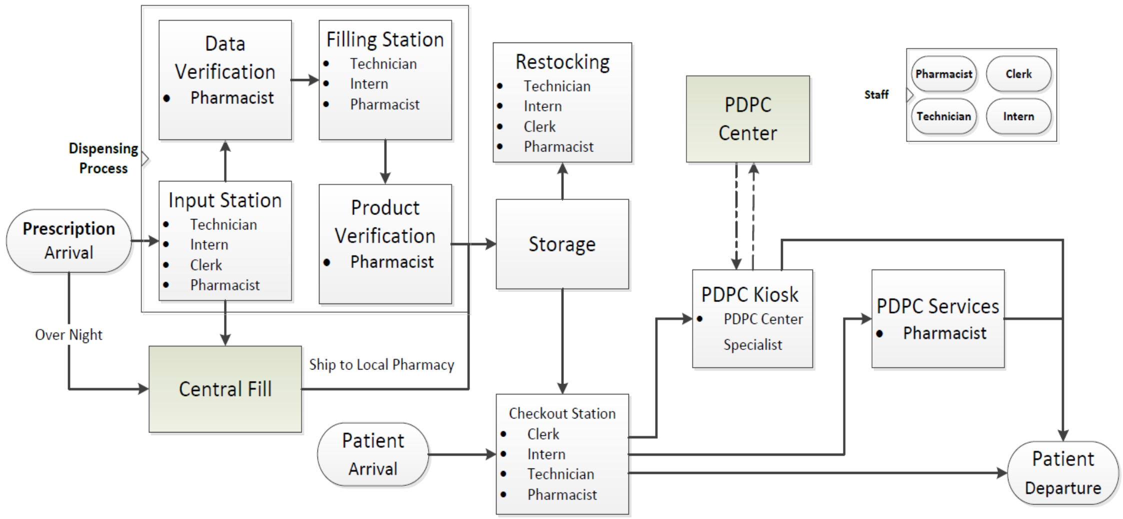

Figure 3.2: Community Pharmacy Workflow With External Resources

3.3.1 External Central Fill

An automated CF is a facility built in a remote location in the community pharmacy chain network that is capable of dispensing eRx efficiently in terms of cost and time and shipping them to the local pharmacy. Local pharmacies have control over which eRx should be dispensed in the CF. The CF is capacitated and serves as part of the community pharmacy chain network. We begin by assuming that the CF has enough capacity to satisfy any eRx the local pharmacy sends. There are two different polices the local pharmacy can use to utilize a CF. The first one is redirecting all after hours eRx to the CF, the second, shown in Figure 3.3, is to contact customers to identify possible next day or later pickup times and use the CF to dispense these eRx. Initially it is assumed that customers can always be contacted and will always arrive accurately to the pharmacy according to the time they provide, though these assumptions are relaxed in later analyses.

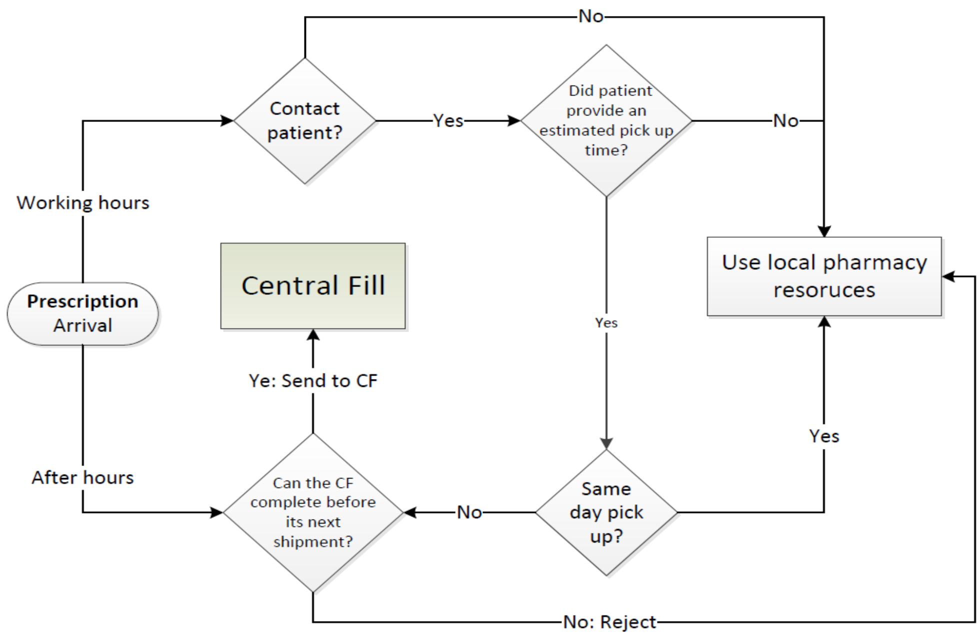

Figure 3.3: CF Operating Policy: Contacting Customers

A CF is only justified when used in a community pharmacy chain network that utilizes the capabilities of the CF. Having several pharmacies use the same CF requires careful planning to avoid capacity related problems. If the CF does not fill a portion of a pharmacy's demand before the scheduled shipment time, the pharmacy runs the risk of having to fill that demand locally when the customers show up. This paper studies the effect of a capaciated CF that handles approximately up to 50% of the demand from five pharmacies, with similar workload, size, and working hours, as shown in Figure 3.4. Pharmacy 1 is the local community pharmacy used to test any effect on individual pharmacies. The main objective of studying the capacitated CF is to see how CF related policies behave when the CF is capacitated. The model tracks the percentage of demand rejected from the CF and the percentage of demand that was not filled on time before the truck leaves.

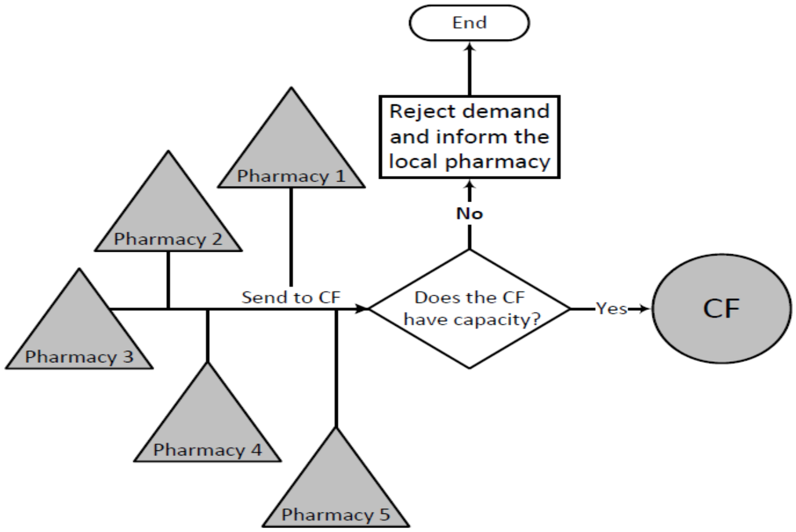

Figure 3.4: Capacitated Central Fill Network

3.3.2 PDPC Center

This strategy assumes that the local community pharmacy has kiosks that are capable of connecting real time to a pharmacist via a video call. The pharmacist is physically located in a PDPC center that is designed to provide PDPC services remotely. Unlike the external CF strategy, providing PDPC using kiosks requires two resources - a kiosk and an external pharmacist. The simulation model is used to understand the value of using PDPC kiosks. Three main PDPC kiosk strategies are evaluated under the assumption that pharmacists inside the PDPC centers are always available. The three polices are:

- **PDPC Kiosks Only**

  This operating policy is designed to evaluate the potential value of PDPC kiosks providing PDPC services. It is assumed that the kiosk provides the same PDPC service as the local pharmacist. The operating policy evaluates adding two or three kiosks to the pharmacy.

- **Assisted PDPC kiosks**

  The previous operating policy utilizes kiosks to perform PDPC services but does not utilize any of the pharmacists inside the local pharmacy. The following operating policy, shown in Figure 3.2, is developed to utilize both resources in order to provide a higher level of PDPC. The first operating policy uses a combination of a local pharmacist and kiosks, where the local pharmacist prioritizes drug verification and validation over PDPC services if there is more than half an hour's worth of drug review work in the pharmacy. This essentially means that during busy periods the pharmacists prioritize dispensing work over PDPC services. This operating policy is called assisted kiosks and is explained in more detail in Figure 3.5.

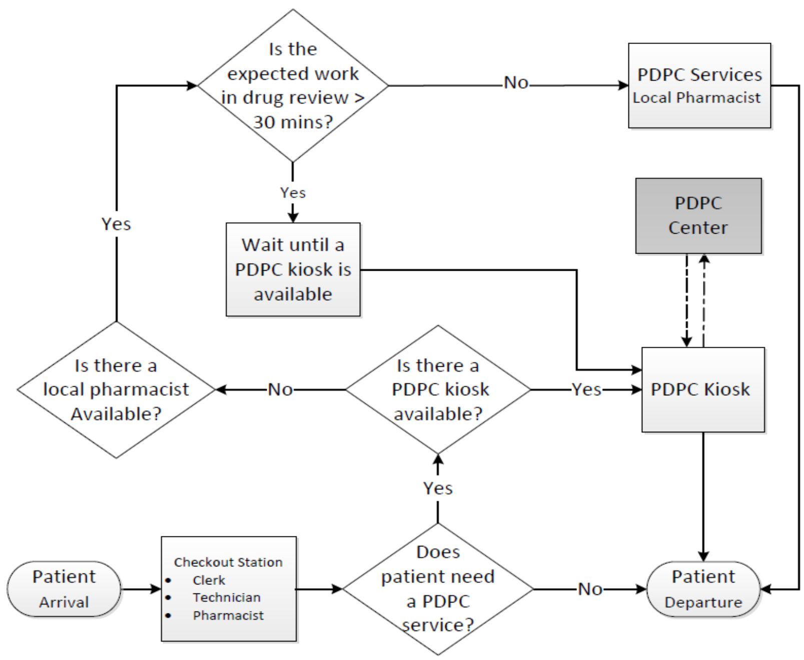

Figure 3.5: Central Fill Operating Policy: Assisted Kiosks

The previous two policies consider a single pharmacy and assume that a pharmacist is always available at the PDPC center to staff the kiosk. In the capacitated PDPC center operating policy we relax that assumption by analyzing the local pharmacy from a network perspective. The network has five pharmacies and each pharmacy has three kiosks and there are ten pharmacists available inside the PDPC center to service the network.

3.4 Results and Analysis

In this section, an analysis for several external strategies is performed using the simulation model described in Section 2.4. Every external strategy is tested for multiple levels of PDPC services with the main goal of providing the best customer experience (i.e., low waiting time). The first part of this section shows the effects of adding PDPC services. The second part provides a discussion on the effectiveness of using an external CF to offload part of the dispensing process load inside the local pharmacy. The third part of this section evaluates the option of using multiple kiosks inside the community pharmacy that can be used to provide PDPC services to pharmacy customers. The last part of this section provides an analysis of sharing pharmacy resources between several pharmacies in a community pharmacy chain network. It is assumed that resources from one pharmacy (e.g., a technician) can log into the system of another pharmacy and begin working on the input station. The base pharmacy used in all three part of this section has a fixed schedule of three pharmacists, two technicians, and two clerks. The schedule remains fixed for the remainder of this section unless specified otherwise.

3.4.1 Adding PDPC Services to The Local Pharmacy

We begin by showing how the local pharmacy workflow can be interrupted by providing PDPC services after check out. The simulation model was used to emulate a local community pharmacy with different levels of PDPC services. Table 3.1 shows how the pharmacy's performance changes by introducing 10 different levels of PDPC. Case 1 shows the base case pharmacy with two technicians, three pharmacists, and two clerks. Adding PDPC is done in an increment of 10% per case. Case 10 shows the effect of offering PDPC services to all pharmacy customers. Adding PDPC is desirable to community pharmacies to generate a new stream of income while improving patient's health [22]. While the desirable level of PDPC services offered in a community pharmacy changes from one pharmacy to another, generally community pharmacies would not prefer to reach the 100% threshold especially since not all customers really need it. The performance measures shown in Table 3.1 are split into average waiting times, satisfaction percentages, and resource utilizations. Unsatisfied customers are defined as customers that seek either to check out their eRx or get a PDPC service in the community pharmacy but were not able to complete one or the other other or both. For example, unsatisfied PDPC customers are customers that checked out and wanted a PDPC service but could not get one due to high wait time or a long queue. The effective PDPC percentage represents the percentage of the population that successfully finished a PDPC service.

Table 3.1: Adding PDPC Services

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization		
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.	Clerk
0	0%	0.9	0	0.6%	0%	0%	82%	73%	65%
1	10%	1.6	1	1.4%	1%	10%	88%	79%	67%
2	20%	3.0	2	3.0%	5%	19%	94%	83%	70%
3	30%	5.4	3	5.8%	9%	26%	99%	86%	72%
4	40%	10.9	3	13.0%	23%	27%	100%	87%	74%
5	50%	15.2	2	18.2%	33%	27%	100%	87%	75%
6	60%	18.4	2	21.4%	43%	27%	100%	86%	75%
7	70%	21.7	2	25.0%	49%	27%	100%	87%	75%
8	80%	25.1	2	29.3%	52%	27%	100%	87%	76%
9	90%	28.7	2	34.8%	53%	27%	100%	87%	77%
10	100%	31.9	2	39.7%	54%	28%	100%	88%	78%

The results shown in Table 3.1 indicate that the community pharmacy is capable of handling up to 20% added PDPC services, case 2, while still providing good service. It is also clear that the maximum possible effective PDPC service level is 28% as that value stays approximately the same throughout cases 4 to 10. Adding PDPC services to the base case deteriorates every performance measure presented in Table 3.1. The Unsatisfied PDPC customer percentage shows an increase in value from 0% in the first case up to 5.8% in case 3. Any additional PDPC services immediately increase the unsatisfaction percent rapidly from case 4 to case 10.

3.4.2 External Central Fill

This subsection evaluates using an automated CF to outsource part of the dispensing load. This strategy is analyzed from the local community pharmacy's perspective. The first set of experiments assumes that the CF always has enough capacity to dispense any eRx sent to it.

We begin by evaluating the effect of dispensing after hours eRx inside the CF and ship them back to the local community pharmacy. After hours eRx volume is approximately 20% of the daily dispensing load that typically makes the opening hours of the community pharmacy busy. Table 3.2 shows the results of the first operating policy for different levels of PDPC services.

Table 3.2: CF Dispensing after Hours eRx (Two Clerks)

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization		
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.	Clerk
0	0%	0.5	0	0.1%	0%	0%	70%	62%	55%
1	10%	1.1	1	0.7%	2%	10%	77%	67%	58%
2	20%	2.2	2	2.0%	4%	19%	85%	70%	60%
3	30%	3.9	3	4.1%	8%	26%	91%	73%	61%
4	40%	5.2	3	5.9%	17%	31%	95%	75%	63%
5	50%	6.5	4	8.0%	23%	36%	98%	76%	64%
6	60%	9.2	4	11.7%	30%	37%	100%	77%	64%
7	70%	13.2	4	16.6%	36%	37%	100%	77%	64%
8	80%	16.1	3	19.5%	42%	37%	100%	77%	65%
9	90%	18.7	3	21.8%	47%	37%	100%	77%	65%
10	100%	21.8	3	25.4%	51%	37%	100%	77%	65%

The results shown in the previous table indicate that using the CF to dispense after hours eRx does help reduce resource utilization and hence improve the average check out time across all cases. Without the CF, the local pharmacy was able to handle up to 20% PDPC services with two clerks, three pharmacists, and two technicians. With the CF, the pharmacy can handle up to 40% PDPC services that will effectively reach 31% of the total population which is a 50% increase in the effective PDPC services provided. Reducing the dispensing load by 20% can also provide an opportunity to reduce the number of clerks working inside the local pharmacy. Table 3.3 shows the effect of using the CF to dispense after hours eRx with one clerk.

Table 3.3: CF Dispensing after Hours eRx (One Clerk)

Cases	PDPC (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization		
		Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.	Clerk
0	0%	1.3	0	0.8%	0%	0%	76%	73%	73%
1	10%	2.7	1	2.7%	2%	10%	82%	79%	78%
2	20%	4.3	2	5.3%	4%	18%	88%	84%	82%
3	30%	5.4	2	6.9%	9%	25%	93%	87%	86%
4	40%	6.5	3	8.4%	16%	31%	97%	90%	89%
5	50%	7.9	4	10.1%	23%	34%	99%	92%	91%
6	60%	10.8	4	13.8%	32%	35%	100%	93%	92%
7	70%	14.3	4	18.3%	38%	36%	100%	93%	92%
8	80%	17.9	3	21.8%	44%	35%	100%	93%	92%
9	90%	21.0	3	24.7%	49%	35%	100%	92%	92%
10	100%	23.2	3	27.5%	52%	35%	100%	93%	92%

Reducing the number of clerks while using a CF for after hours eRx results in a local pharmacy that can provide up to 30% PDPC services which effectively reaches 25% of the population. This means that using the CF to dispense after hours eRx with one clerk in the local pharmacy provided 25% better effective PDPC services than a local pharmacy with two clerks and no CF. This indicates that using the CF lowers the cost of dispensing in the local pharmacy by lowering the number of clerks needed and lowering the cost of dispensing after hours eRx.

It is important to note that the same can not be said for pharmacists or technicians. The clerk only performs the input station and check out tasks, which are tasks that can be performed by both the pharmacist and the technician. We ran experiments with one less pharmacist (as well as one less technician) and they showed a significant deterioration in all performance measures. The second CF operating policy, shown in Figure 3.3, offloads a bigger portion of the dispensing load (depending on the percentage of customers contacted) to the CF.

Table 3.4: Using The CF to Dispense Contacted Customers eRx

Cases	PDPC (%)	Customers Contacted (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
0	0%	0%	0.5	0	0.1%	0.0%	0%	70%	62%
1	0%	25%	0.3	0	0.0%	0.0%	0%	63%	55%
2	0%	50%	0.2	0	0.0%	0.0%	0%	55%	49%
3	0%	75%	0.2	0	0.0%	0.0%	0%	47%	42%
4	0%	100%	0.1	0	0.0%	0.0%	0%	36%	36%
5	20%	0%	2.2	2	2.0%	4.4%	19%	85%	70%
6	20%	25%	1.7	2	1.4%	3.5%	19%	78%	62%
7	20%	50%	1.3	2	0.9%	3.3%	19%	71%	55%
8	20%	75%	0.8	2	0.4%	3.5%	19%	64%	48%
9	20%	100%	0.7	2	0.2%	3.3%	19%	54%	40%
10	40%	0%	5.2	3	5.9%	16.6%	31%	95%	75%
11	40%	25%	4.8	3	5.5%	15.7%	32%	90%	67%
12	40%	50%	4.3	3	5.0%	14.6%	32%	83%	60%
13	40%	75%	3.9	3	4.3%	15.9%	32%	75%	52%
14	40%	100%	3.9	3	4.4%	16.0%	32%	67%	44%
15	60%	0%	9.2	4	11.7%	29.9%	37%	100%	77%
16	60%	25%	6.2	4	7.7%	28.1%	40%	96%	70%
17	60%	50%	5.8	4	7.3%	27.7%	40%	90%	61%
18	60%	75%	5.6	4	7.2%	28.4%	40%	83%	54%
19	60%	100%	5.4	4	7.1%	28.1%	40%	74%	46%
20	80%	0%	16.1	3	19.5%	42.5%	37%	100%	77%
21	80%	25%	10.2	4	13.3%	37.0%	43%	100%	71%
22	80%	50%	6.9	5	9.2%	37.0%	46%	96%	63%
23	80%	75%	6.4	5	8.6%	37.0%	46%	90%	55%
24	80%	100%	6.1	5	8.5%	37.8%	46%	81%	47%

Table 3.4 shows the results of the second operating policy with five different levels of PDPC services tested (0%, 20%, 40%, 60%, and 80%) combined with contacting different percentages of customers. All cases with 0% customer contacted represent a local pharmacy that sends after hours eRx to the CF which means that cases 0, 5, 10, 15, and 20 in Table 3.4 are equivalent to cases 0, 2, 4, 6, and 8 in Table 3.2.

The results shown in Table 3.4 indicate that contacting patients so that it is possible to dispense their eRx at CF is much more effective than just using the CF to dispense after hours eRx. The effect of the second operating policy is highlighted when higher PDPC services are offered. Case 15 shows a local pharmacy that offered 60% PDPC services and had approximately 12% of all patients leave before check out. Contacting 50% of customers ahead of time showed approximately a 40% improvement for the average waiting time and the percentage of unsatisfied check out customers. Using the first CF operating policy, the pharmacy was able to effectively offer PDPC services to 30% of all customers, whereas the second CF operating policy showed a local pharmacy capable of effectively servicing (i.e. PDPC services) at least 40% of customers. Even if only 50% of customers were contacted, the results showed an improvement for the local pharmacy. It is important to note that perhaps the biggest advantage of using the second CF operating policy is maintaining a low average waiting time for checked out customers while offering more PDPC services by redirecting part of the pharmacists' focus toward providing PDPC services. This can be seen in case 22 as almost 20% of the customers were unsatisfied and reneged before check out without calling customers but that number dropped almost in half to 9.2% when customers are contacted (the same behavior can also be seen in cases 15 and 17).

The previous experiment assumes that any attempt to contact a patient is successful (with a probability of 1), and the patient provides an accurate pick up time which is used to determine whether their eRx can be filled at the CF or not. The first assumption can be relaxed by including a probability τ that an attempt to contact a patient is successful. A sensitivity analysis was performed on τ which showed results similar to the ones in Table 3.4. Essentially contacting everyone with a probability of $\tau = 0.5$ is similar to contacting only 50% of the population with $\tau = 1$.

The second assumption deals with the accuracy of the pick up times provided by the customers and that can be modeled by providing an error probability to the pick up time provided. Table 3.5 shows that even with a 20% pick up time error, contacting customers during the day was still beneficial as the value of the effective PDPC did not have any significant drop. Thus, even if 20% of patients provide the wrong information, the CF reduces the dispensing burden inside the local pharmacy dramatically.

Table 3.5: 80% Customer Pick Up Time Accuracy

Cases	PDPC (%)	Customers Contacted (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
0	0%	0%	0.5	0	0.1%	0.0%	0%	70%	62%
1	0%	25%	0.6	0	0.2%	0.0%	0%	65%	57%
2	0%	50%	0.8	0	0.2%	0.0%	0%	59%	52%
3	0%	75%	1.0	0	0.4%	0.0%	0%	53%	48%
4	0%	100%	1.0	0	0.3%	0.0%	0%	45%	43%
5	20%	0%	2.2	2	2.0%	4.4%	19%	85%	70%
6	20%	25%	2.4	2	2.0%	4.2%	19%	80%	64%
7	20%	50%	2.5	2	1.8%	4.2%	19%	74%	59%
8	20%	75%	2.7	2	1.9%	5.1%	19%	68%	54%
9	20%	100%	2.8	2	1.9%	5.0%	19%	61%	49%
10	40%	0%	5.2	3	5.9%	16.6%	31%	95%	75%
11	40%	25%	5.2	3	5.7%	16.3%	32%	91%	69%
12	40%	50%	5.5	3	6.1%	15.9%	32%	85%	64%
13	40%	75%	5.5	3	5.8%	15.7%	32%	80%	58%
14	40%	100%	6.1	3	6.6%	17.5%	31%	72%	53%
15	60%	0%	9.2	4	11.7%	29.9%	37%	100%	77%
16	60%	25%	7.1	4	9.0%	28.0%	39%	97%	72%
17	60%	50%	6.8	4	8.3%	28.9%	39%	93%	66%
18	60%	75%	7.0	4	8.6%	29.1%	39%	87%	60%
19	60%	100%	7.5	4	9.1%	28.9%	39%	80%	54%
20	80%	0%	16.1	3	19.5%	42.5%	37%	100%	77%
21	80%	25%	11.3	4	14.4%	38.4%	42%	100%	73%
22	80%	50%	8.4	5	10.3%	37.3%	45%	98%	67%
23	80%	75%	7.8	5	10.1%	37.5%	45%	93%	62%
24	80%	100%	8.1	5	10.4%	37.6%	45%	86%	56%

The previous experiments evaluated the use of two CF policies inside the local community pharmacy under the assumption that the CF always has enough capacity to dispense any portion of the local pharmacy's workload. We now relax that assumption and look at the CF as part of a community pharmacy chain network containing 5 pharmacies of similar size with similar staff schedules. It is assumed that the CF has enough capacity to handle 60% of the total dispensing demand from all the pharmacies. It is also assumed that one truck would pick up the filled prescriptions from the CF and deliver them to the five pharmacies on time.

Table 3.6 presents an experiment similar to the one shown in Table 3.4 but with a capacitated CF. The results shown in 3.6 have various levels of workload outsourced to the CF. It is assumed that the other four pharmacies are fully utilizing the CF (i.e. pharmacies contact 100% of customers and send their eRx to the CF). The capaciated CF keeps track of the expected completion time of its current inventory and compares it to the estimated shipment departure time. If the expected completion time for the current workload waiting in the queue exceeds the estimated shipment time, the CF starts rejecting dispensing orders and returns them back to the local pharmacy. This is tracked in the last column of the experiment results table.

Table 3.6: The Effects of Using The Second CF Operating Policy on a Capacitated CF

Cases	PDPC (%)	Customers Contacted (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Pharm. Utilization (%)	CF Rejection (%)
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)			
0	0%	0%	0.7	0	0.2%	0.0%	0%	76%	43%
1	0%	25%	0.4	0	0.0%	0.0%	0%	69%	26%
2	0%	50%	0.4	0	0.0%	0.0%	0%	64%	32%
3	0%	75%	0.4	0	0.1%	0.0%	0%	64%	47%
4	0%	100%	0.2	0	0.0%	0.0%	0%	63%	56%
5	20%	0%	2.8	2	2.6%	4.9%	19%	90%	43%
6	20%	25%	2.1	2	1.9%	3.5%	19%	84%	26%
7	20%	50%	1.7	2	1.3%	3.6%	19%	80%	32%
8	20%	75%	1.4	2	1.0%	3.1%	19%	79%	47%
9	20%	100%	0.8	2	0.3%	3.7%	19%	78%	56%
10	40%	0%	6.3	3	7.1%	16.3%	31%	99%	43%
11	40%	25%	4.7	3	5.2%	15.4%	32%	95%	26%
12	40%	50%	4.7	3	5.3%	14.8%	32%	90%	32%
13	40%	75%	4.5	3	4.8%	15.9%	32%	90%	47%
14	40%	100%	4.4	3	4.4%	15.4%	32%	89%	56%
15	60%	0%	15.3	3	18.8%	34.7%	32%	100%	43%
16	60%	25%	9.0	4	11.3%	28.8%	38%	100%	26%
17	60%	50%	6.4	4	8.0%	27.6%	40%	97%	32%
18	60%	75%	6.4	4	7.5%	28.2%	40%	96%	47%
19	60%	100%	6.2	4	7.5%	28.5%	40%	92%	56%
20	80%	0%	20.6	2	23.8%	48.0%	32%	100%	43%
21	80%	25%	15.7	3	19.1%	40.6%	38%	100%	26%
22	80%	50%	11.2	4	14.6%	36.7%	43%	100%	32%
23	80%	75%	10.3	4	12.8%	36.2%	44%	99%	47%
24	80%	100%	7.4	5	9.2%	37.4%	46%	98%	56%

It is expected that CF rejection % does not change as more PDPC services are offered. The percentage rejected depends on the amount of work sent to the CF and the time it was sent. The closer the order time is to the shipping time, the higher the chance that it will be rejected. This can be seen in the high value of rejection in case 0 which represents sending eRx to the CF after hours.

Table 3.7: Fully Utilizing an Uncapacitated Central Fill Strategy While Using Dynamic PDPC

Cases	PDPC (%)	Customers Contacted (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Utilization	
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		Pharm.	Tech.
0	0%	0%	0.5	0	0.1%	0.0%	0%	70%	62%
1	0%	25%	0.3	0	0.0%	0.0%	0%	63%	55%
2	0%	50%	0.2	0	0.0%	0.0%	0%	55%	49%
3	0%	75%	0.2	0	0.0%	0.0%	0%	47%	42%
4	0%	100%	0.1	0	0.0%	0.0%	0%	36%	36%
5	20%	0%	1.6	1	1.2%	2.0%	19%	82%	68%
6	20%	25%	1.1	1	0.8%	1.7%	20%	76%	60%
7	20%	50%	0.8	1	0.4%	1.8%	20%	69%	53%
8	20%	75%	0.5	1	0.2%	1.7%	20%	60%	46%
9	20%	100%	0.4	1	0.1%	1.4%	20%	51%	39%
10	40%	0%	3.8	2	4.2%	4.9%	36%	92%	73%
11	40%	25%	3.1	2	3.4%	4.5%	37%	86%	64%
12	40%	50%	2.6	2	2.6%	5.0%	37%	79%	57%
13	40%	75%	2.1	2	2.1%	4.2%	37%	72%	50%
14	40%	100%	1.7	2	1.7%	4.1%	38%	63%	42%
15	60%	0%	6.0	3	7.1%	12.1%	49%	98%	76%
16	60%	25%	5.0	3	5.9%	10.8%	50%	93%	68%
17	60%	50%	4.4	3	5.4%	10.3%	51%	87%	60%
18	60%	75%	4.1	3	4.9%	10.5%	51%	80%	53%
19	60%	100%	4.0	3	4.9%	10.5%	51%	71%	44%
20	80%	0%	11.0	3	13.7%	24.4%	52%	100%	77%
21	80%	25%	7.0	3	9.1%	18.1%	60%	99%	70%
22	80%	50%	5.8	3	7.6%	18.0%	61%	93%	62%
23	80%	75%	5.5	3	7.1%	17.6%	61%	86%	54%
24	80%	100%	5.3	3	7.2%	17.5%	61%	77%	46%

The CF sends a shipment to the local pharmacy at the beginning of the day (i.e. 7:00 am), any eRx sent to the CF 2-3 hours before the scheduled truck departure has a very high probability that it will be rejected. The rejection % is at its lowest in case 1 as only 26% of customer's eRx are eligible to be sent to the CF, but it does increase to its highest in case 4 as expected. That being said, even with a highly capacitated CF, the results show that it provides significant benefit to the local pharmacy and offers more PDPC services.

Table 3.7 shows a similar experiment to the one in the previous table while reducing PDPC services during busy hours (i.e. dynamic PDPC as discussed in Section 2.5.4). The results show a significant improvement in both the effective PDPC percentage and average waiting times. The local pharmacy provides up to 60% effective PDPC, but it is hard to compare the value of effective PDPC in Table 3.7 with effective PDPC values in Section 3.4.2 due to the fact that in this experiment, shorter PDPC services are offered during busy hours. In fact, in a typically busy pharmacy with dynamic PDPC, almost 50%-60% of the customers would end up getting the shorter duration PDPC service. The short PDPC service might not be able to cover lengthy PDPC services such as MTM which makes it difficult to compare dynamic PDPC to full duration PDPC.

3.4.3 PDPC Center

The previous experiments showed the effect of using an external resource to outsource the dispensing process in order to provide high levels of PDPC services. The PDPC center is an external resource that can be used to outsource PDPC from local pharmacies using kiosks. This subsection provides a discussion on the value of using kiosks for both local pharmacies and the community pharmacy chain network. Inside the local pharmacy, two PDPC kiosk polices are tested to understand the effect of using this strategy on the local pharmacy.

Initially, the PDPC center is assumed to be available any time the kiosk requests it. The first experiment shown in Table 3.8 investigates the effect of using only kiosks to provide PDPC services. Instances are evaluated for two and three kiosks.

Table 3.8: Providing PDPC Services Using PDPC Kiosks Only

	Cases	PDPC (%)	Average Wait Time: Check Out (min)	Average Wait Time: Kiosk (min)	Unsatisfied Customers: Check Out (%)	Unsatisfied Customers: PDPC (%)	Effective PDPC (%)	Pharm. Utilization (%)
Two Kiosks	0	0%	0.9	0	0.6%	0%	0%	82%
	1	10%	0.9	1	0.6%	1%	10%	82%
	2	20%	0.9	4	0.6%	11%	18%	82%
	3	30%	0.9	5	0.6%	22%	23%	82%
	4	40%	0.9	6	0.6%	32%	27%	82%
	5	50%	0.9	7	0.6%	39%	30%	82%
	6	60%	0.9	7	0.6%	45%	33%	82%
	7	70%	0.9	8	0.6%	50%	35%	82%
	8	80%	0.9	8	0.6%	54%	37%	82%
	9	90%	0.9	8	0.6%	57%	39%	82%
	10	100%	0.9	9	0.6%	60%	40%	82%
Three Kiosks	0	0%	0.9	0	0.6%	0%	0%	82%
	1	10%	0.9	0	0.6%	0%	10%	82%
	2	20%	0.9	2	0.6%	1%	20%	82%
	3	30%	0.9	3	0.6%	8%	28%	82%
	4	40%	0.9	5	0.6%	17%	33%	82%
	5	50%	0.9	5	0.6%	23%	38%	82%
	6	60%	0.9	6	0.6%	30%	42%	82%
	7	70%	0.9	7	0.6%	36%	45%	82%
	8	80%	0.9	7	0.6%	40%	47%	82%
	9	90%	0.9	7	0.6%	43%	51%	82%
	10	100%	0.9	7	0.6%	47%	53%	82%

The previous operating policy shows how valuable using PDPC kiosks can be. The following operating policy,tested in Table 3.9 , combines local pharmacists with PDPC kiosks in order to provide a higher level of PDPC. The local pharmacists prioritize drug verification and validation, shown in Figure 3.5, over PDPC services if there is more than 30 minutes worth of drug review work in the pharmacy. This essentially means that during busy periods the pharmacists prioritize dispensing work over PDPC services.

Table 3.9: The Effects of the Pharmacist-Assisted PDPC Kiosks Operating Policy

	Cases	PDPC (%)	Average Wait Time			Unsatisfied Customers		Effective PDPC (%)	Pharm. Utilization (%)
			Check Out (min)	PDPC (min)	Kiosk (min)	Check Out (%)	PDPC (%)		
Two Kiosks	0	0%	0.9	0	0	1%	0%	0%	82%
	1	10%	1.5	1	0	1%	1%	10%	88%
	2	20%	2.0	2	3	2%	3%	19%	91%
	3	30%	2.2	2	5	2%	11%	26%	93%
	4	40%	2.3	3	7	2%	18%	32%	95%
	5	50%	2.3	3	8	2%	26%	36%	96%
	6	60%	2.2	3	8	2%	32%	40%	97%
	7	70%	2.1	3	8	2%	38%	43%	98%
	8	80%	2.1	3	9	2%	43%	45%	98%
	9	90%	2.1	3	9	2%	46%	48%	99%
	10	100%	2.2	3	9	2%	49%	50%	99%
Three Kiosks	0	0%	0.9	0	0	1%	0%	0%	82%
	1	10%	1.5	1	0	1%	1%	10%	88%
	2	20%	2.1	2	1	2%	2%	19%	92%
	3	30%	2.2	2	3	2%	4%	28%	93%
	4	40%	2.2	3	5	2%	10%	35%	95%
	5	50%	2.3	3	6	2%	16%	41%	96%
	6	60%	2.2	3	7	2%	23%	45%	97%
	7	70%	2.2	3	7	2%	28%	49%	98%
	8	80%	2.1	3	8	2%	32%	53%	98%
	9	90%	2.1	3	8	2%	36%	56%	99%
	10	100%	2.1	3	8	2%	40%	59%	99%

The previous operating policy showed that the community pharmacy can offer PDPC services at any level without disrupting the dispensing process. Even when the pharmacy offers PDPC to 100% of customers, the pharmacy is still able to keep a low value for both the check out satisfaction percent and the average waiting time. Table 3.10 shows the same experiment as in the previous table but with dynamic PDPC included inside the local pharmacy. The results showed that the local pharmacy can reach up to 70% effective PDPC with almost no changes in the dispensing process performance measures (e.g customer check out waiting time).

Table 3.10: Pharmacist-Assisted PDPC Kiosks Operating Policy Combined With Dynamic PDPC

	Cases	PDPC (%)	Average Wait Time Check Out (min)	Average Wait Time PDPC (min)	Average Wait Time Kiosk (min)	Unsatisfied Customers Check Out (%)	Unsatisfied Customers PDPC (%)	Effective PDPC (%)	Pharm. Utilization (%)
Two Kiosks	0	0%	0.9	0	0	1%	0%	0%	82%
	1	10%	1.3	1	0	1%	1%	10%	87%
	2	20%	2.0	1	1	2%	2%	19%	90%
	3	30%	2.2	1	4	2%	5%	28%	92%
	4	40%	2.1	2	5	2%	9%	36%	94%
	5	50%	2.2	2	6	2%	14%	42%	95%
	6	60%	2.3	2	6	2%	19%	48%	96%
	7	70%	2.2	2	7	2%	24%	52%	97%
	8	80%	2.2	2	7	2%	28%	56%	98%
	9	90%	2.2	3	7	2%	32%	60%	98%
	10	100%	2.1	3	7	2%	36%	63%	99%
Three Kiosks	0	0%	0.9	0	0	1%	0%	0%	82%
	1	10%	1.3	1	0	1%	1%	10%	87%
	2	20%	1.9	1	1	2%	1%	19%	90%
	3	30%	2.1	1	2	2%	2%	29%	92%
	4	40%	2.2	2	3	2%	4%	38%	94%
	5	50%	2.2	2	4	2%	8%	45%	95%
	6	60%	2.3	2	5	2%	10%	53%	96%
	7	70%	2.3	2	5	2%	14%	59%	97%
	8	80%	2.2	2	5	2%	18%	65%	98%
	9	90%	2.2	2	6	2%	22%	69%	98%
	10	100%	2.1	2	6	2%	25%	73%	99%

The previous two experiments were done inside a local pharmacy assuming that a PDPC center pharmacist is always available. The following experiment relaxes that assumption by analyzing the local pharmacy from a network perspective. Five pharmacies will compete to seize the PDPC center pharamcist to assist in providing PDPC to customers. We assume that each pharmacy has three kiosks and the PDPC center has ten pharmacists available. A pharmacist in the PDPC center decides to work according to a dynamic priority rule that allocates resources to local pharmacies according to the pharmacy with the least number of allocated PDPC resources and the highest number in PDPC kiosk queue. maintains a balanced distribution of resources to the pharmacies. The goal of the dynamic rule is to make sure that no pharmacy falls behind on the percentage of effective PDPC offered. Table 3.11 shows how both kiosk policies are affected by the limited resources available in the PDPC center.

Table 3.11: The Effects of Using Kiosks With a Capacitated PDPC Center

	Cases	PDPC (%)	Average Wait Time			Unsatisfied Customers		Effective PDPC (%)	Pharm. Utilization (%)
			Check Out (min)	PDPC (min)	Kiosk (min)	Check Out (%)	PDPC (%)		
Kiosks Only	0	0 %	1.0	0.0	0.0	0.5%	0%	10%	83%
	1	10%	1.0	0.0	0.2	0.5%	0%	10%	83%
	2	20%	1.0	0.0	1.3	0.5%	1%	20%	83%
	3	30%	1.0	0.0	3.3	0.5%	7%	28%	83%
	4	40%	1.0	0.0	4.8	0.5%	16%	34%	83%
	5	50%	1.0	0.0	5.5	0.5%	23%	38%	83%
	6	60%	1.0	0.0	6.6	0.5%	36%	39%	83%
	7	70%	1.0	0.0	6.8	0.5%	41%	41%	83%
	8	80%	1.0	0.0	7.2	0.5%	45%	44%	83%
	9	90%	1.0	0.0	7.4	0.5%	48%	46%	83%
	10	100%	1.0	0.0	7.8	0.5%	52%	48%	83%
Pharmacist Assisted Kiosks	0	0%	1.0	0	0.0	0.4%	0%	0%	83%
	1	10%	1.6	1	0.0	1.1%	1%	10%	89%
	2	20%	2.2	2	1.6	1.7%	2%	19%	93%
	3	30%	2.3	2	3.6	1.8%	6%	28%	95%
	4	40%	2.3	3	5.5	1.8%	13%	34%	96%
	5	50%	2.3	3	7.0	1.7%	21%	39%	97%
	6	60%	2.3	3	7.5	1.8%	26%	43%	98%
	7	70%	2.3	3	8.0	1.8%	32%	47%	98%
	8	80%	2.3	3	8.1	1.7%	36%	50%	99%
	9	90%	2.3	3	8.1	1.8%	40%	53%	99%
	10	100%	2.3	3	8.3	1.7%	43%	56%	99%

The results shown in the previous table are for a local community pharmacy with three kiosks (all connected to the capaciated PDPC center). The experiment showed that the effective PDPC does drop for both polices by about 2% which is not a significant drop. The experiment solidifies the value of using PDPC kiosks as an alternative to providing PDPC services inside the local pharmacy.

3.4.4 Combining Strategies

In this section, a combination of several strategies are used to determine how effective using multiple strategies can be. A combination of the capacitated CF policies (an external strategy shown in Section 3.4.2), PDPC kiosk policies (an external strategy shown in Section 3.4.3) with capacitated PDPC centers, and Dynamic PDPC (an internal strategy shown in Section 2.5.4) are evaluated. The first experimental results, shown in Table 3.12, evaluate the effectiveness of maximizing the benefits of the CF combined with shortening the durations of PDPC services during busy hours (Dynamic PDPC).

Table 3.12: Fully Utilizing a Capacitated Central Fill Strategy While Using Dynamic PDPC

Cases	PDPC (%)	Customers Contacted (%)	Average Wait Time		Unsatisfied Customers		Effective PDPC (%)	Pharm. Utilization
			Check Out (min)	PDPC (min)	Check Out (%)	PDPC (%)		
0	0%	100%	0.2	0	0.0%	0%	0%	63%
1	10%	100%	0.3	1	0.0%	1%	10%	69%
2	20%	100%	0.5	1	0.1%	1%	20%	75%
3	30%	100%	1.0	2	0.6%	3%	29%	81%
4	40%	100%	2.1	2	2.0%	5%	37%	86%
5	50%	100%	3.3	2	3.4%	7%	45%	89%
6	60%	100%	4.5	3	4.9%	11%	51%	93%
7	70%	100%	5.5	3	6.5%	14%	56%	96%
8	80%	100%	6.0	3	7.4%	17%	61%	99%
9	90%	100%	6.7	4	8.5%	22%	65%	100%
10	100%	100%	9.3	4	10.9%	26%	66%	100%

The results show that the pharmacist can easily be overutilized due to the PDPC services but the community pharmacy can offer up to 66% effective PDPC due the effectiveness of the CF even when its capacitated. If the objective is to offer 60% PDPC services, this operating policy will assure that 51%of all customers at least get a short duration service while dramatically improving the dispensing process in terms of workflow and costs. The next experiment, shown in Table 3.13 , we evaluate the effect of combining the use of PDPC kiosks with dynamic PDPC.

Table 3.13: The Effects of Using Kiosks With Capacitated PDPC Centers

	Cases	PDPC (%)	Average Wait Time			Unsatisfied Customers		Effective PDPC (%)	Pharm. Utilization (%)
			Check Out (min)	PDPC (min)	Kiosk (min)	Check Out (%)	PDPC (%)		
Kiosks Only & Dynamic PDPC	0	0%	1.0	0.0	0.0	0.5%	0%	0%	83%
	1	10%	1.0	0.0	0.0	0.5%	0%	10%	83%
	2	20%	1.0	0.0	0.0	0.5%	1%	20%	83%
	3	30%	1.0	0.0	0.0	0.5%	6%	28%	83%
	4	40%	1.0	0.0	0.1	0.5%	11%	35%	83%
	5	50%	1.0	0.0	0.1	0.5%	18%	41%	83%
	6	60%	1.0	0.0	0.1	0.5%	24%	45%	83%
	7	70%	1.0	0.0	0.1	0.5%	29%	49%	83%
	8	80%	1.0	0.0	0.1	0.5%	34%	53%	83%
	9	90%	1.0	0.0	0.1	0.5%	38%	55%	83%
	10	100%	1.0	0.0	0.1	0.5%	41%	58%	83%
Pharmacist Assisted Kiosks & Dynamic PDPC	0	0%	1.0	0.0	0.0	0.5%	0%	0%	83%
	1	10%	1.4	1.0	0.0	1.0%	1%	10%	88%
	2	20%	2.1	1.2	0.0	1.7%	1%	19%	92%
	3	30%	2.2	1.3	0.1	1.7%	3%	29%	94%
	4	40%	2.3	1.5	0.1	1.9%	5%	37%	95%
	5	50%	2.4	1.8	0.1	1.9%	10%	44%	96%
	6	60%	2.3	2.0	0.1	1.9%	13%	51%	97%
	7	70%	2.4	2.3	0.1	1.9%	18%	56%	98%
	8	80%	2.4	2.3	0.1	1.9%	23%	61%	98%
	9	90%	2.2	2.4	0.1	1.7%	27%	64%	99%
	10	100%	2.2	2.5	0.1	1.7%	30%	69%	99%

The previous experiment shows how high percentages of the population can be reached by a PDPC service without having to use a CF to reduce dispensing load. The two experiments shown in this section really highlight the influence of Dynamic PDPC as it can improve the performance of any of the external strategies significantly. The is no need to combine the CF strategy and PDPC kiosks because the pharmacy's dispensing load is not affected with the increase in PDPC services due to the use of PDPC kiosks.

3.5 Conclusions

This study proposes two strategies to improve the performance of a community pharmacy's workflow in order to provide PDPC services to a significant portion of the population. We begin by outsourcing the dispensing process to a CF using two policies. The results show that the base case community pharmacy can possibly handle 10-20% of PDPC services. Sending after hours eRx to the CF was shown to improve the PDPC levels provided up to 40% (with a 31% effective PDPC).

The use of a CF was also shown to minimize a local pharmacy's dispensing cost by lowering the number of clerks inside the local pharmacy. The second CF operating policy further utilizes the use of a CF by sending eRx during working hours to be dispensed externally. The portion of demand sent to the CF depends on the percentage of customers contacted during the day. Fully utilizing a CF allows the local pharmacy to offer 60% PDPC services and effectively serve 40% of the population which is a 25% improvement over the first operating policy. Using a CF can also lower the inventory cost inside local pharmacies and consolidate it in a CF which is known in supply chain management as one of the ways to reduce the total inventory cost. Essentially using the CF will reduce dispensing costs, reduce inventory costs, reduce clerk costs, and improve PDPC services across the network.

The second external strategy is aimed towards increasing PDPC service capacity utilizing PDPC kiosks and PDPC centers. PDPC centers contain a limited number of pharmacists that can be used to service several pharmacies based on which is more urgently in need of assistance. Thus, while hiring a pharmacist inside the local pharmacy can only help the local pharmacy's PDPC, adding a pharmacist to the PDPC center will provide support to the entire network. Two PDPC kiosk policies were tested inside local pharmacies, using only PDPC kiosks, and combining PDPC kiosks with local pharmacists to provide PDPC. The two policies were tested with an uncapacitatetd PDPC center and a capacitated one. Both policies permit the pharmacy to maintain good performance measures for preparing prescriptions while offering PDPC up to 100% of the population but the effective PDPC service is often limited to about 40%-50% and depends on the number of kiosks and the ability to seize a pharmacist from the PDPC center.

In general, the first operating policy does provide less PDPC to the population but it does not disrupt the dispensing process inside the local pharmacy. The second shows higher effective PDPC percentages, but leaves the pharmacist overutilized and vulnerable to unexpected interruptions inside the local pharmacy. Combining both policies with Dynamic PDPC improves the effective PDPC rates by 10% (more in some cases) but it does not address the over utilization issue in the second operating policy. Finally, While the CF does improve the dispensing cost, one can argue that the PDPC center can only improve effective PDPC services as it does not lower the cost of PDPC services. However, PDPC services can generate a huge stream of income that was not included in this study.

4.0 Locating A Central Fill (CF) Pharmacy For a Community Pharmacy Chain Network: a Chance Constraint Model

This paper focuses on locating a CF that can support multiple pharmacies under stochastic demands. The problem is modeled as a joint Chance Constrained P-median Capacitated Facility Location Problem. A Benders decomposition solution procedure is proposed to improve the efficiency of the solution procedure. The model and solution methodology are used in a case study to improve patient care provided by a pharmacy network. The resulting network is a more capable community pharmacy chain network that is robust to stochastic demands and provides higher levels of patient care.

4.1 Introduction and Motivation

Pharmacy automation is playing a major role in changing the work dynamics inside a community pharmacy [66]. The automation systems in community pharmacies can be classified into two models: decentralized and centralized. The first describes a system where an automated dispensing machine is installed in a community pharmacy. The decentralized automation system works well for large individual pharmacies (for example an in-hospital pharmacy) but for a community pharmacy chain network that would mean an automated dispensing machine would be installed in each pharmacy location which would be very expensive. The centralized system is more cost efficient and requires the development of a CF pharmacy that is capable of filling prescriptions for a network of pharmacies over a large geographical area [67]. According to multiple reports published by Chain Drug Review, almost all major pharmacy chains are evaluating the use of a centralized model [14]. Note that there are several benefits to using an automated CF, including improved inventory control [73], enhanced patient safety [14], lower filling costs [14], and fewer dispensing errors [67]. Currently Boots, a British community pharmacy chain network, is considering the development of a similar system in the UK [5]. The main reasons cited to use this system are increased efficiency in the dispensing process, reduced cost, reduced dispensing errors, and allowing pharmacies to allocate more time for pharmacists to interact with patients and provide more enhanced therapeutic services. The last benefit of permitting pharmacists to have more time to engage with patients is of increasing interest to many pharmacy chains in the US.

Currently, the most popular form of CF in community pharmacy chain networks is one which mails prescriptions directly to the customer and is referred to as Mail Order Pharmacy automation (MOP). MOP is the most common centralized outpatient/community pharmacy automation system world wide. It was developed to provide medication to stable patients with chronic diseases. For example, the Chronic Dispensing Unit (CDU) is one such system developed in South Africa that has been providing medication since 2005. Research shows that the role of the CDU has significantly expanded during the last decade due to technological advances made in medication dispensing [49]. Consequently, the role of MOP systems have been evolving to service a network of pharmacies for a wider range of medications. In the United states, almost thirty percent of all chronic disease prescriptions are being dispensed by a MOP bypassing local community pharmacies [16]. Compared to traditional pharmacies, MOPs can provide medication at a lower price due to a more efficient dispensing and inventory management system.

The effects of automation in pharmacies, more specifically MOPs, have been systematically studied in the literature. The difference in completion time between the first and last medication orders for one patient is called the collation time, also known as the fill time window, which is a common performance measure used in evaluating a MOP system. Note that minimizing collation time depends on the order scheduling inside the centralized pharmacy. Dauod [20] used a genetic algorithm to solve a multi-objective optimization problem that deals with minimizing collation time in a MOP system. Wang [79], developed a discrete event simulation model to evaluate the effect of different work scheduling rules in a CF pharmacy on collation time. Li [42], used an adaptive parallel tabu search algorithm to provide a solution to the fill window problem.

One criticism of MOPs is that they lack the pharmacist to patient interactions that can be seen inside an outpatient or a retail pharmacy. Pharmacist-Delivered Patient Care (PDPC) is an essential part of the healing process and has been shown to reduce patient's misuse of medication [36][28], improve patient's understanding of medication [36], and improve overall patient health [28]. The CF hub and spoke model suggested in this paper assumes that a CF is used to dispense a significant portion of the local pharmacy's prescriptions and that these are then shipped directly to the pharmacy for customer pickup. This lets the pharmacist spend more time engaging with patients rather than filling prescriptions. Then the local community pharmacy in the network would be able to allocate more resources towards providing additional PDPC services.

To better understand the hub and spoke model proposed in this paper, we now provide and example based on the Washington Metropolitan Area. Figure 4.1 shows community pharmacy locations and potential CF locations in the Washington DC Metropolitan Area. The optimization model discussed in this paper aims to outsource a significant portion of the local community pharmacy dispensing load to a CF which enables the pharmacists to focus on providing more clinical services. Specifically, the CF is used to dispense prescriptions that would not be picked up on the same day they arrived at the pharmacy. In order to optimally locate CFs and improve the levels of PDPC provided, the optimization model accounts for the prescription's cost of dispensing (COD) in CFs as well as the local pharmacies, the fixed costs associated with building the CFs, and the shipping costs for transporting the prescriptions from the CF to the pharmacy. The output from the model is a balanced solution that utilizes CFs and local pharmacy resources to provide maximum PDPC services across the network while also providing low prescription COD.

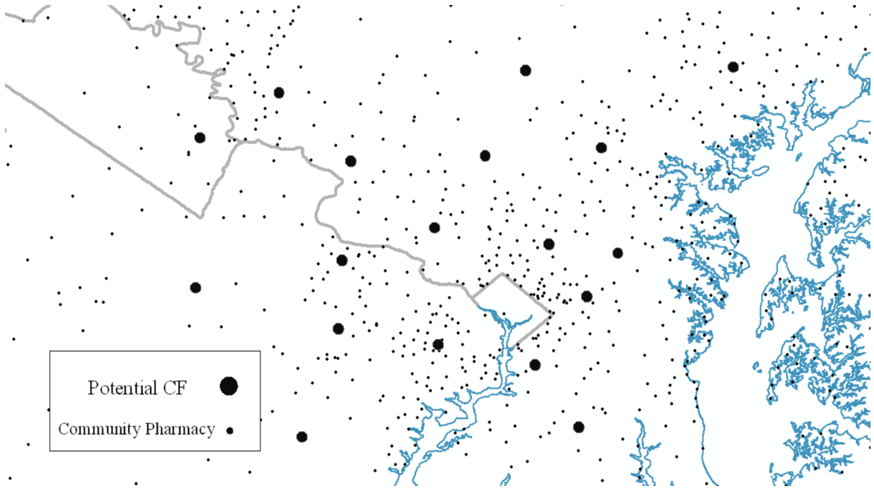

Figure 4.1: Washington Metropolitan Area: Pharmacy Locations and Possible CF Locations

Performing PDPC services in a community is rewarding both in terms of improving patient's overall health and generating a substantial income to the community pharmacy. There are three methods to satisfy the demand shown in Figure 4.1: A community pharmacy chain network that does not use any CF, a MOP network that bypasses community pharmacies (assuming that the MOP network expands to dispense all types of prescriptions rather than focusing on maintenance drugs), and the hub and spoke network studied in this paper. The proposed hub and spoke network can possibly act as a MOP network in addition to it's original intended role (i.e CFs dispensing prescriptions for local pharmacies and mail prescriptions directly to patients). However, our work focuses on a community pharmacy chain network that does not mail prescriptions to patients and only ships prescriptions from CFs to local pharmacies.

The Cost Of Dispensing (COD) prescriptions and the potential revenue generated from providing PDPC services are completely different for the three networks. The no CF network uses pharmacy resources to dispense prescriptions which yields a high COD for prescriptions and lowers the potential for PDPC services to be provided. The MOP network can provide low prescription COD but the benefits are negated by losing a huge potential for providing PDPC services. The hub and spoke network provides low prescription COD and allows local pharmacies to focus on providing PDPC services that can generate substantial revenue.

In the proposed model, the location of the CF directly affects the shipping logistics in terms of time and cost. A bad location nullifies the benefits of the proposed network as it could force the community pharmacy to locally dispense prescriptions and lose an opportunity to provide PDPC services to a patient. The main factors that affect the CF location are the cost of dispensing prescriptions locally compared with dispensing them in a CF, and the effects of stochastic demands on CF capacity. This paper provides a model that takes into consideration both factors while providing the decision maker with the ability to choose the extent to which stochastic demands can affect the CF location. The CF location problem is modeled as a chance constrained stochastic program and is applied to a community pharmacy chain network in Pennsylvania containing 247 local pharmacies. The model objective is to reduce dispensing errors, reduce patient waiting time, and increase the levels of clinical and PDPC services provided by pharmacists in hopes of adding more revenues and improving the overall health of patients at the same time.

It is important to recognize that the CF hub and spoke model suggested in this paper would not have worked on a pharmacy network before the invention of electronic prescriptions. Prior to electronic prescriptions the majority of prescriptions were paper printed which implied that the majority had to be filled while the patient was waiting. Currently, most prescriptions arrive electronically to a pharmacy and are typically filled on the same day they arrive. Additionally, the majority of patients do not pick their prescriptions up on the same day they arrive in the pharmacy. Electronic prescriptions make it easier to fill prescriptions prior to patient arrival and patient pick up habits often provide enough time to fill prescriptions in a CF and then ship them to the pharmacy.

The organization of this paper is as follows: section 4.2 shows the literature review for similar location models in healthcare, section 4.3 shows the chance constraint formulation and solution methodology, section 4.4 shows the computational results of the algorithm, and finally in section 4.5 a case study is used to show the value of using the model.

4.2 Literature Review

Applications of location problems in health care are often labeled Healthcare Facility (HCF) location problems. The applications can vary including disaster management facilities, humanitarian logistics facilities, community healthcare clinics, hospitals, pharmacies, and other primary care centers [3]. In disaster management, dynamic facility location problems are widely used in locating and relocating a fleet of ambulances [52] and locating a temporary facility for an emergency response [35]. The problem of locating a warehouse in anticipation of a disaster was studied by Horner [78] in which a capacitated warehouse location model was built to make sure the necessary flow of important supplies was well maintained in case of a disaster. Feng [80], applied the emergency warehouse location problem on a national level for China and proposed a variable neighborhood search heuristic to provide good quality solutions to the problem. In humanitarian logistics, the problem of locating an uncapacitated central depot and a number of capacitated temporary central depots was studied in Lin [44]. Kongsomsaksakul et al. [37] modeled a two level capacitated shelter location problem with the upper level determining the location of shelters and the lower level determining the evacuation plan

Gould and Leinbach [25] provided one of the earliest location models on hospital services. The study was also one of the earliest applications of the capacitated P-median model in healthcare. This paper studied the location of an automated central pharmacy that can supply busy retail pharmacies with filled prescriptions which could be classified a non-emergency location model. Hodgart [29] classified a CF as one of the three classical types of facilities in healthcare. The problem of locating a CF for a community pharmacy chain network could also be part of pharmaceutical supply chain. In the pharmaceutical supply chain domain, Dessouky et al. [21] explored the importance of exact solutions for facility location problems and vehicle routing problems accounting for a large-scale medical emergency. The design of location and distribution systems in a pharmacy network has direct impact on the quality of healthcare. Despite the fact the CF location problem is categorized under non-emergency location models, the location of a CF plays a major role in the supply of medication in the case of an emergency. The hub and spoke model suggested in this paper does not take into consideration any epidemic event in locating a CF, but it accounts for it in the objective cost as part of a the local pharmacy's dispensing cost. Additionally, the network intends to switch local pharmacies/pharmacists to a more clinical role which can easily be switched back to a dispensing role in case of an emergency.

Our work focuses on locating a CF pharmacy that can act as a hub to service several community pharmacies. This would imply that each pharmacy is serviced by one (or more) CFs which in terms leads to a p-median capacitated facility location problem (PCFLP). The PCFLP is an NP-Hard problem on a general graph that is difficult to solve using traditional methods for realistic size networks [19]. The model presented in this paper deals with stochastic demands due to the nature of prescription demand in pharmacy networks. The common Stochastic P-median location model (S-PCFLP) only considers uncertainty in the transportation cost. The hard capacity constraint forced by the S-PCFLP is relaxed in our model and replaced by a chance constraint that can be violated in certain situations. The chance constraint optimization problem (CCS-PCFLP) provides the user with the ability to choose the level of demand to be covered by the CF. Additionally, Any unsatisfied demand by the CF is dispensed locally in the community pharmacy at a higher cost. For more details on the benefits of using the CCS-PCFLP refer to the case study in section 4.5.

Chance constraint facility location models are an example of left hand side uncertainty. Several studies have focused on the Stochastic Single Source Capacitated Facility Location Problem (S-SSCFLP) when demand points are independent and follow a known distribution. Lin [43], discussed a chance constrained S-SSCFLP when the demands are independent and identically distributed Normal (iid) random variables. Lin provided several heuristic algorithms to solve the S-SSCFLP. This work was the first attempt to solve the chance constraint version of the S-SSCFLP. Salemi [63], studied the S-SSCFLP under similar assumptions to Lin's paper but with Poisson distributions. The use of the Poisson distribution was easily incorporated into the S-SSCFLP by exploiting the fact that the sum of Poisson random variables is a Poisson random variable. Salemi expanded the work of Lin and provided a hybrid algorithm that combines lagrangian relaxation and genetic algorithms to provide bounds for the S-SSCFLP. Both Salemi and Lin assumed that pharmacy demands are iid.

Our work discusses a problem similar to the S-SSCFLP without any assumptions regarding the type of demand distribution or the independence assumption. We also consider multiple potential sources rather than just one. Murali [57] presented a chance constrained formulation for a capacitated covering model. The objective is to maximize the portion of the population that was successfully able to receive medication in a major emergency. The demand in this problem was uncertain which leads to a chance constrained model with right hand side uncertainty. A location allocation heuristic introduced by [17] was modified and used to provide solutions to the problem. Our problem contains demand uncertainty in all parts of the optimization model as well as multiple chance constraints.[57]

Maass et al. focused on creating realistic nurse schedules for multiple units in a hospital. They consider three types of nurses while accounting for stochastic demand. The resulting stochastic optimization model was solved easily using traditional linear programming solution methods. The model was expanded to account for nurse absenteeism which introduced a new form of stochasticity to the model. The expanded model is similar in structure to the model shown in this paper as it contains both a chance constraint that limits nurse absenteeism, and an expected value in the objective function that provides an expected monetary value for the resulting schedule under different demand scenarios. The solution method seemed to work well for the chance constraint model but does not always guarantee an optimal solution. [48]

Over the past decade, joint chance constraint models with left hand uncertainty have been transformed into a mixed integer program using a big-M approach which can lead to a computationally intractable formulation [72][47][62]. Zeng [81], showed the advantage of using a bilinear formulation for chance constraint mathematical modeling over the generic big-M formulation for problems with recourse variables. The paper suggested that using Bender's decomposition on the bilinear formulation can provide better solutions compared to the Big-M formulation.

The problem of locating a CF under stochastic demand is modeled a joint Chance Constrained CCS-PCFLP with left hand side uncertainty. The problem at hand is an NP-Hard problem since the deterministic version of the problem is considered NP-Hard on general graphs (it can be solved polynomially on a tree) [19]. The following section will formally define the location problem and present different variations of the formulation as well as provide a solution method for the CCS-PCFLP. To the best of our knowledge, our work is the first application of chance constraint modeling with generic left hand side uncertainty in locating a CF for a community pharmacy chain network.

4.3 Chance Constrained Stochastic P-median Capacitated Facility Location Problem (CCS-PCFLP)

This section shows the model variables and parameters, the main model used in this paper, a different reformulation of the model, and the solution methodology. The deterministic version of the CF location problem does not take into consideration the inherent risk associated with stochastic demands. Including random demand from each pharmacy complicates the problem and requires a more involved model. The main methods to handle randomness in a linear program are Stochastic Programming (SP), Chance Constraint Programming (CCP), and Robust Optimization (RO). Stochastic optimization is a special case of the CCP, and RO deals with a worst case scenario type of analysis. Note that locating a CF according to the worst case scenario could be very conservative, while using the scenario with expected value is acceptable for the transportation cost, modeling the capacity constraint as the expected demand would theoretically mean that the CF would only be able to handle the demand in the average case. Using a SP approach would provide the optimal expected dispensing cost while considering all demand scenarios which is a special case of the joint chance constraint approach. The joint chance constraint can be used to model the capacity constraint more accurately by setting a service level parameter δ that can be used to control the chances that the capacity constraint is violated. The SP is a Joint chance constraint model with $\delta = 0$ which implies that the SP is the most conservative chance constraint model. The main problem variables, sets, and parameters are shown as follows:

Sets:

$\mathscr{F}$: The set of all possible CF locations, $\mathscr{F} = \{i \in \mathbb{Z}_+ | i = 1 \dots m\}$

$\mathscr{L}$: The set of all possible pharmacy points, $\mathscr{L} = \{i \in \mathbb{Z}_+ | i = 1 \dots n\}$

Variables:

x_{ij}: The portion of pharmacy i's demand satisfied by CF j , $x_{ij} \in \mathbb{R}^+$

$$y_j = \begin{cases} 1, & \text{if the } j^{th} \text{ CF is built,} \\ 0, & \text{otherwise} \end{cases}$$

$c_j \in \mathbb{R}^+$

Parameters:

$p =$ Number of CFs to build,

$f_j =$ Cost of CF j,

$h_j =$ Unit capacity cost at CF j,

$w_{ij} =$ Unit transportation cost from CF j to pharmacy i,

$d_i =$ Expected demand for each location i

$U_j =$ An upper bound for each CF's capacity j

It is assumed that demand scenarios are sampled from discrete random variables with finite support that represent pharmacy demands. The left hand side of the capacity constraint deals with the sum of demand random variables serviced by a CF. The formulation (4.3a-4.3g) is referred to as M1 and it shows the general chance constraint formulation discussed in this paper. A feasible scenarios (ω) is feasible when $\Theta^{(\omega)} = 1$, where $\Theta^{(\omega)}$ is defined as follows:

$$\Theta^{(\omega)} = \begin{cases} 1, & \sum_{i \in \mathscr{L}} d_i^{(\omega)} x_{ij}^{(\omega)} \leq c_j, \quad \forall j \in \mathscr{F} \\ 0, & otherwise \end{cases} \tag{4.1}$$

M1 is a representation for the stochastic version of the problem under service level requirements δ. The conditional expectation cost in the objective function is directly influenced by the chance constraint in the model. Conditioning on feasible scenarios implies that the capacity and locations of the optimal CFs are not affected by an infeasible scenario. consequently, the cost of servicing infeasible scenarios are ignored from the objective function. In practice, infeasible scenarios are associated with a high spike in demand that could be attributed to a medical emergency that can vary in intensity from a bad flu season to a major epidemic. However, a major assumption in M1's design is that there are local pharmacy resources that can be used to dispense prescriptions in the case of an infeasible scenario, hence M1 only considers the costs of feasible scenarios in the decision making process.

$$
\begin{aligned}
M1: \quad \text{minimize} \quad & \sum_{j\in\mathscr{F}} f_j y_j + \sum_{j\in\mathscr{F}} h_j c_j + \mathbb{E}\left[\sum_{j\in\mathscr{F}, i\in\mathscr{L}} w_{ij} d_i^{(\omega)} x_{ij}^{(\omega)} \middle| \Theta^{(\omega)} = 1\right] && \text{(4.2a)}\\
\text{subject to} \quad & \sum_{j\in\mathscr{F}} y_j \le p, && \text{(4.2b)}\\
& P_d\left(\sum_{i\in\mathscr{L}} d_i^{(\omega)} x_{ij}^{(\omega)} \le c_j, \quad \forall j \in \mathscr{F}\right) \ge 1-\delta, && \text{(4.2c)}\\
& \sum_{j\in\mathscr{F}} x_{ij}^{(\omega)} = 1, \quad \forall i \in \mathscr{L}, && \text{(4.2d)}\\
& c_j \le U_j y_j, \quad \forall j \in \mathscr{F}, && \text{(4.2e)}\\
& x_{ij}^{(\omega)} \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} \cup \{\hat{\delta}\}, && \text{(4.2f)}\\
& y_j \in \{0,1\}, c_j \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} && \text{(4.2g)}
\end{aligned}
$$

A feasible scenario in M1 is a scenario (ω) such that the total capacity is greater than or equal to the total demand in the scenario (ω). Depending on the locations of CFs in M1, a pharmacy may be serviced by a CF hundreds of miles away from the pharmacy which can be impractical. The distance element is crucial to the supply of the pharmacy since it plays a major role in the number of shipments, the size of shipments, and the responsiveness of a CF to the pharmacy's demand. Model $\overline{M1}$ addresses the distance issue as it limits the CFs that pharmacy i can be linked to. We define, $\mathscr{F}_{\gamma_i}$ as the set of CFs within a γ mile radius of pharmacy i. M1 can be thought of as relaxation of $\overline{M1}$ where γ_i is relatively large.

$$
\begin{aligned}
\overline{M1}: \quad \text{minimize} \quad & \sum_{j\in\mathscr{F}} f_j y_j + \sum_{j\in\mathscr{F}} h_j c_j + \mathbb{E}\left[\sum_{j\in\mathscr{F}, i\in\mathscr{L}} w_{ij} d_i^{(\omega)} x_{ij}^{(\omega)} \middle| \Theta^{(\omega)} = 1\right] && \text{(4.3a)}\\
\text{subject to} \quad & \sum_{j\in\mathscr{F}} y_j \le p, && \text{(4.3b)}\\
& P_d\left(\sum_{i\in\mathscr{L}} d_i^{(\omega)} x_{ij}^{(\omega)} \le c_j, \quad \forall j \in \mathscr{F}\right) \ge 1-\delta, && \text{(4.3c)}
\end{aligned}
$$

$$\sum_{j \in \mathscr{F}_{\gamma_i}} x_{ij}^{(\omega)} = 1, \quad \forall i \in \mathscr{L}, \tag{4.3d}$$

$$c_j \leq U_j y_j, \quad \forall j \in \mathscr{F}, \tag{4.3e}$$

$$x_{ij}^{(\omega)} \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} \cup \{\hat{\delta}\}, \tag{4.3f}$$

$$y_j \in \{0, 1\}, c_j \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} \tag{4.3g}$$

Both M1 and $\overline{M1}$ only include the cost of dispensing medication from CFs. Model M2, shown in (4.4a-4.4g), includes the COD prescriptions using a CF and using local pharmacy resources. Local pharmacy resource are modeled as an uncapacitated supply node "$\hat{\delta}$" with a COD denoted by "P_C".

$$\begin{aligned}
M2: \quad \text{minimize} \quad & \sum_{j \in \mathscr{F}} f_j y_j + \sum_{j \in \mathscr{F}} h_j c_j + \mathbb{E}\left[\sum_{j \in \mathscr{F}, i \in \mathscr{L}} w_{ij} d_i^{(\omega)} x_{ij}^{(\omega)}\right] + \mathbb{E}\left[\sum_{i \in \mathscr{L}} P_C d_i^{(\omega)} x_{i\hat{\delta}}^{(\omega)}\right] && (4.4a)\\
\text{subject to} \quad & \sum_{j \in \mathscr{F}} y_j \leq p, && (4.4b)\\
& P_d\left(\sum_{i \in \mathscr{L}} d_i^{(\omega)} x_{ij}^{(\omega)} \leq c_j, \quad \forall j \in \mathscr{F}\right) \geq 1 - \delta, && (4.4c)\\
& \sum_{j \in \mathscr{F}_{\gamma_i} \cup \{\hat{\delta}\}} x_{ij}^{(\omega)} = 1, \quad \forall i \in \mathscr{L}, && (4.4d)\\
& c_j \leq U_j y_j, \quad \forall j \in \mathscr{F}, && (4.4e)\\
& x_{ij}^{(\omega)} \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} \cup \{\hat{\delta}\}, && (4.4f)\\
& y_j \in \{0, 1\}, c_j \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F} && (4.4g)
\end{aligned}$$

The introduction of "$\hat{\delta}$" changed the structure of the problem as the location and capacity variables (y_i, c_i) do not have any effects on the feasibility of M2. In fact, M2 is feasible even if there are no CFs built in the network, in that case, the local pharmacy resources dispense all medications in all scenarios. Restricting local pharmacy resources can be easily done by adding constraint (4.5) to the M2 where ρ represent the percentage of pharmacy demand that can be satisfied by local pharmacy resources.

$$x_{i\hat{\delta}}^{(\omega)} \leq \rho, \quad \forall i \in \mathscr{L} \tag{4.5}$$

It is important to note that M2 is a special case of M1 with a major change. An additional uncapacitated supply node "$\hat{\delta}$" is added with no fixed or capacity costs associated to it. The idea behind M2 is that it will include all scenarios in the objective function and will provide an optimal CF capacity and location. This is an alternative to using M1 with a chance constraint because there are local pharmacy resources that can be used if they are more cost effective than building additional CFs. Hence, this option explicitly considers the cost trade-off between using a CF to handle extreme scenarios or using the local resources. M1 with a chance constraint also can be used to consider that safe trade-off but does not do it explicitly, rather it is doing it implicitly by ignoring the effects of the top 1, 5, or 10 percent of the scenarios.

4.3.1 Solution Methodology

This subsection provides a detailed discussion on M1's linearization, reformulation, and decomposition approach. The chance constraint (4.3c) and the conditional expectation (4.3a) are the two nonlinear part of the model. It is important to note that the solution procedure discussed in this section is not limited to any restrictions on the demand distributions. The following definitions will be used in the process of linearizing the model shown in (4.3a-4.3g). Let $\Gamma_{(g(x)\leq 0)}$ be an Indicator Variable defined as follows:

$$\Gamma_{(g(x)\leq 0)} = \begin{cases} 1, & (g(x) \leq 0) \\ 0, & otherwise \end{cases} \tag{4.6}$$

Let $\mathscr{K}$ be the set of demand scenarios, where each scenario is an m-dimensional demand vector d^k that represents all the demand points for m different pharmacies.

We denote d_i^k as the i^{th} row in the vector d^k and P_k as the probability of scenario k. The chance constraint in (4.3c) can be written as:

$$\sum_{k\in\mathscr{K}} P_k \Gamma \left(\sum_{i\in\mathscr{L}} d_i^k x_{ij}^k - c_j \leq 0 \right) \geq 1-\delta \tag{4.7}$$

let $z_k \in \{0,1\}$ be 1 if in scenario k the CF(s) does not have enough capacity to handle the total demand, which indicates that constraint (4.3c) is infeasible. Using z_k, the non-linear constraint (4.7) can be reformulated using the big-M approach discussed in [72][47][62] and replaced by:

$$\sum_{k\in\mathscr{K}} p_k z_k \leq \delta \tag{4.8}$$

$$\sum_{i\in\mathscr{L}} d_i^k x_{ij} - c_j \leq U_j z_k \tag{4.9}$$

The expected cost shown in (4.3a) is equivalent to:

$$\sum_{k\in\mathscr{K}} \nu_k \sum_{j\in\mathscr{F}, i\in\mathscr{L}} w_{ij} d_i^k x_{ij}^k \tag{4.10}$$

where ν_k is the conditional probability that scenario k is a feasible scenario. ν_k is equal to $\frac{1}{\sum_k (1-z_k)}$. It is assumed that all demand scenarios are sampled with equal probability. Under that assumption, the value of ν can be obtained as follows:

$$\nu = \frac{1}{(1-\delta)K}$$

where K is the number of scenarios. Using equations (4.8), (4.9), and (4.10) and the model in (4.3a-4.3g), the resulting model is the general CCS-PCFLP problem formulated using the Big-M approach.

$$\begin{aligned}
\text{minimize} \quad & \sum_{j\in\mathscr{F}} f_j y_j + \sum_{j\in\mathscr{F}} h_j c_j + \sum_{k\in\mathscr{K}} \nu \sum_{j\in\mathscr{F}, i\in\mathscr{L}} w_{ij} d_i^k x_{ij}^k && (4.11a)\\
\text{subject to} \quad & \sum_{j\in\mathscr{F}} y_j \leq p, && (4.11b)\\
& c_j \leq U_j y_j, \quad \forall j \in \mathscr{F}, && (4.11c)\\
& \sum_{i\in\mathscr{L}} d_i^k x_{ij}^k - c_j \leq U_j z_k \qquad \forall k \in \mathscr{K}, j \in \mathscr{F}, && (4.11d)
\end{aligned}$$

$$\sum_{k\in\mathscr{K}} p_k z_k \leq \delta, \tag{4.11e}$$

$$\sum_{j\in\mathscr{F}} x_{ij}^k = (1 - z_k), \quad \forall i \in \mathscr{L}, \tag{4.11f}$$

$$y_j \in \{0,1\}, c_j \in \mathbb{R}^+ \quad \forall j \in \mathscr{F}, \tag{4.11g}$$

$$x_{ij}^k \in \mathbb{R}^+, z_k \in \{0,1\}, \quad \forall i \in \mathscr{L}, j \in \mathscr{F}, \forall k \in \mathscr{K} \tag{4.11h}$$

The previous model was reformulated using Big-M and can be solved a generic solver but it can be very time consuming as shown in section 4.4. Alternatively, constraint (4.3c) can be reformulated using the same definition for z_k as follows:

$$\sum_{i\in\mathscr{L}} d_i^k x_{ij} - c_j \leq U_j z_k \implies \sum_{i\in\mathscr{L}} d_i^k x_{ij} - U_j z_k \leq c_j \tag{4.12}$$

$$\sum_{i\in\mathscr{L}} d_i^k x_{ij} - U_j z_k \leq c_j \implies \sum_{i\in\mathscr{L}} d_i^k x_{ij} * (1 - z_k) \leq c_j \tag{4.13}$$

$$\sum_{i\in\mathscr{L}} d_i^k x_{ij} * (1 - z_k) \leq c_j \implies \sum_{i\in\mathscr{L}} d_i^k x_{ij} * (1 - z_k) \leq c_j * (1 - z_k) \tag{4.14}$$

$$\sum_{i\in\mathscr{L}} d_i^k x_{ij} * (1 - z_k) \leq c_j * (1 - z_k) \implies (\sum_{i\in\mathscr{L}} d_i^k x_{ij} - c_j) * (1 - z_k) \leq 0 \tag{4.15}$$

If z_k equals zero, that implies that scenario k is feasible which would imply that the demands from that scenario are less than the capacity. The Big-M constraint in equation (4.9) can replaced by the following constraint:

$$(\sum_{i\in\mathscr{L}} d_i^k x_{ij} - c_j) * (1 - z_k) \leq 0 \qquad \forall k \in \mathscr{K}, j \in \mathscr{F} \tag{4.16}$$

Despite the fact that constraint (4.16) is non-linear, this paper will show how helpful it can be if the problem is decomposed and solved using a benders' decomposition type algorithm. Constraint (4.16) is a bilinear reformulation that was first discussed in [81] along with several benders' decomposition algorithms. The following model is the bilinear reformulation for the general CCS-PCFLP represented by model M1:

$$\text{minimize} \quad \sum_{j \in \mathscr{F}} f_j y_j + \sum_{j \in \mathscr{F}} h_j c_j + \sum_{k \in \mathscr{K}} \nu \sum_{j \in \mathscr{F}, i \in \mathscr{L}} w_{ij} d_i^k x_{ij}^k \tag{4.17a}$$

$$\text{subject to} \quad \sum_{j \in \mathscr{F}} y_j \leq p, \tag{4.17b}$$

$$c_j \leq U_j y_j, \quad \forall j \in \mathscr{F}, \tag{4.17c}$$

$$(\sum_{i \in \mathscr{L}} d_i^k x_{ij} - c_j)(1 - z_k) \leq 0 \qquad \forall k \in \mathscr{K}, j \in \mathscr{F}, \tag{4.17d}$$

$$\sum_{k \in \mathscr{K}} p_k z_k \leq \delta, \tag{4.17e}$$

$$\sum_{j \in \mathscr{F}} x_{ij}^k = (1 - z_k), \quad \forall i \in \mathscr{L}, \tag{4.17f}$$

$$y_j \in \{0, 1\}, c_j \in \mathbb{R}^+ \quad \forall j \in \mathscr{F}, \tag{4.17g}$$

$$x_{ij}^k \in \mathbb{R}^+, z_k \in \{0, 1\}, \quad \forall i \in \mathscr{L}, j \in \mathscr{F}, \forall k \in \mathscr{K} \tag{4.17h}$$

It is clear that the general formulation for the CCS-PCFLP shown in (4.11a-4.11h) is more efficient to solve using a general solver than the bilinear formulation shown in (4.17a-4.17h). Nevertheless, Both approaches are extremely difficult to solve as a general MIP solver mainly due to the sheer number of variables and constraints in (4.17d), (4.17e), and (4.17f). The solution method proposed in this paper decomposes the bilinear formulation shown in (4.17a-4.17h). The recourse problem can be formulated as follows:

$$SP_k: \quad \text{minimize} \quad \sum_{j \in \mathscr{F}, i \in \mathscr{L}} w_{ij} d_i^k x_{ij}^k \tag{4.18a}$$

$$\text{subject to} \quad \sum_{j \in \mathscr{F}} x_{ij}^k = (1 - z_k), \quad \forall i \in \mathscr{L}, \tag{4.18b}$$

$$\sum_{i \in \mathscr{L}} d_i^k x_{ij}^k \leq c_j \qquad j \in \mathscr{F}, \tag{4.18c}$$

$$x_{ij}^k \in \mathbb{R}^+, \quad \forall i \in \mathscr{L}, j \in \mathscr{F} \tag{4.18d}$$

The k^{th} subproblem, denoted by SP_k, has an optimal value of ϕ_k, and a constant value for the capacity variable c_j. Let O^k and F^k be the set of extreme points and the set of extreme rays for SP_k. Note that z_k can be omitted from constraint (4.18b) in SP_k, mainly due to the fact that the effect of z_k will be represented by the bilinear optimality cuts (4.3.1) and infeasibility cuts (4.3.1). The dual problem for SP_k, denoted as DSP_k, is as follows:

$$
\begin{aligned}
DSP_k: \ \text{maximize} \quad & \sum_{j \in \mathscr{F}} c_j \theta_j + \sum_{i \in \mathscr{L}} \lambda_i && \text{(4.19a)} \\
\text{subject to} \quad & \lambda_i + d_i^k \theta_j \leq w_{ij} d_i^k, \quad \forall i \in \mathscr{L}, && \text{(4.19b)} \\
& \theta_j \leq 0, \quad j \in \mathscr{F}, && \text{(4.19c)} \\
& \lambda_i \in \mathbb{R}^+, \quad \forall i \in \mathscr{L} && \text{(4.19d)}
\end{aligned}
$$

The answer to the DSP_k can either be finite feasible or unbounded. If the solution is finite feasible the following optimality cut is generated:

$$\left(\sum_{j \in \mathscr{F}} c_j \theta_j + \sum_{i \in \mathscr{L}} \lambda_i \right) (1 - z_k) \leq \phi_k, \quad (\theta, \lambda) \in O^k, k \in \mathscr{K} \tag{4.20}$$

If the solution is unbounded the following feasibility cut is generated:

$$\left(\sum_{j \in \mathscr{F}} c_j \theta_j + \sum_{i \in \mathscr{L}} \lambda_i \right) (1 - z_k) \leq 0, \quad (\theta, \lambda) \in F^k, k \in \mathscr{K} \tag{4.21}$$

Cuts from the DSP_k depends on the value of z_k to be active in the master problem. This indicates that when the k^{th} scenario is not feasible the corresponding cuts are not included as both the left and right hand sides are zeros. The Master Problem (MP) is as follows:

$$
\begin{aligned}
MP: \ \text{minimize} \quad & \sum_{j \in \mathscr{F}} f_j y_j + \sum_{j \in \mathscr{F}} h_j c_j + \sum_{k \in \mathscr{K}} \nu \phi_k && \text{(4.22a)} \\
\text{subject to} \quad & \sum_{j \in \mathscr{F}} y_j \leq p, && \text{(4.22b)}
\end{aligned}
$$

$$\left(\sum_{j\in\mathscr{F}} c_j\theta_j + \sum_{i\in\mathscr{L}} \lambda_i\right)(1-z_k) \le \phi_k, \quad (\theta,\lambda)\in O^k, k\in\mathscr{K}, \tag{4.22c}$$

$$\left(\sum_{j\in\mathscr{F}} c_j\theta_j + \sum_{i\in\mathscr{L}} \lambda_i\right)(1-z_k) \le 0, \quad (\theta,\lambda)\in F^k, k\in\mathscr{K}, \tag{4.22d}$$

$$\sum_{k\in\mathscr{K}} p_k z_k \le \delta, \tag{4.22e}$$

$$c_j \le U_j y_j, \quad \forall j\in\mathscr{F}, \tag{4.22f}$$

$$y_j, z_k \in \{0,1\}, c_j\in\mathbb{R}^+ \quad \forall i\in\mathscr{L}, j\in\mathscr{F}, k\in\mathscr{K} \tag{4.22g}$$

The algorithm used to solve the problem is shown in Appendix (1)

4.3.2 Jensen Inequality

In this section, Jensen Inequality, represented by equation (4.23), will be used to develop cuts to improve the performance of the algorithm shown in Appendix (1). The main idea is to generates a cut that provides a good lower bound for the conditional expectation in the objective function. Let $Q(x,\omega)$ be the expected transportation cost for feasible scenarios in the objective function of M1 (and $\overline{M1}$).

$$\mathbb{E}(Q(x,\omega) \ge Q(E(x)) \tag{4.23}$$

Applying Jensen Inequality to the conditional expectation is shown as follows:

$$\begin{aligned}\mathbb{E}\left[\sum_{j\in\mathscr{F},i\in\mathscr{L}} w_{ij}d_i^{(\omega)}x_{ij}^{(\omega)}\middle|\Theta^{(\omega)}=1\right] &\ge \sum_{j\in\mathscr{F},i\in\mathscr{L}} \mathbb{E}\left[w_{ij}d_i^{(\omega)}x_{ij}\middle|\Theta^{(\omega)}=1\right]\\ &\ge \sum_{j\in\mathscr{F},i\in\mathscr{L}} w_{ij}\overline{x}_{ij}\mathbb{E}\left[d_i^{(\omega)}\middle|\Theta^{(\omega)}=1\right]\\ &\ge \sum_{j\in\mathscr{F},i\in\mathscr{L}} w_{ij}\bar{d}_i\overline{x}_{ij}\end{aligned} \tag{4.24}$$

Where $\overline{d_i}$ as defined as follows:

$$\overline{d_i} = \frac{\sum_{k \in \mathscr{K}} d_i^k P_k * (1 - z_k)}{\sum_{k \in \mathscr{K}} P_k * (1 - z_k)} = \frac{1}{1-\delta} \sum_{k \in \mathscr{K}} d_i^k P_k * (1 - z_k) \tag{4.25}$$

Using equations (4.24,4.25), the Jensen cut, shown in equation (4.26), is generated which can be added to the problem to improve solution times. Its important to note that $\overline{x}$ is a new variable that needs to be added to the model as well as the constraints in (4.27). The variable $\overline{x}$ and its constraints are not linked to any particular scenario (ω) and are part of the first stage master problem. The product of $z_k \overline{x}_{ij}$ is linearized just like $c_j z_k$ was linearized in the MP.

$$\eta \geq \sum_{j \in \mathscr{F}, i \in \mathscr{L}} w_{ij} \overline{d}_i \overline{x}_{ij} \tag{4.26}$$

$$\begin{aligned} &\sum_{i \in \mathscr{L}} \overline{d}_i \overline{x}_{ij} \leq c_j, \ \forall j \in \mathscr{F} \\ &\sum_{j \in \mathscr{F}} \overline{x}_{ij} = 1, \forall i \in \mathscr{L} \end{aligned} \tag{4.27}$$

The new MP is shown as follows:

$$\begin{aligned}
MP: \quad \text{minimize} \quad & \sum_{j \in \mathscr{F}} f_j y_j + \sum_{j \in \mathscr{F}} h_j c_j + \eta && \text{(4.28a)} \\
\text{subject to} \quad & \sum_{j \in \mathscr{F}} y_j \leq p, && \text{(4.28b)} \\
& \left(\sum_{j \in \mathscr{F}} c_j \theta_j + \sum_{i \in \mathscr{L}} \lambda_i \right) (1 - z_k) \leq \phi_k, \quad (\theta, \lambda) \in O^k, k \in \mathscr{K}, && \text{(4.28c)} \\
& \left(\sum_{j \in \mathscr{F}} c_j \theta_j + \sum_{i \in \mathscr{L}} \lambda_i \right) (1 - z_k) \leq 0, \quad (\theta, \lambda) \in F^k, k \in \mathscr{K}, && \text{(4.28d)} \\
& \eta \geq \sum_{k \in \mathscr{K}} \nu \phi_k, && \text{(4.28e)} \\
& \eta \geq \sum_{j \in \mathscr{F}, i \in \mathscr{L}} w_{ij} \overline{d}_i \overline{x}_{ij}, && \text{(4.28f)}
\end{aligned}$$

$$\sum_{i\in\mathscr{L}} \overline{d}_i\overline{x}_{ij} \le c_j,\ \forall j \in \mathscr{F}, \tag{4.28g}$$

$$\sum_{j\in\mathscr{F}} \overline{x}_{ij} = 1, \forall i \in \mathscr{L}, \tag{4.28h}$$

$$\sum_{k\in\mathscr{K}} p_k z_k \le \delta, \tag{4.28i}$$

$$c_j \le U_j y_j, \quad \forall j \in \mathscr{F}, \tag{4.28j}$$

$$y_j, z_k \in \{0,1\}, c_j \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F}, k \in \mathscr{K} \tag{4.28k}$$

The previous MP shows how the Jensen Inequality can be used to solve M1 (and $\overline{M1}$) using the bilinear benders algorithm described in 4.3.1. However, Jensen Inequality can also be used to generate a tight lower bound for M1, $\overline{M1}$, and M2 regardless of the solution method. The following section provides a more detailed discussion of how such a bound can be created.

4.3.3 Bounds

In this section, several bounds for M1 are discussed which can be helpful computationally for both the MIP formulation and the bilinear benders formulation. Jensen Inequality was used to bound the conditional expectation of M1 in equations (4.26, 4.27). A general lower bound for M1 can be obtained by solving the following MIP. JMIP is mainly used to get a lower bound for η which is helpful to any exact solution approach used.

$$JMIP: \quad \text{minimize} \quad \sum_{j\in\mathscr{F}} f_j y_j + \sum_{j\in\mathscr{F}} h_j c_j + \eta \tag{4.29a}$$

$$\text{subject to} \quad \sum_{j\in\mathscr{F}} y_j \le p, \tag{4.29b}$$

$$\eta \ge \sum_{j\in\mathscr{F}, i\in\mathscr{L}} w_{ij}\overline{d}_i\overline{x}_{ij}, \tag{4.29c}$$

$$\sum_{i\in\mathscr{L}} \overline{d}_i\overline{x}_{ij} \le c_j,\ \forall j \in \mathscr{F}, \tag{4.29d}$$

$$\sum_{j\in\mathscr{F}} \overline{x}_{ij} = 1, \forall i \in \mathscr{L}, \tag{4.29e}$$

$$c_j \le U_j y_j, \quad \forall j \in \mathscr{F}\ , \tag{4.29f}$$

$$\sum_{k\in\mathscr{K}} p_k z_k \le \delta\ , \tag{4.29g}$$

$$\bar{x}_{ij} \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F}, \tag{4.29h}$$

$$y_j, z_k \in \{0,1\}, c_j \in \mathbb{R}^+ \quad \forall i \in \mathscr{L}, j \in \mathscr{F}, k \in \mathscr{K} \tag{4.29i}$$

Another set of bounds are developed for a special case where the demands in each scenario are assumed to be *iid* uniformly distributed with parameters (b_i, a_i). We define the deterministic version of M1 using the demand percentiles $d_i^{\alpha\%}$ as $\mathrm{M1}_Q(\alpha)$. The optimal solution of $\mathrm{M1}_Q(\alpha)$ is Ψ_α. We also define $\mathrm{M1}(\delta)$ represent M1 with a chance level δ, Ψ_{CC_α} be the optimal value for $\mathrm{M1}(1-\alpha)$.

Proposition 1. *For $\alpha_2 \geq \alpha_1$, the following inequality is true:*

$$|\Psi_{CC_{\alpha_1}} - \Psi_{\alpha_1}| \leq |\Psi_{CC_{\alpha_2}} - \Psi_{\alpha_2}| \tag{4.30}$$

Proposition (1) indicates that the gap between the chance constraint model and its deterministic equivalent increases as α increases. Two insights can be inferred from Proposition (1). First, the optimal of $\mathrm{M1}_Q(\alpha_1)$, denoted as Ψ_{α_1}, is a lower bound for for chance constraint $\mathrm{M1}(\alpha_1)$. Second, larger value of α provide much tighter lower bounds.

Proof:

The gap between $\Psi_{CC_{50\%}}$ and $\Psi_{\alpha_{50}\%}$ is significantly smaller than the gap between $\Psi_{CC_{95\%}}$ and $\Psi_{\alpha_{95}\%}$. This behavior can be explained by looking at the total demand satisfied by each model, the total demand satisfied by $\Psi_{CC_{50\%}}$ (denoted by $d_{cc}^{\alpha\%}$, $\alpha = 0.5$) is identical to the the total demand satisfied by $\Psi_{\alpha_{50}\%}$ (denoted by $d^{\alpha\%}$, $\alpha = 0.5$) which can be easily shown. Let $Z_{\alpha\%}$ be the critical value for the standard normal distribution, and (μ_i, σ_i) be the mean and standard deviation for the demand distribution of pharmacy i. If pharmacy demands are iid then the total demand satisfied by the chance constraint model $d_{cc}^{\alpha\%}$, shown in equation (4.31), is normally distributed with mean $\sum \mu_i$ and a standard deviation $\sqrt{\sum \sigma_i}$.

$$d_{cc}^{\alpha\%} = \sum \mu_i + Z_{\alpha\%}\sqrt{\sum \sigma_i^2} \tag{4.31}$$

When $\alpha = 0.5$ the critical value $Z_{\alpha\%}$ equals zero which means $d_{cc}^{50\%} = \sum \mu_i = d^{50\%}$. This essentially means that regardless of the type of demand distribution, the expected value model is equivalent to the chance constraint model with $\alpha = 50\%$. Moreover, The optimality gap for $0.5 \geq \alpha$ increases as α increases, but in this case the rate of growth depends on the distribution type. The computational results shown in section (4.4) assumes that pharmacy demands are uniformly distributed with parameters (b_i, a_i), hence the total demand for the chance constraint model and the deterministic model are shown as follow:

$$d_{cc}^{\alpha\%} = \sum \mu_i + Z_{\alpha\%}\sqrt{\sum \sigma_i^2} \tag{4.32}$$

$$d^{\alpha\%} = \sum \mu_i + (\alpha - 0.5)\sqrt{12}\sum \sigma_i \tag{4.33}$$

The total demand satisfied by $\Psi_{CC_{95\%}}$ is significantly less than the total demand satisfied in it's deterministic equivalent due to $(0.95-0.5)\sqrt{12}\sum \sigma_i$ being much larger than $Z_{95\%}\sqrt{\sum \sigma_i^2}$. This indicates that $\Psi_{.95\%}$ provides a loose upper bound when compared with lower values of α that would provide tighter bounds.

4.4 Computational Results

The following results show M1's computational times for the MIP solver using Gurobi 8.0 and the algorithm discussed in the previous section. Table (4.1) shows the first set of experiments performed to show the performance of both solution procedures. K refers to the number of scenarios used in the problem, The total time shows the total script running time, Gap% refers to the optimality gap at the end of each run, and NULL refers to the inability to find a feasible solution within the time limit. The experiment shown in Table (4.1) has 20 facility locations, 100 demand points, and a maximum of 11 CF allowed. All runs in the experiment had a time limit of 30 minutes (not including setting up the problem), the optimality gap limit of 1%, and using the 95% chance constraint model.

Table 4.1: A 30 Minutes, 1% Optimality Gap Experiment

	Solver		Algorithm	
K	**Total Time (Seconds)**	**Gap%**	**Total Time (Seconds)**	**Gap%**
10	31	0%	33	0%
20	206	0%	87	0%
30	1860	28.5%	314	0%
40	1879	NULL	763	0%
50	1952	NULL	327	0%
60	1946	NULL	284	0%
70	1953	NULL	789	0%
80	1988	NULL	1254	0%
90	2015	NULL	1086	1%
100	2037	NULL	1808	3%

The results shown in Table (4.1) indicated that the solver was able to find an optimal solution for the first two experiments, but only a feasible solution for the third with a 28.5% optimality gap. However, it was clear that as the number of scenarios increased the solver was not able to handle the problem since no solution was obtained in seven out of ten experiments. The decomposition approach showed ideal performance as the algorithm was able to handle all ten problems and provided an optimal solution with acceptable optimality gap.

Table (4.2) shows a more extensive set of experiments with 60 minutes time limit and a 1% optimality gap limit. The results highlighted the effects of changing the Number Of CFs, Number Of Pharmacies, and the number of scenarios (K). Cases 1 through 23 showed that using the decomposition approach was beneficial in almost every case. In fact, solving for 250 scenarios (Case 24) the MIP solver was not able to obtain a feasible solution within 5 hours of running time and was only able to find an optimal solution after multiple days of running.

Table 4.2: A 60 Minutes, 1% Optimality Gap Experiment

				Solver		Algorithm	
Case	**Number Of CFs**	**Number Of Pharmacies**	**K**	**Total Time (Seconds)**	**Gap%**	**Total Time (Seconds)**	**Gap%**
1	10	100	25	41	0%	46	0%
2	10	100	50	1930	0%	72	0%
3	10	100	75	3699	0%	335	0%
4	10	100	100	3735	5%	216	0%
5	10	200	25	112	0%	75	1%
6	10	200	50	3739	0%	175	0%
7	10	200	75	3801	2%	213	0%
8	10	200	100	3863	3%	349	0%
9	10	250	25	89	0%	110	0%
10	10	250	50	3763	0%	254	0%
11	10	250	75	3589	3%	419	0%
12	10	250	100	3930	17%	638	0%
13	20	100	25	96	0%	231	0%
14	20	100	50	3736	26%	857	0%
15	20	100	75	3758	NULL	2110	0%
16	20	100	100	3839	NULL	3846	14%
17	20	200	25	252	0%	191	0%
18	20	200	50	3796	NULL	479	0%
19	20	200	75	3933	NULL	854	0%
20	20	200	100	4033	NULL	1898	0%
21	20	250	25	269	0%	209	1%
22	20	250	50	3852	NULL	826	0%
23	20	250	75	3981	NULL	2839	0%
24	20	250	100	4288	NULL	4134	7%

In theory a strategic decision such as locating a CF for a community pharmacy chain network should not be affected by a 5 day run time to obtain an optimal location. However, in practice companies typically perform a more extensive sensitivity analysis which requires several runs to the model.

For example, if it takes a company 5 days to obtain an optimal solution for an optimal CF location, and the company runs the model with different input 10 times, the results would take more than a month in computational time. Due to the expensive computational effort and lengthy process, a time efficient heuristic would be more appealing to use in practice. The solution approach provided in this paper could save major computation time, effort, and provide an optimal CF location.

4.5 Case Study

The previous section showed a time efficient solution methodology to the CCS-PCFLP. This section highlights the benefits of using the model in a realistic case study. The study was performed on a community pharmacy chain network in Pennsylvania (PA) that consists of 247 pharmacies spread around the state. The current network only uses local pharmacy resources to dispense medications. The main objectives of the community pharmacy chain network are to improve patient safety, patient satisfaction, and the overall customer experience. These objectives can be achieved by reducing customer waiting time, adding clinical services (e.g. immunization services), and reducing medication errors. Furthermore, management is determined to focus on improving patient safety by providing more PDPC services in each pharmacy. PDPC includes services such as Medication Therapy Management (MTM), patient counseling, and disease management that help patients better understand their medication/condition which reduces medication non-adherence and provides a better patient experience. PDPC services require a pharmacist and can be time consuming tasks depending on the patient.

Increasing PDPC service levels across the network can be achieved by adding more pharmacist so that there is more pharmacist capacity. However, this is a costly strategy. The average annual salary for a pharmacist in the state of Pennsylvania is $113,630 [23]. According to the 2015 National Cost Of Dispensing (COD) study [55], commissioned by the Coalition for Community Pharmacy Action (CCPA) on behalf of the National Association of Chain Drug Stores (NACDS) and the National Community Pharmacists Association (NCPA), the mean COD for a prescription in Pennsylvania is $9.31. Currently, the total dispensing time for a prescription in a pharmacy is nine minutes. Six out of the nine minutes are spent on drug review and drug verification which are tasks only pharmacists can perform. In a busy pharmacy, the pharmacist spends more time dispensing medication than providing PDPC to patients which is a missed opportunity. Adding an extra pharmacist in each location to satisfy PDPC demand is expensive, cost inefficient, and does not utilize the full capabilities of existing pharmacists. Note that, the average revenue generated from performing PDPC services is $2 per minute [26]. Thus, a 30 minute MTM session generates an average revenue of $60. There is an opportunity to increase revenue and improve patient safety but this opportunity may be missed if the pharmacist is mainly focusing on filling/validating prescriptions. This case study evaluates the utilization of a CF that can dispense prescriptions efficiently and enables pharmacists to focus on providing more PDPC services. Using a CF system is only economical for stores within a reasonable distance of the CF.

The data for this case study was gathered using a combination of expert opinions and data collected from multiple pharmacy locations in the state of Pennsylvania. The road distance matrix was obtained using Google's Distance Matrix API. The number of stores in the community pharmacy chain network is 247. It can be seen that store locations are directly influenced by population density. For instance, Philadelphia and Pittsburgh are the two major population centers in the state of Pennsylvania and have the highest number of stores per city in the network. There are 55 pharmacy locations in Philadelphia and 22 pharmacy locations in Pittsburgh. Figure 4.2 shows the distribution of pharmacy locations in PA (grey zip codes), and the possible CF location (black zip codes).

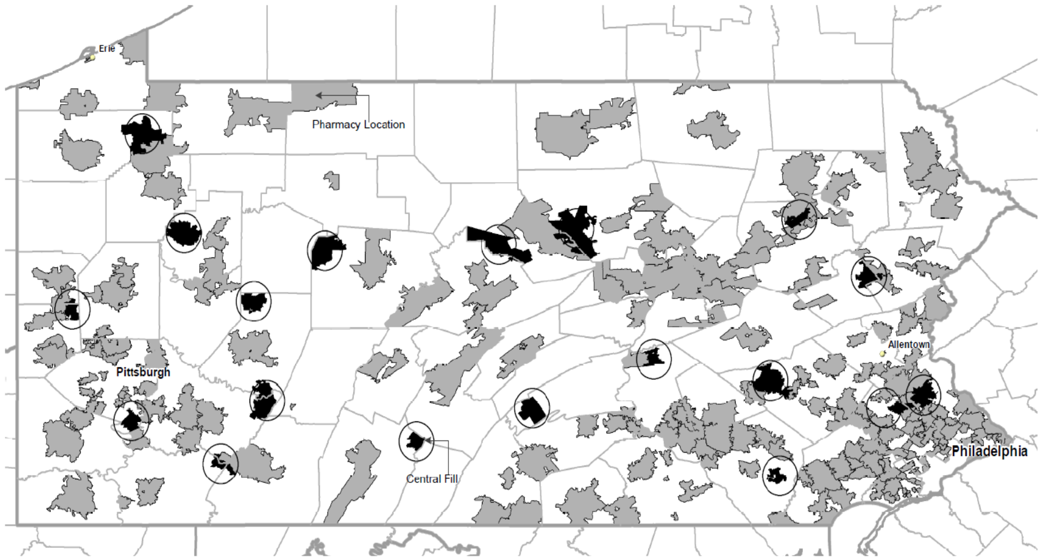

Figure 4.2: PA Pharmacy Locations and Possible CF Locations

Each pharmacy in the network has a demand range and a staff schedule. It is assumed in this case study that each pharmacy is staffed with enough resources (pharmacists, technicians, and clerks) to handle its daily prescriptions. For example, a rural pharmacy in central Pennsylvania has a daily demand range of [211, 560] prescriptions, and a pharmacy in downtown Pittsburgh has a daily demand range of [286, 874]. For both locations the staff can handle up to 560 and 874 prescriptions, respectively. If the demand is high on a given day, the pharmacy staff work overtime to fill all of the prescriptions. Additionally, the busier the pharmacist is the less PDPC services can be provided. The problem in the case study has 247 pharmacies and 20 candidate CF locations. The decomposition solution approach discussed in the previous sections is used to obtain the results shown below.

4.5.1 Case Study: Results and Analysis

There are two factors that directly affect the overall CF locations which are P and δ. P is the number of possible CF locations that can be built and δ is the probability in the chance constraint (4.3c).

In this section, the effects of P and δ are discussed from economical and patient safety perspectives. Patient safety can be judged by the number of hours dedicated in the pharmacy for PDPC services. The following experiments were performed using the solution algorithm with 100 demand scenarios and with a 40,000 (daily prescriptions) CF Capacity.

Figure 4.3 shows prescription dispensing cost inside the local pharmacy, dispensing cost from using a CF, and the potential PDPC revenue added by utilizing a CF. in the CF and using pharmacy resources. The model in this experiment has a 95% chance constraint which implies that the highest 5% of demand scenarios do not have any effects on the CF's capacity, hence, they do not affect the overall location problem. The total COD for prescriptions is highest when P equals zero. As P increases the total COD decreases due to having a less constrained problem with the potential to create a more cost efficient dispensing process. The maximum number of CFs for this experiment was 6 facilities (i.e. if P was greater than 6, the number of CFs located would still be 6). At P equals 6 the COD using pharmacy resources is minimized but is not completely eliminated. This is due to the fact that it is more economical to use pharmacy resources to dispense prescriptions for pharmacies that are far away from the CF.

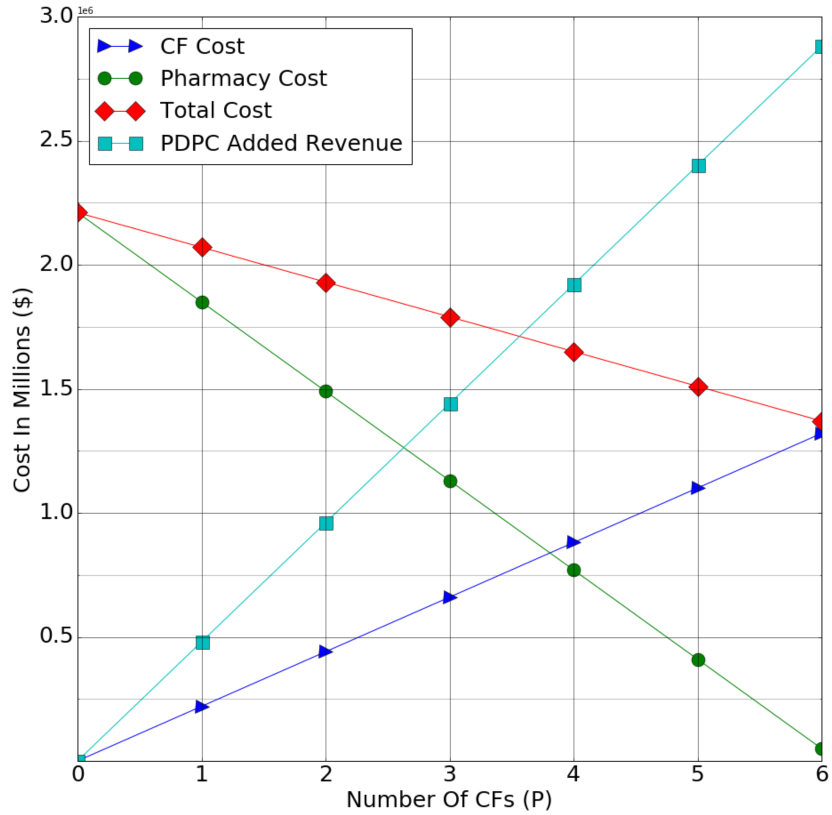

Figure 4.3: Total Cost Summary For a 95% Chance Constraint Model

Adding more CFs to the network reduces the overall COD as shown in the Figure 4.3, but most importantly it allows the pharmacist/pharmacy to focus on patient safety by providing more PDPC services. Each prescription filled using the CF clears 6 minutes from the pharmacists' dispensing workload. PDPC services include a wide range or services, some are considered revenue generating but others are not. For example, as previously noted MTM is an essential PDPC service that can generate a revenue of 2 dollars per pharmacist minute. In Contrast, Patient Counseling (PS) services are considered complementary services that improve patient safety and patient satisfaction. The resulting network for a 95% chance constraint model is shown in Figure 4.4, the map shows six CF locations (in black) that service prescription demand from the entire network.

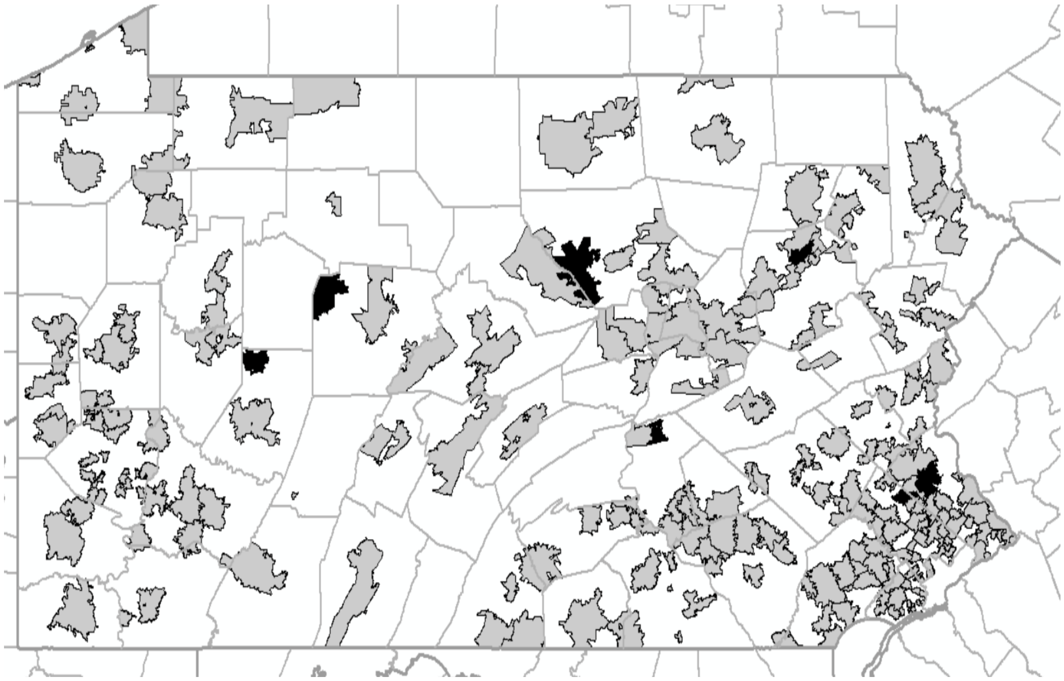

Figure 4.4: CF Locations for a 95% Chance Constraint Model

The following experiment shows the effects of changing δ which controls the probability in the chance constraint (4.3c). Table 4.3 shows the effect of increasing δ on the number of CFs and the average PDPC services provided in the network. It can be concluded that as δ increases the number of CFs built in the network increases.

Table 4.3: Chance Sensitivity Analysis

Case	$(1-\delta)$**(%)**	**No. Of CFs**	**Potential PDPC hours**
1	10%	4	14,026
2	20%	5	18,830
3	30%	5	18,537
4	40%	5	18,327
5	50%	5	18,012
6	60%	5	17,815
7	70%	5	17,820
8	80%	5	17,090
9	90%	6	21,801

The potential PDPC hours provided by the pharmacy is directly influenced by the the number of CFs used. Case 1 has an optimal number of CFs built when 90% of demand scenarios are ignored which leads to case 1 having the lowest number of CFs built across the network. Consequently, the potential PDPC is at its lowest level even though case 1 has the lowest average demand. This is due to the fact that only 4 CFs are used which means more pharmacy resources are being consumed to dispense medications. Case 2 however, has double the amount of feasible scenarios and shows a 25% increase in the potential PDPC hours provided in the network due to the addition of a CF. As the average prescription demand increases in cases 2-7, the number of potential PDPC hours show a slight decrease. Case 8 has an additional CF built due to the increased demand, but also leads to a higher number of potential PDPC hours. Table (4.3) shows that the number of CFs directly influences the potential PDPC services offered in the community pharmacy chain network improving overall patient safety and generating potential new income to the pharmacy.

4.6 Conclusions

This paper purposes a new approach to locate an automated CF in a community pharmacy chain network. Three different large scale optimization problems were presented. The main model M1 showed how to locate CF under stochastic demands, and showed that the objective function provides the optimal CF dispensing cost by ignoring (1-δ)% of the top demand scenarios. M2 showed a similar model but the objective function implicitly include the local pharmacy dispensing cost for any demand that was not met by the CF. Both M1 and M2 provided the optimal CF location under a chance level δ but M2 included the total cost of dispensing rather than just the CF cost of dispensing. A third version of the location model was presented $\overline{M1}$ that limits the distance between the CF and the local pharmacy, as well as limits the portion of the demand the local pharmacy can fill. The main structure of all three models is similar and they all are considered NP-hard problems that can not be solved efficiently using general solvers. The decomposition approach proposed in section (4.4) is shown to be an effective approach to solve the problem in the general case. The value of using the hub and spoke model was further investigated in section (4.5) using a hub and spoke model for a community pharmacy chain network in PA.

The case study showed that utilizing a certain number of CFs into the network allowed for more PDPC and clinical services to be provided by the community pharmacy chain network thus improving the overall health of the community and provide a new potential income for the community pharmacy. The potential income is depends on the exact services provided (e.g. PS is typically considered a complementary service but MTM services can be billed to the insurance). The joint chance constraint model presents a way to evaluate the trade-offs between dispensing prescriptions in the pharmacy versus dispensing them in a CF. The model showed that ignoring the top 10% of demand scenarios saved the network from building a sixth CF and showed that if the sixth CF was built the network would be able to provide approximately 4000 more PDPC hours. The true value of the sixth CF would depend on how many PDPC hours can actually generate income to the network. The case study showed how the model can provides the decision maker with the ability to make system design decisions that limits the effects of the stochastic demand on the location solution.

5.0 Conclusions

The work discussed in this dissertation has been in the realm of community pharmacy chain networks and their operations. Specifically, we study the impact of adding PDPC services which can be highly disruptive to community pharmacy workflow as they increase the overall workload in the pharmacy. More importantly, the added PDPC services can easily increase the expected workload of the pharmacist which is a bottleneck resource. The addition of PDPC services impacts the different stakeholders involved with community pharmacies. On one hand, the added services provide a revenue stream for the pharmacy that can be as high as $120 per hour [26] but on the other hand it increases the workload inside the pharmacy. However, the income generated and the added health benefits of providing such services provide a compelling motivation for community pharmacies to add more PDPC services.

Adding more PDPC not only adds economic value to the pharmacy but also tackles one of the most prominent problems in healthcare. According to the Nashville project [11], PDPC services caused cardiovascular medication use to increase more than 300% (i.e better medication adherence) and actual cardiovascular medical costs decreased by 45%. The effects of the added services even go beyond cost cutting as the improvement in medication adherence led to a significant improvement in the quality of life of cardiovascular patients. Finally, according to a 7 year analysis of the effect of MTM services, the average estimated cost avoidance per patient was $93 [7]. MTM was also shown to improve medication adherence by 4.6% among outpatients with chronic illnesses which can also be thought of as a cost avoidance of 4.6 billion dollars since medication non-adherence costs the US health care system $100 billion per year[8].

The first thing this dissertation expands on the idea that there is great benefits to the community, the pharmacy, and the patients when adding more PDPC services. However that clearly requires more dedicated pharmacist time. Chapter 2 showed how an individual community pharmacy can handle more PDPC using internal strategies. The three main strategies evaluated are adding an extra staff member, predicting pick up times, and dynamically changing how PDPC services are offered in the pharmacy. The main contributions from Chapter 2 can be summarized as follows:

- The results showed that adding a pharmacist, as opposed to a technician, produces a more effective pharmacy especially if PDPC services were increased by more than 40%. For lower levels of PDPC services, an extra technician could be a cost efficient solution. In general, adding an extra staff member might be an effective strategy for an individual pharmacy, but would be very costly for a large community pharmacy chain network.
- The next set of experiments evaluated the value of using pick up time prediction models. The results indicated that if the goal is to have 20% PDPC services then strategies such as knowing precise pick up time could be beneficial. The simulation showed that there is no difference between using precise pick up prediction models and imprecise pick up prediction models (fully accurate). Both cases prioritize work according to predicted pick up information and both cases benefit greatly from being able to predict eRx abandonment. Prioritizing work based on predicted pick up times does not provide significant improvements over using a FIFO work scheduling rule when the overall staff utilization is low.
- Imprecise pick up time prediction was only better than no pickup information if the day of pickup was known with high accuracy. In most cases, the accuracy must be at least 87% or else the system performance was worse than having no pickup information. The accuracy level needed depends mainly on the workload in the pharmacy and the portion of eRx that need to be finished in the same day.
- The third internal strategy tested, using dynamic PDPC services, showed higher effective PDPC rates than hiring an extra pharmacist. However, this comes at the price of higher check out wait times and higher rates of unsatisfied customers. A better strategy would be to use a combination of dynamic PDPC and hiring a pharmacist which produces the highest effective PDPC rates. It is important to note that dynamic PDPC does change the duration of PDPC services which can limit the PDPC services provided. For example, MTM is known to be a PDPC service that requires a long time commitment from the pharmacist, a short PDPC service interval would not be enough to complete an

MTM service. However, dynamic PDPC operates under the assumption that a customer receiving no MTM is worse than a one receiving an abbreviated MTM session.

Chapter 2 showed that a community pharmacy committed to provide PDPC services (i.e. at least 40% of the population) needs to minimize pharmacist dispensing time and increase pharmacist PDPC time. Chapter 3 builds on this idea and introduces a different class of strategies (i.e. external strategies) that either reduce the dispensing load or increase PDPC capacity. First, the CF strategy dispenses eRx cost efficiently and reduces a local pharmacy's resource commitment in the dispensing process. The second external strategy introduces a new way to provide PDPC services in the community pharmacy in the form of PDPC kiosks which essentially provided PDPC capacity without disrupting the dispensing process. We can summarize the key contributions of the chapter in the following points.

- The CF strategy was shown to be effective to divert pharmacist time to PDPC services. The first operating policy, which dispenses after hour demand, can provide up to 40% PDPC (31% effective). Additionally, using this operating policy the CF lowers the cost of dispensing in the pharmacy, and lowers the number of clerks required. The second CF operating policy maximizes the effects of the CF and allows the local pharmacy to offer 60% PDPC services and effectively 40% of the population which is a 25% improvement over the first operating policy. Essentially using the CF reduces dispensing costs, reduces inventory costs, reduces clerk costs, and improves PDPC services across the network.
- The PDPC kiosk strategy also has two polices, the first is designed not to interrupt the dispensing process, and the second maximizes the amount of PDPC services provided. Both use PDPC centers which can be an effective way to balance the amount of PDPC services provided in each pharmacy from a network prospective. In other words, hiring a pharmacist inside the local pharmacy can only help the local pharmacy's PDPC but adding a pharmacist to the PDPC center will provide support to the entire network. The two policies were tested with an uncapacitatetd PDPC center and a capacitated one, and the difference was not significant. Both policies seem to be able to handle offering PDPC to 100% of the population but the effective service level depends on the number of kiosks and the ability to seize a pharmacist from the PDPC center. The first operating policy

offers lower PDPC services (with or without a capacitated PDPC center) and it does not affect the dispensing process. The second operating policy, maximizes the amount of PDPC services by seizing the local pharmacist when the pharmacy has a low dispensing work load. This leaves the pharmacy with a highly utilized pharmacist which makes the pharmacy vulnerable in case of an emergency or an unanticipated event.

The previous chapters evaluated different policies that can be used inside the local community pharmacy to provide higher levels of PDPC. One of these strategies was utilizing a CF in a community pharmacy chain network. It was assumed that the CF is located to minimize transportation costs. Chapter 4 shows how a CF can be located under stochastic demand using large scale optimization modeling. The main optimization problem minimizes the expected dispensing cost for the CF under a capacitated chance constraint. Two other versions of the problem were introduced that included extensions to the main problem such as a distance limit between the CF and its pharmacy, the ability to dispense eRx locally at a higher cost, and the ability to limit the portion of demand filled in the local pharmacy. We summarize the key contributions of the chapter in the following points.

- The main structure for all three NP-hard problems is similar and a solution algorithm for the general model can be used to solve all three. Several bounds were proposed for the general problem that can be used to improve any proposed solution algorithm. A bilinear decomposition approach was proposed, and implemented. The algorithm was shown to be an effective approach to solve the problem in the general case.
- The last section of Chapter 4 showed the value of using the hub and spoke model in a real community pharmacy chain network in PA. The case study showed that utilizing a certain number of CFs in the network allowed for more PDPC and clinical services to be provided by the community pharmacy chain network, thus, improving the overall health of the community and providing a new potential income stream for the community pharmacy. The optimization model was used to evaluate the number of pharmacist hours saved inside local pharmacies. The total number of hours can potentially be used to provide PDPC services and generate income depending on the service (e.g. PS is typically considered a complimentary service but MTM services can be billed).

- Applying the model on a real life case study showed that it can be used to evaluate different trade-offs between the amount of prescriptions dispensed in the CF and the local pharmacy. One of the benefits of using the model is that the user can decide what percentile of demand to consider (95th, 99th, etc.). For example, ignoring the last 10% of the demand scenarios saves the network from building an extra CF that would not be highly utilized on a regular basis.

Appendix

Bilinear Benders Decomposition

Algorithm 1 Bilinear Benders Decomposition

Set LB = $-\infty$, UB=∞, $O^k = F^k = \emptyset$
while $\frac{LB-UB}{LB} \leq Gap\%$ **do**
    Solve Master problem (MP)
    if MP is infeasible **then**
        Stop
    else
        obtain the optimal value, V, and the optimal vector $(\bar{y}, \bar{c}, \bar{z})$
        LB = P
    end if
    End if
    for $k \in \mathscr{K}$ **do**
        Solve the the Sub Problem $SP_k(\bar{y}, \bar{c}, \bar{z})$
        if SP_k is unbounded **then**
            $F^k = F^k \cup (\theta, \lambda)$
        else
            SP_k is feasible $O^k = O^k \cup (\theta, \lambda)$
            let SP_k be the optimal solution for the subproblem
        end if
        End if
    end for
    End for
    UB = $min\{UB, V + \sum_k p_k SP_k\}$
end while
End while

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