MACRO LEVEL DESIGN OF HEALTHCARE NETWORKS USING OPTIMIZATION AND SIMULATION

A Thesis Presented

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Abstract

Macro level design of networks is usually considered as determining the locations and capacity levels of the resources as well as the assignment of entities to these resources. Given the high costs of healthcare coupled with a focus on access and preventive health, many healthcare systems are engaged in macro-level planning of their overall network topology, care location, market expansion, and merger strategies. The use of systems engineering models to help inform these decisions can be very effective at designing both cost-efficient and qualified healthcare services, especially in cases involving complex and competing considerations.

This thesis presents several systems engineering approaches and applications to design cost efficient, patient centered and easy to access healthcare systems. The approaches have been applied to a variety of problems ranging from locating care services to designing regional healthcare networks in different healthcare delivery systems, particularly the U.S. Department of Veterans Affairs (VA) and Harvard Vanguard Medical Associates (HVMA). Approaches for service location have been applied to colonoscopy screening services at the VA and ultrasound screening services at HVMA. Similarly, VA telehealth network and HVMA Ob/Gyn network have been picked to apply regional network design approaches. In each case, it is shown that care
services can be optimally located or re-located within a geographic region in a way that provides greater access to a larger population at lower costs.
Acknowledgements

The pages of this thesis hold far more than the conclusion of years of study; they also reflect the relationships with many great people to whom I owe my deepest gratitude for being a part of this journey.

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Chapter 1 - Introduction

In 2001, the Institute of Medicine described the current state of the healthcare system as being far from ideal and recommended that several emergent actions be taken [1]. Today, besides being the most expensive healthcare system with inadequate service level, the U.S. healthcare system has the fastest pace of cost increase among any other countries in the Organization for Economic Cooperation and Development (OECD) [2]. In 2005, the Institute of Medicine collaborated with the National Academy of Engineering to release another report, *Building a Better Delivery System* [3] which defined the use of systems and industrial engineering techniques as one of the core areas to effectively improve the healthcare system. Using engineering tools to prevent inefficiencies and eliminate waste in every field of the system is still a substantial concern.

Macro level design of a healthcare network which involves in finding the optimal locations of the care services, capacity levels and allocation of demands to these services plays an important role on the efficiency and cost-effectiveness of the overall system. Among many systems engineering approaches, location-allocation models play a critical role and help create a healthcare network with minimum social cost or equivalently maximum individual benefit [4], [5].
This thesis focuses on multiple systems engineering approaches to solve real life network design problems such as locating care services and designing regional healthcare networks. The approaches have been applied to two different healthcare systems, U.S. Department of Veterans Affairs (VA) and Harvard Vanguard Medical Associates (HVMA). In this chapter, general information about the VA and HVMA healthcare systems, unifying framework of the systems engineering approaches used to design networks and the outline of the thesis are provided.

1.1 U.S. Department of Veterans Affairs

U.S. Department of Veterans Affairs (VA) is the largest integrated healthcare network in the United States, with 21 regional networks providing health services to 8.76 million U.S. veterans across the country each year. Figure 1 shows the regional networks which are referred as Veteran Integrated Service Networks (VISNs). The mission of the VA is to fulfill President Lincoln’s promise by serving and honoring the men and women who are America’s veterans [6]. With more than 1,700 sites of care scattered all around the country, the VA strives to provide accessible, timely and quality care to the veterans.

![Figure 1: Veteran Integrated Service Networks by region](image-url)
The VISN1 is one of 21 VISNs within the Department of Veterans Affairs. VISN1 provides healthcare services at 9 medical centers and 40 outpatient clinics. They are located throughout the New England states (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut) and provide comprehensive medical services to 235,000 veterans residing in the New England states (Figure 2).

Figure 2: Location of VA Medical Centers and demand points in VISN1
In addition to the medical centers and outpatient clinics, VISN 1 operates 6 nursing homes and 2 additional institutional facilities for aged and disabled veterans. With its large network area, wide range of services, and well-developed electronic medical record data warehouse, VISN 1 provides an ideal setting to apply network design tools discussed in this thesis.

1.2 Harvard Vanguard Medical Associates

Harvard Vanguard Medical Associates (HVMA) is a non-profit, multi-specialty medical group practice providing care to more than 530,000 adult and pediatric patients at more than 20 offices across eastern Massachusetts with 3,700 employees, including more than 600 physicians and 1,000 other healthcare professionals [7]. Figure 3 shows the locations of HVMA distributed across the Greater Boston Area.

![Figure 3: Location of HVMA centers](image-url)
Although HVMA covers a relatively smaller area compared to VISN1, patient volume of HVMA is almost two times more than VISN1 thus locating care services within HVMA network and determining capacities is quite crucial.

1.3 Unifying Framework

Location-allocation models, which determine the location of facilities and match supply and demand in order to optimize predefined objectives such as facility cost, travelled distance, and demand coverage, are one of the systems engineering approaches that try to cope with the complexity of macro level network design problem. They have been extensively applied over a wide range of application areas such as telecommunication [8], web services [9], energy and spanning retail [10], and manufacturing industries [11]. Professionals both in and outside of academia have made tremendous efforts to implement findings from location-allocation studies. A total of 730 source titles related with facility location have been discovered via a statistical report received in SCOPUS. Moreover, most of these studies were performed within the last two decades which indicates an increasing interest in the area [12].

Location and allocation of resources have been regarded as a significant problem in industry since insufficient strategic decisions on network planning may lead to poor customer service and/or increased operational costs. In healthcare, the effects of the location models extend well beyond customer convenience and cost effectiveness. Inadequate access to care can lead to increases in mortality and morbidity rates. Therefore, the application of location models in healthcare is especially important [13]. Healthcare applications offer significant improvements in both cost and accessibility, including locating ambulances [14] and hospitals in rural regions.
[15], trauma care resources [16], organ transplant services [17], blood facilities [18], emergency medical service vehicles [19], hospital networks [20], and specialized healthcare services such as Traumatic Brain Injury (TBI) treatment [21], [22] and sleep apnea services [23], [24]. Furthermore, models for optimal healthcare facility locations for moving populations [25] and healthcare planning with explicit geographical considerations [26] have been developed and applied in real-life case studies.

Location problems can be classified as either discrete or continuous. In continuous models, facilities can be located anywhere within the boundaries of a given geographic area, whereas in discrete models the candidate locations are assumed to be a finite set of locations where facilities can be sited. Demand is aggregated in both of the models to form a finite set of demand nodes. The finite set assumptions improve the solvability of the problem in terms of the running time. All models aim to choose the best facility locations, where “best” is usually defined by the users, based on the performance measures they seek to optimize.

The basic models used for facility location problems include set covering, maximum covering, and $P$-median models. The first two models emphasize coverage. A coverage distance is predetermined in both of these models in order to limit the travelling distance of customers. The set covering model, introduced by Toregas and ReVelle [27], aims to minimize the total number of facilities while covering all demand nodes. Hence, the relative volume of demand nodes is not distinguishable in the set covering model. In order to overcome the impact of this problem, the maximum covering model was introduced by Church and ReVelle [28]. This model considers the relative demand of each demand node in the objective function and aims to maximize population coverage with a limited number of facilities. Finally, the $P$-median model aims to minimize the
weighted average distance travelled by demand while optimally locating $P$ number of facilities. Literature consists of various extensions of these models over the past decades in several areas such as manufacturing [11], distribution networks [8], and web services [9].

All of the studies described above present that use of location–allocation models provide helpful insight for the decision maker. We have also used these models in all of the applications presented in this study to help the decision maker and reduce the overall cost of the care network. Results indicate significant savings and the importance of using analytical tools.

One downside of these models is that most of the time they assume demand is deterministic and precisely known in advance however in real life demand for many services is stochastic and not known ahead. In order to address this issue and account for the variability in demand, we have used Monte Carlo Simulation and generated random demand for the care services. The optimization models have been solved many times with the randomly generated demand and the solutions have been presented.

The remainder of this thesis is organized as follows. Chapter 2 presents two applications related to locating care services. In the first application, colonoscopy units have been located across the VA New England network using deterministic location-allocation models then Monte Carlo Simulation is used to address the variability in demand. Similar to the first application, in the second application, ultrasound units have been located within HVMA network and the impact of patient allocation on capacity and utilization has been inspected using stochastic models. In Chapter 3 we present optimization models to design regional care networks for the same healthcare providers. In the first application, we design a network using deterministic optimization for telehealth usage in VA White River Junction catchment area and later use
simulation to address stochastic demand. In the second application, we have used allocation models to redistribute the HVMA delivery volume to the candidate hospitals. Finally, a summary of conclusions, limitations, and recommendations for future work are addressed in Chapter 4 -
Chapter 2 - Locating Care Services

Extended traveling distances for patients is a common problem in healthcare throughout the United States. It is therefore essential to find the optimal location of care units in order to increase access to these units and improve patient satisfaction. This chapter presents the application of systems engineering techniques to two different healthcare networks.

2.1 Locating Colonoscopy Screening Units in VISN1

Cancer care is a vital field that can be improved in terms of cost efficiency and quality. According to a National Cancer Institute report, cancer care in the United States cost $124.57 billion in 2010, accounting for 5% of total medical costs. With a 30% increase in the cancer survival population by 2020, annual spending on cancer care is expected to reach $207 billion [29]. Colorectal cancer (CRC) is the second leading cause of cancer-related deaths in the U.S. On average, a U.S. person at an age of fifty has a 5% chance of contracting the disease, and a 2.5% chance of dying from it [30]. Early detection and treatment of the disease is a crucial step for preventing its spread and reducing the mortality rate. Typically, no symptoms are seen at the early stages of colorectal cancer. Hence, screening for the disease is vitally important [31] and the past studies show that CRC screening has potential benefits in reducing mortality rates [32].
The American Cancer Society recommends that all average risk individuals should undertake one of five screening methods: an annual fecal occult blood test (FOBT), a flexible sigmoidoscopy every 5 years, an annual FOBT combined with flexible sigmoidoscopy, a colonoscopy every 10 years, or a double-contrast barium enema every 5 years. Colonoscopy is the endoscopic examination of the colon that diagnoses the disease at an early stage and removes colonic polyps. Even though colonoscopy is the most burdensome and expensive screening option, there is an increasing interest for it since it examines the entire colon and removes colonic polyps during the screening session [33]. It is unique among screening methods in that the definitive treatment (removal of a cancerous or pre-cancerous growth) can be accomplished as part of the screening in many cases. Recently, there has been increasing debate about the use of colonoscopy due to limited availability of endoscopic resources [34]. The American Cancer Society suggests an average risk person preferring colonoscopy screening option for colon cancer should start the screening at the age of 50, and repeat the test every 10 years. In addition, any alternative screening options that result in a positive test result should be followed up with colonoscopy [35]. The continuity and recurrence of the service leads to high demand, which in turn leads to concerns on meeting the demand with the limited resources. Because many patients will need multiple colonoscopies over a period of decades and because colonoscopies are a limited resource, using engineering tools to optimally allocate colonoscopy services may be useful by suggesting strategies improve accessibility in the most cost efficient way. This section explores such opportunities by optimizing location-allocation decisions for colonoscopy screening services across the Veterans Health Administration New England Network (heretofore called Veterans Integrated Service Network 1, or VISN1).
2.1.1 VA Colonoscopy Services

In 2008, 16,912 veterans received colonoscopies at a total cost of $20,796,635. Figure 4 summarizes number of screening colonoscopies provided in VISN 1 in 2010, with patients residing in Connecticut and Massachusetts receiving the majority of screenings.

![Colonoscopy visits by state across VISN1 (January 2008 – December 2008)](image)

Currently, six of nine VA medical centers in VISN 1 provide colonoscopy screening service. VISN 1 leadership has reported that multiple facilities claim inadequate access to service causes a large number of veterans to be sent to out-of-network providers to be tested. The fees for these out-of-network services are reimbursed by the VA (so-called “fee basis” visits) and can represent a substantial expenditure. In the case of colonoscopy, 45.6% of the colonoscopy tests were directed to the out of network facilities for a total cost of $9,106,102. Table 1 describes where VA patients from each New England state received colonoscopy screenings and the percentage of fee type visits at each VA facility in 2008. For example, 481 patients living in Massachusetts accessed screening colonoscopies by going to Providence, and 17% of them were directed to out of network facilities from there in order to get their screening test.
Table 1: Allocation of patients to the current facilities and corresponding capacities in 2008 (WRJ: White River Junction, row 1: total # of patients assigned to each facility, row 2: directed fee type visits %)

<table>
<thead>
<tr>
<th>Patients by state</th>
<th>Facility</th>
<th>Boston (fee%)</th>
<th>West Haven (fee%)</th>
<th>Manchester (fee%)</th>
<th>Providence (fee%)</th>
<th>Togus (fee%)</th>
<th>WRJ (fee%)</th>
<th>Northampton (fee%)</th>
<th>Bedford (fee%)</th>
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<tr>
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<td>481</td>
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<td>9%</td>
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</table>

Table 1 points out of the trends in patients’ travels to specific VA facilities in order to get their treatment. The last row indicated as capacity refers to the total number of colonoscopy screening units (staffed colonoscopy beds) at each location. On average, 5 screening tests can take place per day at each colonoscopy unit. It is also noted by the specialists in VA that because of the time variety of each operation, 30% more capacity is available. The majority of patients received colonoscopy screening at a facility in their state. However, a certain number of visits in each state occurred at various VA facilities in other states, leading to an increase in the variation and average time of travel distance. Significant amount of patients were directed to out-of-network facilities from Northampton and Bedford, whose capacities are 0. Some facilities with multiple screening units, including West Haven and WRJ, used a substantial number of fee-type visits.

The relationship between fee-type visits and current capacities was analyzed in more detail. As shown in Figure 5: Number of fee type visits vs. monthly utilization at facilities located in (a) West Haven, (b) WRJFigure 5, the utilizations for West Haven were always between 60% and
80%, but a large number of fee visits took place in the facility. On the other hand, even though the utilization rates were lower for WRJ, fee visits were still reported in the facility. It can be concluded that fee-type visits were not evenly matched with capacities or utilization levels, since correlation between house visits and fee visits also support the weak agreement between them ($r = .264, p = .407; r = -.074, p = .820$ for West Haven and WRJ, respectively).

Figure 5: Number of fee type visits vs. monthly utilization at facilities located in (a) West Haven, (b) WRJ

Figure 6 summarizes the distances patients travelled to receive care, with a mean of 39.36 miles (min 0, max 526 miles). Approximately 80% of patients travelled less than 60 miles, a typical distance threshold used to define acceptable versus unacceptable access. The 30 mile threshold is particularly important measure for VA since VA reimburses travel expenses of veterans who travel more than 30 miles. In the colonoscopy case, 56% of patients drove distances typically eligible for travel reimbursement in 2008.
In the following section, we construct a Mixed Integer Linear Programming (MILP) model to solve the problem of assigning patients to VA facilities, determining their optimal capacity, and opening new screening units if necessary.

### 2.1.2 Methodology

#### 2.1.2.1 Model Overview and Assumptions

In order to design a cost-effective system with higher patient access, we developed a mathematical programming model to determine the optimal location and capacity of screening laboratories as well as to assign patients to each of them in a predefined planning horizon. The overall aim of the model is to modify the existing network of locations and capacities in a rational way that minimizes the overall cost of screening service across the New England area.

The mathematical model is a hybrid model which combines the objectives of \(P\)-median, set covering and maximum covering models by quantifying them in terms of their dollar values provided by stake holders. In the model, we minimize the overall system cost (comprising the total cost of within-network visits, out of network visits, unused capacity, and capacity expansion) by determining the optimal number of colonoscopy screening laboratories and
opening them at existing VA facilities. We adapted a maximum allowable distance, $S$, from the set covering and maximum covering problem to determine the within and out-of-network visits. More specifically, if a patient cannot be assigned to a VA facility, the model directs the patient to an out-of-network provider at VA’s expense, referred to as a fee-type visit cost. On the other hand, patient visits that can be assigned to a VA facility within the acceptable distance are referred to as in-house type visits, and incur operational and travel costs. The model takes travel cost into account for distances more than 30 miles only, as per the VA policy. The model considers capacity expansion for both facilities that are currently providing the colonoscopy service and for those not providing the service. In addition to the capacity expansion cost, the model adds sterilization cost at locations that currently do not have the service since a special sterilization process is needed in order to locate the service at a new facility. Finally, in order to use the resources in an efficient way, the model penalizes underutilization of colonoscopy units at each facility in the objective function.

Modeling assumptions are provided below:

(1) Each patient goes to the facility to which they are assigned.

(2) For the continuity of the care, whenever a patient is assigned to a facility, he or she always gets service from the same facility over time.

(3) Each colonoscopy unit can accommodate at most five screening tests per day.

(4) Demand is equally distributed over time and seasonality effects are ignored.

(5) Facilities that currently provide service continue to do so.

(6) Operation cost includes staffing, overhead and depreciation costs.
(7) The cost of purchasing a colonoscopy unit does not vary over regions.

(8) The purchased colonoscopy units are kept open over time.

(9) Capacity of each screening unit can be expanded up to 30% without any additional cost.

All of the assumptions provided above are because of the special structure of VISN services. According to legal restrictions, and the employment policy of these services, it would be difficult to shut down or move an existing unit.

2.1.2.2 Mathematical Programming Model

Following Mixed Integer Linear Programming (MILP) model has been formulated with the parameters and variables described below:

Parameters:

\[
\begin{align*}
N & = \text{total number of demand nodes}, \\
F & = \text{total number of facility nodes}, \\
T & = \text{total number of periods (planning horizon)}, \\
S & = \text{maximum acceptable distance}, \\
N_1 & = \text{out of network screening cost per patient}, \\
N_2 & = \text{travel cost per mile}, \\
N_3 & = \text{in-house screening cost per patient}, \\
N_4 & = \text{colonoscopy unit purchasing cost}, \\
N_5 & = \text{sterilization cost at each new facility}, \\
N_6 & = \text{unused colonoscopy unit cost per day}, \\
\end{align*}
\]
\( t_{ij} = \) distance between demand node \( i \) and facility \( j \),

\( f_j = \) initial number of colonoscopy units in facility \( j \),

\( n = \) daily capacity of each colonoscopy unit,

\( h_i^t = \) total number of patients at demand node \( i \) at period \( t \),

\( P = \) maximum number of additional facilities to be located,

\( \text{Cap} = \) capacity of each colonoscopy unit,

\( D^t = \) total demand at period \( t \),

\( o_j = \begin{cases} 1, & \text{if facility } j \text{ does not provide service currently} \\ 0, & \text{o.w} \end{cases} \)

\( d_{ij} = \) reimbursed travel distance, \( \begin{cases} t_{ij}, & \text{if } t_{ij} > 30 \\ 0, & \text{o.w} \end{cases} \)

\( c_{ij} = \begin{cases} 1, & \text{if patient can be treated within VA, i.e. } t_{ij} < S \\ 0, & \text{o.w} \end{cases} \)

Decision Variables:

\( x_j^t = \begin{cases} 1, & \text{if facility } j \text{ provides service at period } t \\ 0, & \text{o.w} \end{cases} \)

\( y_{ij}^t = \begin{cases} 1, & \text{if facility } j \text{ provides service to demand point } i \text{ at period } t \\ 0, & \text{o.w} \end{cases} \)

\( u_j^t = \) unused capacity in facility \( j \) at period \( t \),

\( a_j^t = \) number of additional colonoscopy units in facility \( j \) at period \( t \),

\( b_j^t = \) number of total colonoscopy units at the beginning of period \( t \).
Mathematical Model:

\[
\min \left( N_1 \sum_{t=1}^{T} (D_t - \sum_{i=1}^{N} \sum_{j=1}^{F} y_{ij}^t h_i^t) + \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j=1}^{F} y_{ij}^t h_i^t (N_2 d_{ij} + N_3) + N_4 \sum_{t=1}^{T} a_j^t + N_5 \sum_{j=1}^{F} x_j^t + N_6 \sum_{t=1}^{T} \sum_{j=1}^{F} \frac{u_j^t}{n} \right)
\]

s.t

\[x_j^t \geq x_j^{t-1} \quad \forall j \in \{1..F\}, t \in \{2..T\} \quad (1)\]
\[b_j^t = f_j \quad \forall j \in \{1..F\} \quad (2)\]
\[b_j^t = b_j^{t-1} + a_j^{t-1} \quad \forall j \in \{1..F\}, t \in \{2..T\} \quad (3)\]
\[\sum_{j=1}^{F} y_{ij}^t \leq 1 \quad \forall i \in \{1..N\}, t \in \{1..T\} \quad (4)\]
\[\sum_{i=1}^{N} y_{ij}^t \leq N x_j^t \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (5)\]
\[\sum_{i=1}^{N} y_{ij}^t \leq T c_{ij} \quad \forall i \in \{1..N\}, j \in \{1..F\} \quad (6)\]
\[\sum_{i=1}^{N} y_{ij}^t h_i^t \leq 1.3 \times \text{Cap}(b_j^t + a_j^t) \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (7)\]
\[u_j^t = \max\{\text{Cap}(b_j^t + a_j^t) - \sum_{i=1}^{N} y_{ij}^t h_i^t, 0\} \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (8)\]
\[x_j^1 = 1 \quad \forall j \in \{1..F\}: o_j = 0 \quad (9)\]
\[y_{ij}^1 = y_{ij}^t \quad \forall i \in \{1..N\}, j \in \{1..F\}, t \in \{2..T\} \quad (10)\]
\[\sum_{j=1}^{F} o_j x_j^t \leq P \quad (11)\]
\[x_j^t \in \{0,1\} \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (12)\]
\[y_{ij}^t \in \{0,1\} \quad \forall i \in \{1..N\}, j \in \{1..F\}, t \in \{1..T\} \quad (13)\]
\[u_j^t \geq 0 \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (14)\]
\[a_j^t \text{ integer} \quad \forall j \in \{1..F\}, t \in \{1..T\} \quad (15)\]
The objective function aims to minimize the total costs including fee type visits, house type visits, additional colonoscopy unit set up, sterilization and underutilization costs over a predefined planning horizon. The first term of the objective is the cost of fee type visits. The number of patients minus the total number of patients treated in a VA hospital is the number of patients who are allocated to a fee type visit. By multiplying this number by the fixed fee type visit cost, we can derive the total cost of fee type visits in a period. In the second term, we calculate screening and travel costs for patients who are assigned to a VA hospital by multiplying the number of house type visits by operation cost and then adding the reimbursed travel cost. The third term is the cost of setting up a new colonoscopy screening unit. In the fourth term, we calculate sterilization cost for the hospitals that have no screening units currently. Finally in the fifth term, we calculate the cost of unused capacity per day is calculated by dividing the total unused capacity by the daily capacity in order to accommodate the total number of days that colonoscopy units are not used over the planning horizon.

As per VA policy, constraint (1) ensures that if a hospital performs screening service, it continues to provide service throughout the planning horizon. Constraints (2) and (3) calculate the number of colonoscopy units in each facility at the beginning of each period. Constraint (4) implies that a patient can be assigned to at most one hospital. Constraint (5) ensures that patients can only be assigned to facilities with a screening unit. We add constraint (6) to ensure that a patient can receive service from a facility if the patient is inside the coverage area of that facility. Constraint (7) is the capacity constraint and constraint (8) calculates the amount of unused capacity of facility $j$ at period $t$. Constraint (9) ensures that the facilities initially equipped with
colonoscopy units can provide service and (10) ensures the continuity of the care. Constraint (11) implies that the total number of newly opened facilities can be at most $P$. Finally constraints (12), (13), (14), (15) and (16) are sign constraints involved with each variable.

2.1.3 Application and Results

We applied the mathematical model in location and allocation of colonoscopy screening services. In addition to the analysis of 2008 data, we used veteran population projections from the National Center for Veterans Analysis and Statistics to estimate resource need over a 10-year horizon. According to the Veterans Health Administration Directive, colorectal cancer screening starts at the ages of 50 and 40 for an average-risk and high-risk veteran, respectively, and they should be advised to choose one of the five screening options including colonoscopy [29]. In order to avoid underestimation of the demand, the total colonoscopy service demand is projected as the total of all veterans that are expected to be 50, 60, and 70 years old and 25% of the veterans that are going to be 55, 65, and 75 years old in the planning year. Figure 7 provides the 2008 observed demands and the 2012 projected demands by state. In addition, we assumed that colonoscopy would be the preferred screening method. It can be seen that, there is a tremendous difference between the observed and projected demands.
The model has been solved with the demand set which is a projection according to the expected age of veteran population. The demand data set is assumed to follow the same trend with 2008 data, where future years are adjusted according to VA’s New England veteran population projection (http://www.va.gov/VETDATA/Demographics/Demographics.asp). For this data set, a 10 year planning horizon is considered. Yearly estimated demand data is presented in Figure 8.

We used CPLEX 12.2 optimization software to run the mathematical models on a Toshiba laptop computer with 6 GB of RAM running at 2.27 GHz on an Intel Core i5 processor. Several
different scenarios varying based on coverage distance policies ($S$), and periodicity were evaluated. The calculation times were always less than 5 seconds based on the input set. Table 2 summarizes the cost parameters that are used in the model. The costs have been retrieved from VA Decision Support System (DSS) and the VA fee basis care office.

Table 2: Cost parameters provided by VA management

<table>
<thead>
<tr>
<th>Notation</th>
<th>Explanation</th>
<th>Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_1$</td>
<td>Out-of-network cost per patient</td>
<td>$1,200</td>
</tr>
<tr>
<td>$N_2$</td>
<td>Travel cost per mile</td>
<td>$0.70</td>
</tr>
<tr>
<td>$N_3$</td>
<td>In-house screening cost per patient</td>
<td>$1,070</td>
</tr>
<tr>
<td>$N_4$</td>
<td>Colonoscopy unit purchasing cost</td>
<td>$150,000</td>
</tr>
<tr>
<td>$N_5$</td>
<td>Sterilization cost at each new facility</td>
<td>$25,000</td>
</tr>
<tr>
<td>$N_6$</td>
<td>Unused colonoscopy unit cost per day</td>
<td>$1,400</td>
</tr>
</tbody>
</table>

We describe the general results for the multi-period case considering a 10-year period in Table 3 below. Results indicate that, since the cost of opening a new colonoscopy unit is relatively high, only one new facility is opened in Newington for the ($S = 30$) case.

Table 3: Results for multi period (10 year) case with different acceptable travel distance ($S$)

<table>
<thead>
<tr>
<th>$S$ (miles)</th>
<th>Average total cost per year</th>
<th>House (%)</th>
<th>Average under-utilization cost per year</th>
<th>Set up cost</th>
<th>Sterilization cost</th>
<th># of new locations</th>
<th>Optimal location(s)</th>
<th>Average savings per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>$13,221,830</td>
<td>44</td>
<td>$3,257,786</td>
<td>$150,000</td>
<td>$25,000</td>
<td>1</td>
<td>Newington (2012, 1)</td>
<td>-</td>
</tr>
<tr>
<td>60</td>
<td>$11,916,650</td>
<td>75</td>
<td>$2,202,452</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>$876,167</td>
</tr>
<tr>
<td>90</td>
<td>$11,454,440</td>
<td>89</td>
<td>$1,842,932</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>$1,338,377</td>
</tr>
</tbody>
</table>

As described in the table, MILP model avoids adding additional capacities or providing service at new locations. Keeping the current capacities and current locations is superior to opening additional locations because of the extremely expensive colonoscopy unit purchase costs. The last column indicates the possible cost savings (if there is any), which are achieved by optimal
allocation of patients to the current facilities. The solutions for $S = 30$ and $S = 60$ cases are depicted in Figure 9.

Figure 9: MILP solution for $S = 30$ case (a) and $S = 60$ case (b)

Figure 10 shows the tradeoff frontier between acceptable travel distance, total annual cost, and coverage percentage, which is the percentage of house type visits in overall visits. After a certain service distance, both the total cost and coverage percentage are improved. Both of these performance measures indicate the possibility of more improvement as the service distance is expanded.
2.1.4 Monte Carlo Simulation to Account for the Variability in Future Demand

The data used in this study has been projected from the observed 2008 data by considering the future demand estimations of VA as explained in Section 2.1.3. Since using deterministic data for the future predictions would not be realistic, we have allowed up to 20% change which we call change rate in the future demand and used Monte Carlo Simulation approach. As shown in Figure 11, for each demand point $i$, we have randomly generated a number $U_i^t \in [-x, x]$ using uniform distribution and updated the demand of this point for year $t$ accordingly.

![Figure 10: Tradeoff between acceptable distance and (a) total cost, and (b) coverage percentage](image)

![Figure 11: Data Generation Procedure](image)
After running each scenario 100 times using $x = 5, 10, 15$ and $20\%$ for different $S$ values, we obtained the results as shown in Table 4 which shows the different function values of coverage and annual cost for different scenarios and change rates. For instance, for $S = 30$, and $x = 5$, we can cover 43.57\% of all patients inside the network on average. To visualize the simulation results, box plots are used as shown in Figure 12.

Table 4: Simulation results for multi period (10 year) case with different acceptable travel distance ($S$) and change rates (Sd: standard deviation)

<table>
<thead>
<tr>
<th>Change rate (%)</th>
<th>$S = 30$</th>
<th>$S = 60$</th>
<th>$S = 90$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Coverage (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>43.39</td>
<td>43.22</td>
<td>41.82</td>
</tr>
<tr>
<td>Max</td>
<td>43.75</td>
<td>43.92</td>
<td>44.19</td>
</tr>
<tr>
<td>Average</td>
<td>43.57</td>
<td>43.56</td>
<td>43.43</td>
</tr>
<tr>
<td>Sd</td>
<td>0.0008</td>
<td>0.0015</td>
<td>0.0048</td>
</tr>
<tr>
<td>Median</td>
<td>43.57</td>
<td>43.55</td>
<td>43.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual cost</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sd</td>
<td>0.013</td>
<td>0.027</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Box plots in Figure 12 demonstrate that as the change rate increases, the range of the boxes also increases as expected. It is also seen that as $S$ increases, expected coverage value also increases. In contrast, expected annual cost decreases.
Figure 12: Box plots representing the distribution of the coverage and annual cost for different $S$ values and change rates

The results indicate that even for the 20% change rate, no additional screening unit is needed for $S = 60$ and $S = 90$ cases. For $S = 30$, a screening unit is needed in Newington for all different change rate values. In order to evaluate how appealing it is to open a screening unit in Newington for this case, we have excluded it from the candidate locations and re-run the model for different change rates. We have observed that whenever Newington is excluded from the candidate set, no new facility is opened and the objective function has increased $81,000 on average for each change rate. This shows that Newington is a dominant candidate to open a new screening unit.
2.1.5 Discussion

In this section, we use optimization and simulation to show how optimal location, capacity, and allocation of VA specialty care services across VA New England facilities could maximize service while decreasing long-term costs.

The application specifically describes and demonstrates location-allocation modeling for colonoscopy screening services across the VA New England network area. Results show the possibility of improved access and cost efficiency simply by the optimally allocating patients to current facilities. Most of the scenarios suggest keeping the current locations at their current capacities. Since a longer time period is considered in this study, the capacity expansion cost becomes more affordable and some of the results suggest providing additional services at Newington facility. The study also provides insight to the volume of current colonoscopy screening tests. We have also considered the demand variability by changing the future demand and running simulation so that rather than using deterministic data, we have used randomly generated data and tested the robustness of the solution. It is also underlined that opening a new facility in Newington will provide on average $81,000 savings throughout the planning horizon.

There are several limitations to this work. Our model may have inadequately considered non-screening uses of colonoscopy, such as the treatment of internal hemorrhoids and inflammatory bowel disease. The models do not accommodate the risk of having a war and/or disaster, and it is assumed that veterans who are directed to out-of-network facilities (fee type visits) always have available facilities within the coverage distance (S) which may not be the real case. Finally, it is important to note that the implementation of VA travel reimbursement policies differs across VA medical centers, even within VISN 1. For example, some facilities limit reimbursement in
veterans without a service-connected disability. Therefore, our model may overestimate travel costs to VISN 1 as some of these are borne by veterans.

For future studies, demand uncertainty and availability of out-of-network visits should be considered. In addition, the scaling down option can be included in the models. VA managers may wish to avoid “permanent” employment contracts, so that closing a service and capacity decrease may become more feasible options.

Overall, this approach offers many desirable features to VA, especially as compared to the existing method used to decide the size and location of specialty services including colonoscopy. Obvious advantages are the quantities and detailed nature of analysis. Other more subtle aspects may provide even more substantial advantages. The modeling used requires that “optimal” be defined. Health care leaders may be unaccustomed to defining such terms. In this case example, optimal was defined using the hybrid model described above. The process of a health organization defining optimal may provide substantial lasting benefits. A second, less apparent aspect is the specificity the model has for potential savings by various actions. Health care organizations may decide on various courses of action will vague hopes of ill-defined cost savings. The modeling makes explicit the expected savings derived from a course of action. Whether these types of collaborations will result in realized improvements in the quality and cost of care remains an unanswered question. However, this and similar collaborations offer the hope and promise of substantial benefits to the healthcare system.
2.2 Locating Ultrasound Units in HVMA Network

2.2.1 HVMA Ob/Gyn Services

HVMA currently offers ultrasound screening at 4 of their 15 medical centers. Figure 13 shows the density of their patients by zip-code and the locations that provide screening (Wellesley, Kenmore, Burlington, Quincy). They own 6 ultrasound screening units and rent 3 more to meet the patient demand. According to HVMA Ob/Gyn department, demand for their services will increase by 30% hence in addition to finding the optimal number of units to meet the future demand, they also want to re-evaluate the current locations of the units and hopefully reduce traveling distance of the patients and increase accessibility of care.

![Figure 13: Density of HVMA Ob/Gyn patients and location of HVMA centers](image-url)
2.2.2 Methodology

2.2.2.1 Model Overview and Assumptions

In order to find the optimal locations for the ultrasound units and the number of units needed to meet the demand while minimizing the patients’ travel distance, an MILP model has been developed. The model minimizes the total travel distance of the patients while ensuring that the capacity constraints are met. Due to the scarcity of the ultrasound technicians, rather than having 2 units in different centers, HVMA plans to have at least 2 ultrasound units in a center so that one technician can perform the screenings.

Modeling assumptions are provided below:

(1) Each patient goes to the facility to which they are assigned.

(2) Duration of an ultrasound screening does not vary from patient to patient

(3) Demand is known in advance

(4) Increase in demand will be uniform

(5) Each facility will be able to accommodate ultrasound units

2.2.2.2 Mathematical Programming Model

Following Mixed Integer Linear Programming (MILP) model has been formulated with the parameters and variables described below:

Parameters:

\[ I = \text{Set of zip - codes} \]
$J$ = Set of HVMA centers

d_{ij} = Distance between the centroid of zip – code i and HVMA center j

e_i = Number of patients residing in zip – code i

c = Capacity of an ultrasound unit

t = Duration of an ultrasound screening

k = Number of units to be located

Decision Variables:

\[ x_{ij} = \begin{cases} 1, & \text{if patients residing in zip – code i are assigned to center j} \\ 0, & \text{o.w} \end{cases}, \]

\[ y_j = \begin{cases} 1, & \text{if an ultrasound unit is assigned to center j} \\ 0, & \text{o.w} \end{cases}, \]

n_j = Number of ultrasound units assigned to center j.

Mathematical Model:

\[
\min \sum_{i \in I} \sum_{j \in J} e_i d_{ij} x_{ij}
\]

\[ s.t. \]

\[ \sum_{j \in J} x_{ij} \leq 1 \quad \forall i \in I \] (1)

\[ x_{ij} \leq y_j \quad \forall i \in I, j \in J \] (2)

\[ \sum_{i \in I} t e_i x_{ij} \leq c n_j \quad \forall j \in J \] (3)

\[ \sum_{j \in J} n_j = k \] (4)

\[ n_j \geq 2 \quad \forall j \in J \] (5)

\[ n_j \leq k y_j \quad \forall j \in J \] (6)
\( x_{ij} \in \{0,1\} \quad \forall i \in I, j \in J \quad (7) \)
\( y_{j} \in \{0,1\} \quad \forall j \in J \quad (8) \)
\( n_{j} \text{ integer} \quad \forall j \in J \quad (9) \)

The objective function minimizes the patients’ total travel time. Constraint (1) ensures that patients residing in a zip-code can be served by at most one center. Constraint (2) ensures that patients can only be assigned to centers with ultrasound screening units. Constraint (3) sets a capacity limit on the number of screenings. Constraint (4) limits the number of ultrasound units and by HVMA strategy (5) enables having at least 2 units in a center. Constraint (6) ensures that there can be units at a center if and only if a unit has been assigned to the center. Finally constraints (7), (8) and (9) are sign constraints associated to each variable.

### 2.2.3 Application and Results

The model described in Section 2.2.2.2 has been applied to HVMA Ob/Gyn services. In addition to using historical data, we used 30% increased demand data to account for the possible future demand increase. Table 5 presents the values of the parameters used in the model.

<table>
<thead>
<tr>
<th>Explanation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of zip-codes</td>
<td>314</td>
</tr>
<tr>
<td>Total number of HVMA centers</td>
<td>15</td>
</tr>
<tr>
<td>Capacity of an ultrasound unit</td>
<td>3,520/year</td>
</tr>
<tr>
<td>Duration of an ultrasound screening</td>
<td>30 minutes</td>
</tr>
<tr>
<td>Current Demand (historical)</td>
<td>27,691 screenings/year</td>
</tr>
<tr>
<td>Future Demand (30% increase)</td>
<td>35,969 screenings/year</td>
</tr>
</tbody>
</table>
We ran different scenarios varying the number of ultrasound units and the locations. HVMA Ob/Gyn department wanted to evaluate the options of keeping the units at their current locations as well as relocating them. Results if the model under different scenarios have been presented below. Table 6 presents the results for the current demand case. For option 1, where we keep the units at their current location, demand can be satisfied with 8 units as the number of units increase, average travel time decreases as expected. For option 2, where we are allowed to relocate all the units, more reduction in average travel distance is possible. Figure 14 outlines the difference between these options in terms of average travel distance.

<table>
<thead>
<tr>
<th>Number of machines to locate</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Keep units at their current locations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td># of machines at that location</td>
<td>Location</td>
<td># of machines at that location</td>
</tr>
<tr>
<td>Wellesley</td>
<td>2</td>
<td>Wellesley</td>
<td>2</td>
</tr>
<tr>
<td>Kenmore</td>
<td>2</td>
<td>Kenmore</td>
<td>3</td>
</tr>
<tr>
<td>Burlington</td>
<td>2</td>
<td>Burlington</td>
<td>2</td>
</tr>
<tr>
<td>Quincy</td>
<td>2</td>
<td>Quincy</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average Traveling Distance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>8.522 miles</td>
<td>8.401 miles</td>
<td>7.542 miles</td>
</tr>
<tr>
<td><strong>Relocate all the units</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td># of machines at that location</td>
<td>Location</td>
<td># of machines at that location</td>
</tr>
<tr>
<td>Dedham</td>
<td>2</td>
<td>Dedham</td>
<td>2</td>
</tr>
<tr>
<td>Cambridge</td>
<td>2</td>
<td>Cambridge</td>
<td>3</td>
</tr>
<tr>
<td>Chelmsford</td>
<td>2</td>
<td>Chelmsford</td>
<td>2</td>
</tr>
<tr>
<td>Quincy</td>
<td>2</td>
<td>Quincy</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average Traveling Distance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>8.347 miles</td>
<td>7.785 miles</td>
<td>7.253 miles</td>
</tr>
</tbody>
</table>
Figure 14: Average travel time difference between the two options for current demand case.

Figure 15 below represents optimal allocation of patients to the 9 ultrasound units for the option where we are allowed to relocate all the units.

Figure 15: Allocation of patients to the ultrasound units for current demand case where relocating the units is allowed.
For future case, where we assume demand will increase by 30%, minimum number of units needed increases as expected. Similar to the current demand case, for option 1, where we keep the units at their current location, demand can be satisfied with 11 units as the number of units increase, average travel time decreases as expected (Table 7). For option 2, where we are allowed to relocate all the units, more reduction in average travel distance is possible. Figure 16 outlines the difference between these options in terms of average travel distance.

Table 7: Results for the future demand case with varying number of units

<table>
<thead>
<tr>
<th>Number of machines to locate</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Keep Current Locations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wellesley</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Kenmore</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Burlington</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Quincy</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Chelmsford</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Average Traveling Distance</td>
<td>7.606 miles</td>
<td>7.110 miles</td>
<td>6.859 miles</td>
</tr>
<tr>
<td><strong>Relocate All Locations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dedham</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Kenmore</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Medford</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Quincy</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Chelmsford</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Average Traveling Distance</td>
<td>7.283 miles</td>
<td>6.700 miles</td>
<td>6.632 miles</td>
</tr>
</tbody>
</table>
Post-Processing of Optimal Solution to Minimize the Impacts of Over-Capacity and Under-Utilization

The model described above finds the optimal locations for the ultrasound units and allocates patients to these units while ensuring that the total capacity of these units are not exceeded. Similar to the MILP model used in Section 2.1, the model assumes the demand for the ultrasound services is deterministic. In order to evaluate the impact of the optimal solution on the over-capacity and under-utilization, we have developed the probabilistic model described below:

**Parameters:**

\[ x_j = \text{Total number of patients assigned to center } j \text{ by MILP model} \]

\[ p(i, x_j) = \text{Poisson probability of arriving } i \text{ patients while expecting } x_j \]

\[ J = \text{Set of HVMA centers} \]

\[ C = \text{Capacity of an ultrasound unit} \]
\[ n_j = \text{Number of ultrasound units assigned to center } j \text{ by MILP model} \]

\[ E(OC)_j = \text{Expected number of overcapacity at center } j \]

\[ E(UU)_j = \text{Expected number of underutilization at center } j \]

\[ c_{oc} = \text{Cost of overcapacity} \]

\[ c_{uu} = \text{Cost of underutilization} \]

\[ E(Cost)_j = \text{Expected cost of underutilization and overcapacity at location } j \]

\[ E(TC) = \text{Expected total underutilization and overcapacity cost of system} \]

The probabilistic model assumes that patient arrival to the center \( j \) follows Poisson distribution with mean \( x_j \). Expected value of over-capacity and under-utilization is calculated as follows:

\[ E(OC)_j = \sum_{i=1}^{\infty} p(i, x_j) (i - n_j C) \] (10)

\[ E(UU)_j = \sum_{i=0}^{n_j C - 1} p(i, x_j) (n_j C - i) \] (11)

\[ E(Cost)_j = c_{oc} E(OC)_j + c_{uu} E(UU)_j \] (12)

\[ E(TC) = \sum_{j \in J} E(Cost)_j \] (13)

Equation (10) calculates the expected number of patients that will not be able to receive their ultrasound screening due to the capacity issues at center \( j \). Similarly, equation (11) calculates the expected under-utilization at center \( j \) in terms of number of patients. Equation (12) calculates the total cost of over-capacity and under-utilization at center \( j \) and finally (13) calculates the overall network cost associated with over capacity and underutilization.
In order to easily calculate these values and analyze the impact of the allocation found by the MILP model, we have developed an Excel tool which automatically calculates the over-capacity and under-utilization costs by center and the total cost associated with the network. Table 8 shows the impact of optimal allocation on the centers as well as the overall network. For the case where we locate the 9 units to meet the current demand, the units located to Chelmsford will be highly underutilized. Units located at Cambridge center on the other hand will have capacity issues so the decision maker may consider sending some Cambridge patients to Chelmsford.

<table>
<thead>
<tr>
<th>Centers</th>
<th>Unit Numbers</th>
<th>Capacity</th>
<th>Assigned encounter number</th>
<th>Probability of satisfying demand</th>
<th>Total Cost of Under Utilization</th>
<th>Total Cost of Over Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norwood</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dedham</td>
<td>2</td>
<td>7040</td>
<td>6497</td>
<td>1</td>
<td>541.98</td>
<td>0</td>
</tr>
<tr>
<td>Wellesley Hills</td>
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<td>0</td>
<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Chestnut Hill</td>
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<td>0</td>
<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Watertown</td>
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<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Kenmore (Boston)</td>
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<td>0</td>
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<tr>
<td>Copley (Boston)</td>
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<tr>
<td>Post Office Square (Boston)</td>
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<td>0</td>
<td>0</td>
<td>#N/A</td>
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<tr>
<td>Cambridge</td>
<td>3</td>
<td>10560</td>
<td>10553</td>
<td>0.53</td>
<td>42.43</td>
<td>37.58</td>
</tr>
<tr>
<td>Somerville</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>#N/A</td>
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<td>0</td>
</tr>
<tr>
<td>Medford</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Burlington</td>
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<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Chelmsford</td>
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<td>7040</td>
<td>4321</td>
<td>1</td>
<td>2718.61</td>
<td>0</td>
</tr>
<tr>
<td>Quincy</td>
<td>2</td>
<td>7040</td>
<td>6320</td>
<td>1</td>
<td>718.82</td>
<td>0</td>
</tr>
<tr>
<td>Peabody</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>#N/A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>4021.85</strong></td>
<td><strong>37.58</strong></td>
</tr>
</tbody>
</table>

38
2.2.5 Discussion

In this section, we have developed an MILP model to optimally locate the ultrasound units across HVMA network, determine the number of units needed to satisfy current demand as well as future demand where the screenings are expected to increase by 30% and allocate patients to these units. MILP model has been run for different scenarios based on the feedback received by the HVMA Ob/Gyn department.

MILP model identifies at least 7% reduction in average travel distance for the current demand case where a total of 9 units are located. As expected, instead of keeping the units at their current locations, relocating them has more savings in terms of travel distance. For the future demand case, model identifies the additional locations for additional units.

In addition to finding the MILP model, we have developed a probability model which inspects the impacts of the optimal solution on the over-capacity and under-utilization. The probability model inputs the solution and calculates the expected number of patients who will not be able to receive screening due to capacity issues as well as the expected number of under-utilized screenings. The probability model gives the decision maker many insights on the allocation and flexibility to adjust the allocation to reduce the negative impacts of the optimal allocation as the solution does not consider the stochastic nature of the system. For the case presented in Table 8, if the under-utilization cost is too high, decision maker may consider reducing the number of units and re-run the optimization model. Similarly, if we consider the case where we need at least \( x \) units to satisfy the demand however the total cost of over-capacity is too high, decision maker may consider purchasing one more unit to compensate the impact of over-capacity.
The approach presented in this section is a 2-phase approach and does not consider the issues simultaneously. Hence, post processing of the optimal solution will not necessarily yield to an optimal solution. As a future work, these issues may be tackled simultaneously, resulting with a nonlinear optimization problem which is much harder to solve.
Chapter 3 - Design of Regional Network Systems

3.1 Design of VA Telehealth Network for Clinical Video Telehealth Usage

With continued advances in telehealth offering increasingly viable options, it also becomes important to consider how to best use these technologies for timely access to appropriate care in a cost-effective manner. As the largest integrated healthcare network in the U.S., the Veterans Administration (VA) has invested heavily in telehealth technologies to provide service to veterans currently not covered by traditional care services, primarily including Clinical Video Telehealth (CVT), Store and Forward Telehealth (S&F), and Home Telehealth (HT). Among these different telehealth services, CVT has highest initial investment cost thus requires careful planning. CVT clinical applications include use in tele-polytrauma, telemental health, telerehabilitation, and telesurgery. Examples of S&F use include teledermatology, teleretinal imaging, and teleradiology, with HT used to better monitor high-risk patients with symptoms of chronic diseases.

For CVT encounters, our primary focus here, a cart equipped with a high resolution camera provides a real time encounter between an on-site patient and a remote provider. An on-site technician also usually is in the encounter room to assist the remote provider with any basic tasks such as taking a blood pressure or positioning a camera for examining an ear canal. S&F
encounters typically include taking and forwarding an image to a specialist for later review, such as a retina scan or high resolution picture of a skin lesion or mole. HT equipment typically is installed in a patient’s house for remote monitoring, especially for older patients needing frequent consultation [36].

Several reports have underscored the need to address basic infrastructure issues (such as service location) to promote further growth of telehealth services [37], [38], although few efforts have used mathematical models to optimize telehealth services. An Italian healthcare study, for example, recently used a geographic information system to identify patient clusters for locating telehealth neurology services in Italy [39], producing decreased patient travel and cost of care. Given the VA’s significant telehealth investment, we sought to similarly locate telehealth services using optimization models, including considering short and long term uncertainty in CVT usage demand.

This section presents a pilot study to design a network for CVT use in the White River Junction (WRJ) Vermont catchment area. We have developed an optimization model that finds the optimal number and locations for the CVT units and allocation of patients to these units. In addition to the deterministic optimization model, Monte Carlo Simulation has been used to address the variability in demand.

3.1.1 VA Telehealth Services

This study relates to the larger context of ongoing telehealth research and application. The VA has experienced considerable growth and proliferation both in the amount of telehealth services provided to veterans and the types of services offered through distance technologies, with a
300% increase in telehealth visits nationally from 2005 to 2010 [40]. Refinement of telehealth methods and exploration of alternate ways to connect with patients is likely to continue, including the spectrum from older models of care such as the physician house call [41] through new technologies to promote an individualized patient experience [42]. Preliminary efforts to assess the benefit of telehealth services suggest these interventions have a positive effect across a broad range of healthcare problems [43]. Particular success has been seen in telehealth services for mental health conditions, representing a majority of telehealth services in the VA and associated with a 25% reduction in mental health admissions [44].

Figure 17 summarizes the number and percentage of unique VA patients using any type of telehealth services in fiscal year 2011. There is some variation between regional veteran integrated service networks (VISN), with an average of 7.1% nationally. In 2010, CVT accounted for 48.6%, S&F for 41.9%, and HT for 9.5% of all 496,660 telehealth encounters in the VA [45], with $97 million of the total VA budget (roughly 2%) spent on telehealth in 2011. The VA has a goal to increase the percent of unique patients using telehealth to 30% by the end of 2014 [46], with targets of roughly 25% of unique patients using CVT (7.5%), 50% S&F (15%), and 25% HT (7.5%). Given this significant intent to scale-up, it is important to determine the optimal locations and amounts of CVT units, including any benefits of also considering new sites in non-clinical veteran centers.
As a pilot study, we focused on CVT use in the White River Junction (WRJ) Vermont catchment area of the New England region (VISN 1), which includes 24,086 veterans served by a Medical Center (MC), 7 Community Based Outpatient Clinics (CBOC), and 6 Veteran Centers (VC) in Vermont, parts of New Hampshire, and a small section of Massachusetts (Figure 18). CVT units currently are located only in the medical centers and outpatient clinics, although veterans centers are candidates for future expansion locations. Figure 19 summarizes the current use of CVT nationally and across VISN 1. To help inform optimal deployment of CVT telehealth technology, we developed a mixed integer programming (MIP) location optimization model [24], [47] and applied it to a range of possible scenarios, summarized in Section 3.1.2.
Figure 18: Medical center (MC), community-based outpatient clinic (CBOC), and veteran center (VC) locations in the White River Junction (WRJ) Vermont service area

Figure 19: Percentage of unique VA patients using CVT nationally and in VISN 1 (fiscal year 2011)
3.1.2 Methodology

Two classical approaches to discrete location analysis, p-median and p-center, were combined into an iterative multi objective capacitated mixed integer programming model using the following parameters and notation:

\[ L = \text{Set of patient locations} \]

\[ H = \text{Set of candidate facility locations} \]

\[ S = \text{Set of specialties under consideration} \]

\[ l_{ij} = \text{Driving distance between patients in location } i \text{ and site } j \]

\[ d_{ik} = \text{Number of patients residing in location } i \text{ needing care of specialty type } k \]

\[ e_k = \text{Number of annual encounters for a patient needing specialty care } k \]

\[ t_k = \text{Duration of a specialty } k \text{ encounter} \]

\[ c = \text{Annual capacity of a CVT unit} \]

\[ p = \text{Total number of CVT units used across all facilities} \]

and the following decision variables:

\[ n_j = \text{Number of CVT units located at site } j \]

\[ x_{ij}^k = \begin{cases} 1, & \text{if patients in location } i \text{ with specialty } k \text{ are assigned to site } j \\ 0, & \text{otherwise} \end{cases} \]

Using the above notation and parameters, the MILP model is:

\[
\min \sum_{i \in L} \sum_{j \in H} \sum_{k \in S} l_{ij} d_{ik} x_{ij}^k \quad (a)
\]

\[
\min \max l_{ij} x_{ij}^k \quad (b)
\]
The two objective functions minimize the (a) population total and (b) individual patient maximum travel distance of veterans, following the rationale discussed below. Constraint (1) ensures all home locations for patients needing specialty care are assigned to receive treatment at some (and only one) site. Constraint (2) similarly ensures patients are only assigned to a site where a CVT unit has been placed. Constraint (3) is a capacity constraint ensuring that the total workload at a site does not exceed its capacity (number of CVT units on site multiplied by per unit capacity), where total workload is defined by the number of patients assigned to a site multiplied by their CVT encounter frequency and duration. Constraint (4) sets an upper bound on the total number of CVT units across all candidate sites in the region, \( \sum_{j \in H} n_j \), which typically will be maximized in order to minimize the objective functions. Constraint (5) limits the number of CVT units at any site to be integer.
A 2-stage multi objective approach was used to address two stakeholder interests, although results were very similar under both approaches. Objective 1 (total travel distance, or equivalently average travel distance) essentially considers the aggregate benefit to the whole population and also is important from a total travel cost perspective, but possibly resulting in disadvantaged outlier individuals traveling greater distances to receive care. To avoid this potential inequity, objective 2 instead minimizes the maximum distance any patient will travel, an approach often used to improve solution fairness [13], [48].

Letting $z^*$ and $t^*$ denote the separate solutions to objective functions 1 and 2, and $\bar{z}$ and $\bar{t}$ be their resultant values when the other objective is optimized, it follows that $z^* \leq \bar{z}$ and $t^* \leq \bar{t}$ in general. In practice, large differences between $z^*$ and $\bar{z}$ (or between $t^*$ and $\bar{t}$) are not favorable versus a more balanced solution benefitting both the population and each individual. Two multi-stage approaches were taken to find the minimum average distance with minimum maximum distance (Figure 20). The first initially solves objective 1 (minimum average travel) and uses this solution as an upper bound on total travel distance to then solve objective 2 (minimum maximum travel). The second instead initially solves objective 2, then using this solution as an upper bound on maximum travel distance to solve objective 1.
We investigated two general scenarios for the WRJ region, focusing first only on the most common current CVT uses in Vermont (mental health clinic encounter type 502, accounting for roughly 92% of all CVT uses in Vermont) and second on the most common specialties using CVT anywhere in VISN 1, under the assumption these are likely future candidates in Vermont as well: Mental Health Clinic, Move Program (GRP), Mental Health (GRP), Amputation Clinic, PCT-PTSD, Primary Care / Medicine, and Mental Health Integrated Care. The “GRP” denotation indicates encounter types that can occur as group visits. A group encounter generally occurs with face-to-face patients at an MC and with other CVT patients joining remotely from different CBOCs. Group sizes can range from 1-2 virtual patients for the Move Program and 4-5 patients virtually for Mental Health sessions. Since the VA aims to increase the percent of veterans using telehealth and the use of telehealth in more specialties, we primarily focus below on the multiple specialty case.

Due to patient privacy issues in a rural area such as Vermont, we assumed patients are geographically distributed proportional to the general population, rather than use their specific 3-digit zip codes. To illustrate, since approximately 3% of the total New England population are
veterans enrolled in VA programs, if 20,000 people live in a given region then the 7.5% goal for veterans using CVT services produces an estimated 20,000 x 3% x 7.5% = 45 patients. VA regions are pre-defined by the VA and it is assumed that veterans who reside outside of the catchment area will receive care services from other VA centers.

The total capacity for CVT encounters depends on on-site technician staffing, generally assuming CVT units therefore can be open at most 8 hours per day, of which only a percentage are available for a given specialty. Most patients using telehealth do so repeatedly, with the average number of encounters per unique patient for each specialty estimated as:

\[
\# \text{ of CVT encounters for specialty } i = \frac{\text{Total \# of CVT encounters in specialty } i}{\text{Total \# of unique CVT patients in specialty } i}.
\]

Durations for each CVT encounter were estimated to take one hour for the provider visit and an additional 10 or 15 minutes for unit preparation and post-visit tasks for individual or group encounters, respectively.

3.1.3 Application and Results

The MILP model was implemented in CPLEX 12.3 on a PC Core 2 Duo 1.8 GHz (3 GB RAM) running with Windows 7. Run times across a range of percentages of veterans using CVT and number of CVT units varied from several seconds to 30 minutes. The model that considers only current specialties using CVT in Vermont, as opposed to any other potential specialty, produced the same solution under both objective functions. Table 9 summarizes results if considering only current specialties using CVT in Vermont. There currently are 6 CVT units located in the WRJ area (at the WRJ MC and at the Brattleboro, Littleton, Colchester, Keene, and Bennington CBOCs) with 2% of all veterans using CVT services. By relocating current CVT units from
Keene and Bennington to Rutland and Newport, the average and maximum travel distances can be reduced by approximately 14%, with no additional equipment nor cost. If VCs can be considered as additional potential locations, then additionally relocating CVT units from Colchester to South Burlington would further reduce average travel by another 3%, after which the addition of more sites has very marginal value (since most VCs tend to be located close to CBOCs).

Table 9: Results for current CVT specialties

<table>
<thead>
<tr>
<th>Travel distance</th>
<th>Current</th>
<th>Optimal solution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>VCs not considered</td>
</tr>
<tr>
<td>Average</td>
<td>27.8 miles</td>
<td>23.9 miles</td>
</tr>
<tr>
<td>Maximum</td>
<td>77.3 miles</td>
<td>66.6 miles</td>
</tr>
<tr>
<td>Locations (# of units)</td>
<td>WRJ MC (1)</td>
<td>WRJ MC (1)</td>
</tr>
<tr>
<td></td>
<td>Brattleboro CBOC (1)</td>
<td>Brattleboro CBOC (1)</td>
</tr>
<tr>
<td></td>
<td>Littleton CBOC (1)</td>
<td>Littleton CBOC (1)</td>
</tr>
<tr>
<td></td>
<td>Colchester CBOC (1)</td>
<td>Colchester CBOC (1)</td>
</tr>
<tr>
<td></td>
<td>Keene CBOC, (1)</td>
<td>Rutland CBOC (1)</td>
</tr>
<tr>
<td></td>
<td>Bennington CBOC (1)</td>
<td>Newport CBOC (1)</td>
</tr>
<tr>
<td>Average travel distance improvement</td>
<td>14%</td>
<td>17%</td>
</tr>
<tr>
<td>Max travel distance improvement</td>
<td>14%</td>
<td>14%</td>
</tr>
</tbody>
</table>

The VA reimburses the travel cost of veterans if they are traveling more than 30 miles to receive care. In the current case with 2% of the veterans using the CVT services, the VA would reimburse annually $27.7K for the travel cost of the veterans. By optimally locating the CVT units, the total annual cost for the VA would reduce by $8.1K. Similarly, if the VCs are considered an additional annual $1.4K would be saved. Note that savings are not proportional to the improvement in distance as the relationship between the cost and the distance is not linear.

These numbers might seem relatively low however given the current plans to spread the use of telehealth and increase the percent of veterans using CVT to 7.5%, up to $30K annual savings are possible by only optimally locating the CVT units in one of the 8 regions of VISN1. If we...
assume all regions in VISN1 are identical, up to $240K annual savings can be achieved by optimally locating the units.

Figure 21 summarizes the corresponding changes in optimized care destinations for individual patients under the above site changes, also significantly increasing the amount of CVT care already provided at the existing Brattleboro location.

Figure 22 summarizes the decreasing benefits on average and maximum distances of investing in additional CVT units. The dashed and solid lines correspond to the cases for which average and
maximum travel distances are minimized, respectively. Note the decent benefit up to 6 CVT units, after which both performance measures tend to asymptote and improve insignificantly beyond that. Figure 23 similarly compares the results of the multiple-specialty model now allowing for CVTs in VCs with negligible apparent benefit to either performance measure.

![Figure 22: Benefit on average on average and maximum distances of investing in additional CVT units](image)

![Figure 23: Negligible benefit of considering VCs as additional candidate locations](image)

As sensitivity analysis, Figure 24 summarizes the minimum number of CVT units needed to cover different percentage of veterans that use telehealth ranging from 1% to 15% (double the
VA target of 7.5%) by varying the upper bound value $p$. Additionally, Figure 25 summarizes the very minor travel distance difference between these extreme levels. Since there were no feasible solution for 15% service level with $n < 10$, travel distance has been compared for $n \geq 10$.

![Figure 24: Number of CVT units needed to cover different percentage of veterans](image)

![Figure 25: Sensitivity analysis on travel distances under higher and lower percentage of veterans using CVT](image)

### 3.1.4 Stochastic Analysis

Since the model described in Section 3.1.2 assumes both that CVT demand is constant month-to-month and that usage in future years is known deterministically, we investigated these potential issues in two manners. In both cases, results suggest that extending our model to a stochastic
framework, such as via chance constraints or stochastic recourse programming, would not have much value in this particular application.

Throughout the study, it was assumed that the demand for the CVT services are deterministic and known in advance, however, in real world, demand for the health services is stochastic and care providers need to consider the randomness affect for more effective strategic planning. With the aim to provide telehealth service to the 30% of the veterans by the end of 2014 and spread the use of CVT to multiple specialties, the VA should plan the CVT capacity so that at least 7.5% of the veterans will be able to use these services (this is based on estimated use of the spectrum of telehealth services-25% CVT, 50% S&F and 25% HT).

In order to address the stochastic nature of the system, Monte Carlo simulation has been used and it is assumed that the demand for the CVT services will follow a Poisson distribution. 50 different sets of random yearly demand have been generated for each zip code – specialty pair with mean being the number of veterans residing in that zip code * percentage of veterans to use CVT (7.5%) * average number of yearly encounters per specialty. The optimization model has been run with randomly generated data and each solution has been compared with the solution obtained using deterministic demand. Note that approach 1 has been used in which we minimize maximum travel distance when total travel distance is minimized. For each case, at least 6 CVT units are needed to meet the demand and the optimal solution with the deterministic demand offers one CVT unit to be located at WRJ MC, Brattleboro CBOC, Littleton CBOC, Rutland CBOC and 2 units to be located at Colchester CBOC. Table 10 represents the frequency of different optimal solutions obtained by the Monte Carlo Simulation. Note that the solution with the deterministic demand has remained optimal 64% of the time. 34% of the time, the optimal
solution suggested moving one of the CVT units in Colchester CBOC to Newport CBOC and only 2% of the time the optimal solution suggested moving the unit in Brattleboro CBOC to Keene CBOC. If the optimal solution set is examined by location; WRJ MC, Colchester CBOC, Littleton CBOC and Rutland CBOC appears to be optimal locations 100% of the time, Brattleboro CBOC 98% of the time, Newport CBOC 34% of the time, and Keene CBOC 2% of the time. Note that although Bennington CBOC currently has a CVT unit, it never appeared as an optimal location.

Table 10: Frequency of different solutions obtained by Monte Carlo Simulation

<table>
<thead>
<tr>
<th>Location</th>
<th>Solution with Deterministic Demand</th>
<th>Solution 1</th>
<th>Solution 2</th>
<th>Solution 3</th>
<th>Frequency by Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>WRJ MC</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>Bennington CBOC</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Brattleboro CBOC</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>98%</td>
</tr>
<tr>
<td>Colchester CBOC</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>100%</td>
</tr>
<tr>
<td>Littleton CBOC</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>Newport CBOC</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>34%</td>
</tr>
<tr>
<td>Keene CBOC</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2%</td>
</tr>
<tr>
<td>Rutland CBOC</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>100%</td>
</tr>
</tbody>
</table>

Frequency of Different Optimal Solutions 64% 34% 2%

In addition to evaluating how optimal locations of CVT units would change with random yearly demand, the impact of implementing dominating solution, Solution 1, has been evaluated. The optimal locations and zip code assignments in Solution 1 are used as an input and respective average travel distance and maximum travel distance values have been calculated. Figure 26 shows how both the objective functions change for the optimal solutions and for the implemented dominating solution. If the dominating solution is implemented, on average, the average travel distance increases 0.4% (0.11 miles) and the maximum travel distance increases by 0.5% (0.4 miles).
One of the issues with strategic capacity planning is that the yearly demand for the CVT units is aggregated and it is implied in the optimization model that the total yearly available capacity will be more than the total yearly demand however there might be some fluctuations in the demand where monthly demand may exceed the monthly available capacity. To evaluate the impact of monthly fluctuations, locations and the assignments obtained by Solution 1 has been set and random monthly demand for each zip code – specialty combination has been generated using Poisson distribution with mean being the number of veterans residing in that zip code * percentage of veterans to use CVT * average number of yearly encounters per specialty / 12 months. 50 random yearly data set which accounts for 600 months has been generated and the impact of random demand on capacity is shown in Figure 27.

The figure below represents the % of months in which monthly CVT encounters assigned to a center exceeds the monthly available capacity of the center. Note that for all the cases, yearly total demand has never exceeded the yearly available capacity. WRJ MC outranks the other centers with 48.8% over-capacity rate which is not surprising due to the fact that WRJ MC is located in a relatively central location and highly populated are compared to the other centers,
making it an appealing candidate for deployment and patient assignment. Such a high over-capacity rate might not be desirable for the system as it would create cancelled CVT encounters in a center and idle time in others. In order to avoid this case an additional constraint which provides fair work load among centers can be added to the model.

Figure 27: Percent of months in which monthly demand for CVT located in a center is greater than the monthly capacity of the CVT unit in that center

3.1.5 Discussion

Many health systems are exploring or investing in various telehealth technologies as a means to providing greater care at lower costs. As additional remote healthcare models emerge, it also will be important to consider the most effective manner by which to leverage them. Mathematical optimization and other systems engineering methods can be particularly useful for helping inform decisions about these types of complex macro-system logistics problems [23]. The current work, for example, was motivated by an important operational question of if and how to best scale up the VA’s telehealth program, using the Vermont region as a pilot study.

Results indicate that some improvements are possible at no additional expense and that the VA’s planned telehealth expansion could be a significant over investment with little benefit beyond a
certain point. Roughly 14% reductions in average and maximum travel distances would result from changing the locations at which medical centers current CVT units are placed, whereas considering veterans centers as additional possible locations produces limited benefit.

These results have informed VA policy discussions and decisions in two important manners, both avoiding unnecessary investments. First, exploring placement of CVT units in veteran centers has stopped. Second, since greater numbers of CVT units are not likely to produce greater access, attention instead was refocused on the optimal location and use of current existing (and modestly expanded) resources.

Another important finding of the study is that as the planning period increases, the applicability of the solution decreases. Solutions with yearly generated random data showed that there will not be any capacity problem however monthly generated data proved that there might be some months in which the capacity may not be enough to meet all the demand and the solution obtained might not be really desirable as some of the centers having no available capacity vs. others remaining idle.

There are a few limitations of our study. Telehealth is relatively new and demand for CVT may increase over time beyond 15%. Providing greater access to care also may increase demand. We also assumed deterministic exam durations and that all appointments are kept, whereas the effects of randomness and cancellations might warrant a slight increase or decrease in intended capacity. However, results in this application are not affected much by month-to-month care demand variation nor by uncertainty in anticipated CVT usage growth over the next several years.
3.2 Design of HVMA Ob/Gyn Inpatient Admission Network

In addition to providing ultrasound screening services briefly described in Section 2.2 for Ob/Gyn patients, HVMA partners with hospitals for deliveries as well as complex surgeries. As expected, costs associated with each procedure differs from hospital to hospital and the total cost for a year may go up to $80 million. HVMA aims to reduce overall cost of referring patients to these hospitals by realigning inpatient admission network, mainly reducing the admissions to high-cost hospitals.

3.2.1 Methodology

3.2.1.1 Model Overview

In order to reduce the overall cost and reallocate HVMA patients to hospitals, we have developed an MILP model with 2 objective functions. The first objective function reduces the overall cost of inpatient admissions and the second objective function tries to meet the expectations of the physicians. Due to political reasons and proximity of the HVMA centers to the hospitals, physicians are more likely to prefer working with certain hospitals. Ignoring physician preferences would yield having a solution which may not be possible to implement hence the second objective function was added to the model.

3.2.1.2 Mathematical Programming Model

Following MILP model has been formulated with the parameters and variables described below:

Parameters:

\[ i: \text{index used for sites} \]
\( j \): index used for hospitals

\( d_i \): Number of deliveries at Site \( i \)

\( MD_i \): Available total MD at Site \( i \)

\( Cap_j \): Current delivery capacity of Hospital \( j \)

\( Exc_j \): Excess capacity available at Hospital \( j \)

\( c_j \): Cost of a delivery at Hospital \( j \)

\( p_{ij} \): Willingness of MDs in Site \( i \) to work with Hospital \( j \)

\( t \): minimum number of deliveries per MD

\( \alpha \): any number between 0 and 1

**Decision Variables:**

\[
x_{ij} = \begin{cases} 
1, & \text{if center } i \text{ is assigned to hospital } j \\
0, & \text{o.w.}
\end{cases}
\]

**Optimization Model:**

\[
\min \alpha \sum_i \sum_j d_i c_j x_{ij} + (1 - \alpha) \sum_i \sum_j p_{ij} x_{ij}
\]

subject to

\[
\sum_j x_{ij} = 1 \quad \forall i \quad (1)
\]

\[
\sum_i d_i x_{ij} \leq Cap_j + Exc_j \quad \forall j \quad (2)
\]

\[
\sum_i d_i x_{ij} \geq t \sum_i MD_i x_{ij} \quad \forall j \quad (3)
\]
\[ x_{ij} \in \{0,1\} \quad \forall i,j \]

The model minimizes the total delivery cost while trying to assign each MD to a hospital his/her choice. Constraint (1) ensures that each site is assigned to a hospital. Constraint (2) is the capacity constraint which limits the number of deliveries assigned to a hospital to be less than the current capacity and the available excess capacity of that hospital. Finally constraint (3) ensures that each MD assigned to a hospital will have at least \( t \) delivery tasks.

### 3.2.2 Application and Results

Due to the privacy issues, we have worked with relative average cost of assigning a patient to a hospital. For the similar reasons, we cannot display the real names of the hospitals. Table 11 represents the number of deliveries and the relative costs by hospital. Total relative cost for 2012 can be easily calculated using the table below. We found that the total relative cost is $3,462.33.

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Number of Deliveries 2012</th>
<th>Relative Average Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1,083</td>
<td>$0.790</td>
</tr>
<tr>
<td>B</td>
<td>1,351</td>
<td>$1.000</td>
</tr>
<tr>
<td>C</td>
<td>472</td>
<td>$0.786</td>
</tr>
<tr>
<td>D</td>
<td>277</td>
<td>$0.684</td>
</tr>
<tr>
<td>E</td>
<td>901</td>
<td>$0.836</td>
</tr>
<tr>
<td>F</td>
<td>0</td>
<td>$0.812</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>4,084</strong></td>
<td></td>
</tr>
</tbody>
</table>

The optimization model has been solved by changing the \( \alpha \) in the objective function. For \( \alpha = 1 \), the model does not take the preferences into consideration and minimizes the total cost of reallocating patients to the hospitals. As \( \alpha \) decreases, the model starts finding higher total costs to satisfy the preferences. Whenever \( \alpha \) reaches 0, the model will only consider the preferences...
and find the corresponding cost for the given preferences. Table 12 represents different solutions for 2 extreme $\alpha$ values.

Table 12: Results for extreme $\alpha$ values and associated savings

<table>
<thead>
<tr>
<th></th>
<th>$\alpha = 1$</th>
<th></th>
<th>$\alpha = 0$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>Burlington</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Copley</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medford</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Cambridge</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Peabody</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Chelmsford</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dedham</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Wellesley</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Norwood</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>West Roxbury</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Kenmore</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PO Square</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Quincy</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>HUHS</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Somerville</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Watertown</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Relative Total Cost</strong></td>
<td><strong>$3,184.08</strong></td>
<td></td>
<td><strong>$3,261.72</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Improvement</strong></td>
<td><strong>8.04%</strong></td>
<td></td>
<td><strong>5.79%</strong></td>
<td></td>
</tr>
</tbody>
</table>

In addition to developing an MILP model, we have developed the Excel tool shown in Figure 28. HVMA Ob/Gyn physicians have used the tool to find the assignment that is most appealing to them and compared their solution with the optimal solution.
3.2.3 Discussion

In this section, we presented a basic MILP model which re-allocates HVMA patients to the partner hospitals. In addition to reducing total cost, the model also considers physician preference. It is seen that up to 8% reduction in total cost is possible if physician preferences are ignored. Although we are not given the actual cost for each hospital, we were told that 8% saving in the total cost accounts for nearly 3 to 4 million dollars.
In order to make sure physicians are involved in the decision making process, a user-friendly Excel tool has been developed so that physicians can test their own solution and see the improvement. The tool have been used by the physicians and received positive feedback.
Chapter 4 - Conclusions and Future Work

As the slow pace of improvement in U.S. healthcare spending and quality persists, studies focusing on the effective delivery of healthcare are becoming more important. In this thesis, we present the use of systems engineering approaches on macro level design of healthcare networks. The approaches have been implemented to different real-life problems healthcare systems are facing.

Deterministic optimization is the main approach used in this study to determine the locations and capacity levels of the care units as well as the patient allocation to these units. In addition to deterministic approach, simulation is used to account for variability in future demand. The impact of using systems engineering approaches have been evaluated by 4 different applications which can be grouped under 2 categories. First set of applications involve locating care units whereas the second set of applications provide tools to design regional care networks.

In the first application, we first used an MILP model with deterministic demand to find the optimal locations of the colonoscopy screening units within the VA New England Network. In the second step, we generated random demand for these units and used Monte Carlo simulation to evaluate how the optimal solution change with variable demand. Results indicate huge savings and increased patient access by simply reallocating patients to the screening units.
In the second application, which is applied to HVMA care network, we first developed an optimization model to optimally locate ultrasound screening units and determine the optimal capacity levels. The initial results show that at least 7% reduction in average travel time is possible by only relocating the current units. In the second phase, we developed a probability model which uses the optimal solution, assumes Poisson patient arrival to the systems and inspects the patient allocation on capacity levels. The probability model gives the decision maker insight on how to adjust optimal allocation to reduce the cost of over-capacity and under-utilization.

The third and the fourth applications mainly focus on designing care networks. Similar to the first application, the third one has been applied to the VA. An MILP model has been developed to find the locations using estimated deterministic demand. Assuming Poisson patient arrival, a Monte Carlo Simulation model has been developed that tries to find a ‘dominating’ solution. The model shows that the initial solution remained optimal 64% of the randomly generated instances.

Finally with an effort to reduce total cost, the last application presents an MILP model that optimally re-allocates HVMA inpatients to different hospitals. Due to the challenge of implementing the proposed solution and to involve physicians on the decision making process, an Excel based user-friendly allocation tool has been developed. Even though we are not given the actual costs, up to 3 million dollar savings have been identified by re-allocating in patient volume.

All the applications listed above present the benefits of using systems engineering approaches in macro level design of healthcare networks. The analysis and results show potential savings in
terms of cost and patient access are possible by relocating care units and reallocating patients to these units.

This study informs the decision makers in multiple aspects. Firstly, it provides solutions for multiple possible scenarios and guides the decision maker to choose the one that is most likely to be implemented or has the biggest impact. Secondly, by building industry – university collaboration, it helps healthcare professionals be aware of the benefits of implementing systems engineering approaches to healthcare.

There are a few limitations to this study. Although we have worked very closely with healthcare professionals and based our models on relatively realistic assumptions, it is hard to model human behavior and dictate patients to receive their care from the center they have been assigned to. Another limitation is the way we handled demand variability. In all of the applications, we have used a 2-phase approach, solving the deterministic model first then using simulation to generate random demand and re-solving the optimization model. Since these aspects have been handled separately, the resulting solution may not necessarily be optimal. For future work, these could be handled simultaneously by using stochastic optimization techniques.
Bibliography


2007.