3-2021

Allocation of Scarce Healthcare Resources in a Military Treatment Facility during a Pandemic: A Comparison of Goal Programming and Portfolio Decision Analysis Methods

Donald B. Hale

ALLOCATION OF SCARCE HEALTHCARE RESOURCES IN A MILITARY TREATMENT FACILITY DURING A PANDEMIC: A COMPARISON OF GOAL PROGRAMMING AND PORTFOLIO DECISION ANALYSIS METHODS

THESIS

Donald B. Hale, Captain, USAF

AFIT-ENS-MS-21-M-165

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

AFIT-ENS-MS-21-M-165

ALLOCATION OF SCARCE HEALTHCARE RESOURCES IN A MILITARY TREATMENT FACILITY DURING A PANDEMIC: A COMPARISON OF GOAL PROGRAMMING AND PORTFOLIO DECISION ANALYSIS METHODS

THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Operations Research

Donald B. Hale, MS

Captain, USAF

March 25, 2021

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

AFIT-ENS-MS-21-M-165

ALLOCATION OF SCARCE HEALTHCARE RESOURCES IN A MILITARY TREATMENT FACILITY DURING A PANDEMIC: A COMPARISON OF GOAL PROGRAMMING AND PORTFOLIO DECISION ANALYSIS METHODS

Donald B. Hale, MS

Captain, USAF

Committee Membership:

Lt Col Marcelo Zawadzki, PhD
Chair

Dr. Jeffrey D. Weir, PhD
Member

AFIT-ENS-MS-21-M-165

Abstract

In the face of an unprecedented crisis, like a pandemic, healthcare decision makers face a difficult challenge of allocating critical, but scarce healthcare resources in a dynamic, uncertain environment. Their decisions will not only affect the patients coming to the hospital for treatment, both pandemic related and not, but also the Military Treatment Facility's personnel responsible for that treatment. The decision maker must decide the best course of action to allocate these resources in the hopes of achieving multiple, conflicting objectives under multiple resource constraints. In response, we propose a methodology allowing for the implementation of both a Portfolio Decision Analysis model and a Goal Programming model. The steps of this methodology provide a framework with which the decision maker can aim to develop an optimal allocation of resources based on the organization's values and goals. This framework was then applied to a notional case study as a means of comparison for these two models that were explored. Both a linear value function and a piecewise value function were explored to show the effect of the very likely non-linearity of value functions scenario on each method's results. Complementary analysis, namely budget analysis and tradeoff analysis was conducted to illustrate potential insights into the model and the problem itself that could be highlighted. This application showed the merits of both models. PDA allows for the decision maker to decide what values are important to the organization and then maximizes that value generation via the objective function which is driven by the value

function. The GP approach allows for the decision maker to set target level that would be ideal for each objective and then minimizes any deviation from that goal subject to penalty based on the value function. Both, using the framework provided, allow for as little or as much fidelity as required based on the situation. Each model can be easily updated to account for the dynamic environment or as a result of the budget and tradeoff analysis findings. The flexibility and adaptability of these models is especially useful in our problem.

Acknowledgments

I would like to express my sincerest appreciation and deepest gratitude for my thesis advisor, Lt Col Marcelo Zawadzki. His constant support and guidance over the past year is what made this thesis possible. I am thankful for the opportunity to have worked under his advisement.

I would also like to acknowledge my committee member, Dr. Jeffrey Weir, for being a second reader, and I am grateful to him for his aid in developing the model and for his comments that improved the contents of this thesis.

I would also like to thank my family. Their continuous support and encouragement kept me motivated throughout the development of this thesis. Through their lessons and example, they have shown me the importance and value of hard work and education. I would especially like to thank my incredible wife and three (soon to be four) wonderful children for their unwavering love, patience, and sacrifice during the countless hours I have spent working on this thesis. I can honestly say that I would not have made it this far without them by my side.

Donald Bret Hale, Jr

Table of Contents

Page

List of Figures

List of Tables

Table Page

ALLOCATION OF SCARCE HEALTHCARE RESOURCES IN A MILITARY TREATMENT FACILITY DURING A PANDEMIC: A COMPARISON OF GOAL PROGRAMMING AND PORTFOLIO DECISION ANALYSIS METHODS

I. Introduction

1.1 Background

A crisis can arise unexpectedly and, despite preparation, brings about uncertain circumstances and a sudden strain on key resources. Such a crisis can be triggered by a natural disaster, an act of aggression or terrorism, or a pandemic, like the COVID-19 pandemic which has led to a dramatic loss of human life worldwide and presents an unprecedented challenge to public health (ILO, FAO, IFAD, WHO, 2020). Each emergency situation requires a unique, dynamic, and agile response to ever-changing needs. Crisis impacts reflect in multiple environments such as the economic and the social dimensions of society. For example, the Supply Chain Resource Cooperative (2005) outlines how both Hurricane Mitch in Central America in 1998 and the September 11 terrorist attacks in 2001 disrupted supply chains and caused widespread transportation delays. In 2009, the H1N1 influenza prompted shortages of protective respirator masks (HealthLeaders, 2009). Turnquist and Rawls (2012), when seeking to develop a model, examined the sudden influx of people seeking shelter following a natural disaster that created demand for emergency supplies that were immediately needed. Others have looked at the need for a healthcare system and its response to have preplanned and practiced procedures in place to improve responses following a terrorist attack (Chauhan, Conti, and Keene, 2018). In a study about the H1N1 influenza of 2009, Sherlaw and Raude (2013) illustrate the potential public crisis that was averted thanks to, in part, the preparedness of the French government with vaccinations and prioritizations.

A crisis like the COVID-19 pandemic, requires not only an immediate need for general household goods, such as toilet paper, cleaning products and hand soap, but also specific personal protection equipment (PPE) and professional devices for essential workers to conduct their activities. According to the Department of Homeland Security, essential workers are those who conduct operations and services that are necessary to continue critical infrastructure operations (NCSL, 2020). Healthcare workers are among those considered essential and furthermore, federal guidelines, like those of the Occupational Safety and Health Administration (2020) stipulate that healthcare providers with a high exposure risk should use respirators. One of the most critical items for healthcare workers is PPE. PPE is special equipment healthcare workers wear to create a barrier between them and germs. This barrier reduces the chance of touching, being exposed to, and spreading germs. According to the World Health Organization, PPE for protecting against respiratory droplets, which are dangerous with the current pandemic, consists of a gown, medical mask, goggles or a face shield, and gloves (WHO, 2020). In diseases spread by direct contact, such as Ebola, the CDC recommends an impermeable garment, respiratory protection, disposable exam gloves, disposable boot covers, and disposable aprons (CDC, 2019). During the COVID-19 initial phase, the Secretary of Health and Human Services identified several products as scarce to include: N-95 masks, portable ventilators, PPE face masks, PPE surgical masks and PPE shields (WilmerHale, 2020). This type of scarcity directly impacts the performance of essential workers. Specifically, how to prioritize the allocation of scarce resources to properly meet this demand may be considered one of the critical challenges that need to be addressed during such a crisis.

One particular essential organization with employees that face high risk exposure is a hospital. The risks to healthcare workers during a pandemic situation are appreciably greater than those encountered in normal practice. In addition to the risk of contracting the infection, other tolls include physical and mental exhaustion, the torment of difficult triage decisions, and the pain of losing patients and colleagues (Healthcare Heroes, 2020). The burden of the COVID-19 outbreak on healthcare providers makes it extremely likely that healthcare workers involved in the diagnosis, treatment, and care of patients with COVID-19 are at risk of developing psychological distress and other mental health symptoms (PTSD symptoms, 2020). Hospitals must adapt and maneuver through all the regulations and considerations to its workforce. For instance, because of the restrictions put in place by the government of many states, some of the standard medical procedures were not allowed to take place in a hospital during the pandemic (COVID OH, 2020). Simultaneously, other procedures, such as patient intubation in intensive care units become critical during a pandemic, are often required in the clinical environment, and require more specific training (ICU Management, 2020). Healthcare workers require specialized training, so that coupled with the high risk of exposure brings questions about the depth of the workforce available should they contract the virus. Finally, the hospital must be agile in adjusting to new information about the virus as it matures.

A military treatment facility, MTF, is a facility established for the purpose of furnishing medical and dental care to eligible individuals. An MTF acts as a typical civilian hospital, but with the added component of ensuring all active and reserve military members are healthy to complete national security missions and that the MTF personnel in uniform are trained and ready to provide medical care and support of operational forces around the world (Military Health System, 2021).

In military hospitals, the combination of PPE and other resource shortages, workforce risk and potential scarcity, specific military organizational regulations, and the need for specialized training create this complex situation of huge demands against limited financial and personnel resources. A methodical approach to resource allocation can help with leadership decision-making and ensure efficient utilization of these resources.

1.2 Problem Statement

A hospital, specifically a military hospital, during a pandemic crisis has several competing objectives that must be addressed simultaneously with a limited number of available resources. The necessary health care required encompasses a large context under normal circumstances. It is difficult to define this context because there are many competing dynamic objectives and limiting factors. For example, according to the Wright Patterson Air Force Base COVID-19 Commanders and Supervisors Guidebook (2020), healthcare capacity (HC) is "the ability to effectively treat both COVID-19 and non-COVID-19 patients inside and outside of the installation. Limiting factors for HC include the number and type of health care providers, hospital rooms, ICU rooms, ventilators, and personal protective equipment." Furthermore, the document claims that healthcare capacity is critical to support a safe and healthy workforce and ensure the ability to do the mission. With the COVID-19 pandemic situation that means maximizing available beds if admittance is required, available ventilators for patients requiring them, and available personal protective equipment for the doctors and nurses required to treat the patients. Secondly, the hospital needs to minimize the risk to its employees, not only as a moral decision, but also as a means of meeting the first objective. Additionally, as a key role in base operations, the hospital has a requirement to effectively support base personnel to maintain mission ready status. Finally, cost must also be considered and monitored. All of this makes the allocation of resources a complex problem. It requires a robust method capable of dealing with all the complexity while optimizing the utilization of available resources.

1.3 Research Objectives

The main objective of this study is to compare two of the most explored resource allocation methods, PDA and GP, when aiding the optimization of the resource allocation process that would allow for the achievement of optimal performance of a military treatment facility during a pandemic. To achieve the main objective, the following specific objectives are proposed:

1. An investigation into hospital resource allocation problems and approaches to solve them in the past.

2. Research into applications of Portfolio Decision Analysis and Goal Programming for resource allocation optimization.

3. Modeling and solving the healthcare resource allocation optimization as a Portfolio Decision Analysis and a Goal Program.

1.4 Summary

In Chapter 2, this document provides a literature review about the resource allocation problem in the healthcare environment, focusing on the hospital resource allocation problem. Then, it reviews the scientific literature about the most explored methods that support resource allocation, namely Portfolio Decision Analysis (PDA) and Goal Programming (GP), and discusses important aspects of the difference between these two methods. In Chapter 3, it presents the methodology to be followed in this work to allow the comparison of these two methods when seeking to optimize resource allocation on health organizations. Chapter 4 presents a hypothetical case study where the proposed methodology is applied using both the PDA and GP approach, followed by analysis and results from the study. Finally, Chapter 5 concludes the document, presents limitations of the methodologies, and provides recommendations on future research in the field.

II. Literature Review

2.1 Overview

This chapter reviews the scientific literature about hospital resource allocation problems in order to develop intuition into potential approaches that best fit the needs of healthcare resource allocation. Then, it investigates and characterizes two of the most explored methods that support resource allocation, namely Portfolio Decision Analysis (PDA) and Goal Programming (GP). Ultimately, we will seek to understand the main differences that may exist between the problems explored and the results delivered by both methods.

2.2 Hospital Resource Allocation

Health resource allocation refers to the health resources which were distributed and flowed throughout the healthcare industry, at a macro level, or a department at a local level (Yi Tao et al, 2014). Tao continues by claiming these allocations are also influenced by factors such as convenience of medical service, hierarchy of needs, the quantity, quality, and scope of supply, and the degree of effective utilization. The health sector, specifically hospitals, has been asked over the last years to manage fixed resources against increasing healthcare activities from an ever-increasing number of needs from a population which is older and older (Bodina et al, 2017). These resource decisions happen at every level of the healthcare enterprise. Often, national level priorities impact patient-specific allocations. As described by Marino and Quatronne

(2019), national recommendations cannot take into account local factors such as population needs, organizational priorities, budgets, capacity or capability, therefore many crucial decisions need to be made at institutional levels. One national example of resource decision-making comes from the National Institute for Health and Clinical Excellence for England and Wales which sought to reduce spending on treatments that do not improve patient care through divestment (Pearson and Littlejohns, 2007). Divestment is closely linked to efforts to set priorities and allocate resources wisely; and it has logic in taking resources from less effective services and applying them to meet unfilled needs. Despite this logic, the divestment process presents difficult scientific, political, and ethical challenges (Pearson and Littlejohns, 2017). Research shows that healthcare resource priority setting has focused on the macro (national) and micro (bedside) level while leaving the intermediate (hospital) level relatively neglected. This is despite the fact that hospitals play a key role in the delivery of healthcare services and utilize a large proportion of health system resources (Basara et al, 2015). It may not always be hospital-specific resources, but partnerships providing alternatives through other healthcare facilities that provide relief. For example, one suggestion for the COVID-19 pandemic is for pediatric intensive care units, which are less effected due to demographics of infected people, to share resources by either importing adult patients or exporting excess key ICU resources (Wolf et al, 2020). This idea highlights the need to explore alternatives within the organization as well as from outside to achieve the hospital's objectives. Several strategies may be employed to rationalize resource allocations and reduce relative cost, but unfortunately many of these interventions do not provide the intended benefits and the outcomes are not easily measurable (Marino and Quattrone, 2019). Moreover, according to Pearson and Littlejohns (2007), health authorities, hospitals and other health care facilities have always moved resources from one area to another in order to maximize scarce resources, but decisions to restrict or reallocate resources are generally reactive, in response to established or emerging problems (Pearson and Littlejohns, 2007). As evidence above, hospital resource management has multiple objectives with many sets of alternatives that may be adopted to meet the dynamic needs of healthcare. Specific investigations about fundamental values that must be addressed during an extreme situation, like a pandemic, are presented by Emanuel et al. (2020) and converges on four values: maximizing the benefits produced by the scarce resources, treating people equally, promoting and rewarding instrumental value, and giving priority to the worst-off patients. These values yield six specific recommendations for allocating medical resources in a pandemic: maximize benefits; prioritize health workers; do not allocate on a first-come, first-served basis; be responsive to evidence; recognize research participation; and apply the same principles to all pandemic and non–pandemic patients. Emanuel et al. (2020) argue that no single value is sufficient to determine which patients should receive the resources and that an adaptable, multi-value ethical framework is required for fair allocation. These values and proposals are either working in concert together or in competition with one another and, therefore, the distribution of resources requires an optimization of values that are ethically based.

Many researchers have tried to address the resource allocation issue in health organization environment by different optimization approaches. For example, Grant and Hendon (1967) applied a linear programming approach in solving a common problem in the marketing of hospital services. It was an effort to maximum audience exposure while constrained by the hospital's limited finances. The advertising campaign was viewed as a success and the conclusion suggested there were extensions to the approach for other scarce-resource allocation decisions. Mulholland et al. (2005) utilized a linear programming model to optimize financial outcomes for both the hospital and physicians in the department of surgery. This model dealt with the decision of procedure mix or the number of a surgical procedure type. The constraints of the model are the resources that are consumed during the patient's surgical experience. Through this mathematical model, aligning quality surgical care with optimal financial performance produced an increase in both professional payments and the hospital's total margin. A third example of linear programming use in hospital resource allocation estimates the impact of changes in a hospital's operating room time allocation on variable costs (Dexter, 2002). The objective was to maximize variable costs to determine the worst-case scenario for the increase under the assumption of fixed resources. Four phases of analysis were conducted, adding more constraints on additional resource availability in each phase. With this model and methodology, it was shown that allocating operating room time based on utilization can adversely affect the hospital financially. Instead, the operating room manager can reduce this potential increase in costs by considering operating room time, the resulting use of hospital beds and implants.

As a variation of linear programming, researchers have also tried to approach health resource allocation problems using integer programming. Gunipar and Centeno (2015) presented integer programming models to minimize the total cost, shortage, and wastage levels of blood products at a hospital. Each model resulted in reduced total cost, reduced shortages, and decreased wastage rates, respectively. Another methodology consists of a mixed integer programming model to determine a weekly operation room allocation that minimizes inpatients' cost (Zhang et al., 2017). This cost is measured as length of stay and several patient type priority and clinical constraints are included in the formulation. A simulation model then captures some of the randomness of the processes and outputs the average length of stay for each specialty and the room utilization. A case example shows how the hospital length of stay pertaining to surgery can be reduced. In a separate study about operating room allocation, integer programming was used in an effort to minimize the difference between assigned operating room time and the agreed upon target time of hospital departments (Blake and Donald, 2002). A penalty was assigned to avoid the extremely undesirable outcome of a target time shortfall. Constraints on the solution are daily global, daily type, or weekly bounds on the number of rooms that may be assigned to a department. This model provides an allocation of whole blocks of time to departments in a manner that minimizes the shortage of time to each department. This makes the schedule have only whole blocks, resulting in a consistent week to week schedule and the model's bounds ensure the resulting schedule is always feasible. The authors also claim the model has greatly reduced conflict among the departments.

In another example, specifically in the health field, Crown (2018) shows, through the application of constrained optimization, a method that provides insights to decision makers about how to optimally reach the targets set in relation to cost and the associated value of each available policy choice. This maximizes the outcome of health gain. In a separate study, Varghese et al. (2020) describe the use of a constrained optimization model to help prioritize the introduction of various infectious disease interventions within the budget constraints while simultaneously optimizing the health outcome measure of quality-adjusted life-years gained. Since funding for all the specified programs each year far exceeds the available annual budget, this portfolio model helps healthcare decision makers effectively develop health plans aimed at attaining specific health goals over time under constrained budget investment forecasts.

We may conclude that resource allocation problems in the healthcare environment embrace the following characteristics:

1. There are multiple objectives that are critical and must be considered when defining resource allocation policies.

2. A vast list of alternatives may be adopted to meet the situationally dynamic needs of healthcare and these needs may be grouped into different sets of alternatives.

3. There is a level of risk associated with any allocation, even an optimal one, therefore a prioritized list of objectives is necessary and risk management strategies must be considered.

These types of problems are characterized as portfolio problems. Addressing the resource allocation problem in the healthcare sector as a portfolio problem would be interesting since this approach offers the following benefits:

1. Solves problems where the availability of resources is typically limited by constraints while the desirability of consequences depends on the preferences concerning the attainment of multiple objectives.

2. Allows for selecting a subset or portfolio from a large set of alternatives.

3. Considers that there can be uncertainties at the time of decision making and it may be unable to determine what consequences the actions will lead to or how many resources will be consumed.

Two main approaches can be found in the literature concerned with defining efficient portfolios in the resource allocation class of problems: Portfolio Decision Analysis (PDA) and Goal Programming (GP). In the following sections, we study the literature regarding both approaches and examine applications to determine their usefulness and relevance to our resource allocation problem.

2.3 Portfolio Decision Analysis

The use of a portfolio approach is typically categorized into three main fields: (i) economic, (ii) project management, and (iii) risk management. Through the examination of these three types of portfolios, we can determine aspects and methods that may be useful in application for our problem.

Portfolio selection problems related to economic investments, particularly in the stock market, have a root in decision analysis. This root really took hold after Harry Markowitz published his article “Portfolio Selection” (1952). He argued there is a rate at which the investor can increase expected return by taking on variance or reduce variance and decrease expected return. This was characterized as the volatility or risk. Markowitz devised a method to mathematically match an investor’s risk tolerance and reward expectations to create an ideal portfolio that focused on diversification of asset classes and securities, hence "diversifying your portfolio." These economic portfolio problems are examining alternatives that can be used to maximize the organization's or individual's profit objective subject to financial and risk constraints. When there are portfolio constraints, the Black-Litterman model can be used to generate the expected returns for assets and then use a mean-variance optimizer to solve the constrained optimization problem (Black and Litterman, 1991). Kaiser described a simple model constructed to allocate portfolios between stocks and real estate and between bonds and real estate. His conclusion is that fundamental value strategies can offer superior return/risk ratios to any of the single asset comparisons (Kaiser, 1999). This demonstrates that, at times, resources can work in tandem to create a more than summative outcome. Financial portfolios typically rely on past performance as an indicator for future performance. The decision variables are continuous in the markets and the primary objective, is only based on profit.

Another field that largely explores the portfolio approach is in the project management area. Mottley and Newton (1959) brought to light the important decision problem of project selection as part of project management in 1959. Research departments of organizations propose problems for investigation or potential investment at a faster rate than the resources or money for the projects can support. This brought about their method of evaluation based on numerical scores quantifying certain important criteria which included promise of success, time required, cost, market situation, and expected gain. The resulting scores help determine the best project mix given budget allocation.

Risk management is an organized methodology for continuously identifying and measuring the unknowns; developing mitigation options; selecting, planning, and implementing appropriate risk mitigations; and tracking the implementation to ensure successful risk reduction. Effective risk management depends on risk management planning; early identification and analyses of risks; early implementation of corrective actions; continuous monitoring and reassessment; and communication, documentation, and coordination (DoD, 2006). Portfolio optimization is an approach to address the issue of risk (Markowitz, 1952). A large number of studies have applied the portfolio optimization approach to manage risk. For example, in the electricity market, Jun Xu et al. (2006) present a midterm power portfolio optimization model and the corresponding methodology to serve the load, maximize the profit, and manage risk. In this paper, the power supplier has three sources of power available to then distribute across its grid and meet its obligations. This supply comes from forward markets (bought months in advance), day-ahead markets (one day in advance), and real-time markets (bought or sold now). Due to the large amount of power involved, the complex market structure, and the risks in these volatile markets, a power portfolio problem is critical (Jun Xu et al, 2006).

Portfolio Decision Analysis (PDA) is "a body of theory, methods, and practice which seeks to help decision makers make informed multiple selections from a discrete set of alternatives through mathematical modeling that accounts for relevant constraints, preferences, and uncertainties" (Salo, Keisler, & Morton, 2011). The types of problems described before; economic portfolios, project management, and risk management, may seem different, yet share many similarities from a methodological point of view. There are decision makers faced with alternatives which will consume resources, of which are typically limited by constraints. Each also has some level of preference of attaining multiple objectives while facing uncertainty. These are the key parts of the definition above, hence Portfolio Decision Analysis links with each problem type.

In one example where the PDA approach was explored, (Anadon et al, 2014), the United States Department of Energy (DOE) presents a study for supporting research and development resource allocation to facilitate a clean and independent energy future for the nation. A key element to this study is that the DOE and other government agencies sponsor exploration of technologies where market failures and high risk prevent private sector investment and the payoffs exist primarily in the realm of shared social benefits (Anadon et al, 2014). Hence, profit is not the primary driver and there is non-monetary value generated. A decision support system is developed in the form of a PDA model which can determine the greatest overall value of the portfolio. In a similar application using PDA, Kurth et al. (2007) explain that the decision maker's risk attitude can be incorporated into the model to create a risk adjusted score for a given funding allocation plan. The study also shows that funding the options that generate the highest score leads to a greater expected value than other strategies of similar budget proportions. A third example describes how the PDA approach combines optimization and multi-criteria evaluation in environmental decision making (Lahtinen, Hämäläinen, & Liesio, 2017). Kleinmuntz (2007) offers the employment of aspects of PDA in a hospital capital budgeting study leading to a consensus around model recommendations among decision makers.

The main benefits we may observe from the Portfolio Decision Analysis approach are the following:

1. Maximizes value of multiple objectives competing for scarce resources based on the decision maker's preferences or weights.

2. It may incorporate a decision maker's risk attitude to create a risk adjusted score.

3. Exhibits adaptability to changing markets or situations allowing for a quick update based on a dynamic environment.

4. Can be used to incorporate ethical or social considerations as additional criteria.

In our hospital resource allocation problem, decision makers are faced with choosing how best to spread out the constrained resources to achieve the greatest value for the multiple competing objectives based on the stakeholders' preferences and while surrounded by uncertainty. As described above through the examples, PDA offers a methodology equipped to handle such a problem. Therefore, we believe that a PDA approach is a suitable and fruitful method to optimize this resource allocation.

2.4 Goal Programming

The other oft used approach for optimal resource allocation is Goal Programming (GP). It is an extension of linear programming built to handle multiple and competing objectives. Each objective measure is given a goal to achieve and deviations from these targets are minimized. The method of GP was first introduced by Charnes, Cooper, and Ferguson in 1955 (Charnes, Cooper, & Ferguson, 1955).

A wave of research on the subject followed with many approaches being proposed. The use of GP was formalized by Lee and Jerro (1974) to provide a systematic approach to handling multidimensional objectives. Organizations could now seek to maximize their total resources while simultaneously seeking to maximize secondary objectives such as responsible ethics. Further research added the concept of tradeoff among commitment of resources, expected payoff, and risk while exploring the impact of individual preferences among investment opportunities (Schwartz and Vertinsky, 1977). Goal programming is another technique used to solve health care resource allocation problems. Sang Lee (1972) was one of the first to apply GP for hospital administration. This model took the hospital administrator's list of seven goals, based on the hospital's current operations and listed in order of importance, balanced against the hospital's seven constraints. The model's objective function sought to minimize deviations for the goal constraints with certain priorities assigned to them. From this, the top four goals or priorities were achieved, the fifth and sixth goals not precisely achieved, and the final goal of minimizing cost not possible as it was the lowest priority. Lee expanded and adjusted this simple model to account for the potential for growth, capturing hospital operation with expanded facilities. This added revenue variables and shifted or added priorities. The most notable shift was for the cost goal to become of higher importance as well as the addition of priorities related to expansion. The expanded model shows the flexibility of a GP model and its direct application to hospital resource management to find the optimum resource allocation mix. Another GP model, by Blake and Carter (2002), takes a two-model strategic approach for resource allocation. One model sets a case mix and volume for physicians, holding service costs fixed and the other model translates the case mix decisions into a set of practice changes for the physicians. This allows decision makers to set case mix and cost in such a way that the hospital is able to break even while minimizing disturbance to the practice. The model was successfully applied to a real-world scenario where a surgical division faced a 3-year, 18% funding reduction. GP can also be used as an aid to planning and allocation for limited human resources in a health care organization (Kwak and Lee, 1997). Their goal was to assign system personnel to the proper shift to meet the objective of minimizing the total payroll costs and keeping patients satisfied. Three of the most complicated, complex departments were selected to simplify the problem. Five goal constraints, with associated priorities were developed, along with several system constraints, all influencing the objective function. The model allows management to determine in advance what will happen if the outcome deviates from overall objectives. Furthermore, it shows that management can use the information generated by the solution to alter decision variables and create new satisfactory solutions given different operating conditions. Hospital bed allocation models have often taken a simulation and goal programming approach. One such study (Ataollahi et al, 2013), identified important bed allocation constraints through literature review and expert interviews. The objective function was based on the following goal constraints: minimizing the number of empty beds, maximizing use of human resources, minimizing waiting time, definite allocation of bed to patient, and definite allocation of bed to ward. The additional constraints were determined based on the resources that bed allocation affects, like staff resources and budget. The results of the GP approach led to an optimum allocation of the limited resources.

In our hospital resource allocation problem, the decision maker is faced with the allocation of scarce resources to satisfy multiple competing objectives. GP provides a way to accomplish this by setting goals for each objective and minimizing any unwanted deviation from those goals. Therefore, we believe that a GP approach also offers a suitable and effective method to optimize this resource allocation.

2.5 Conclusion

We have reviewed the hospital resource allocation problem and described potential solutions to these problems. We have observed that health resource allocation problems, in contrast to economic problems, are characterized by more than just profit. Additionally, the resources in economic problems, namely money, are easier to divide and apply to different aspects of the portfolio than are the resources in the healthcare industry. While project management problems share attributes of the hospital resource allocation problem such as multiple objectives and risk, they tend to focus on time required and cost tradeoffs, whereas hospital resources during a crisis typically are focused around supplies, equipment, and personnel. The hospital resource allocation problem may present some overlap with the risk management field as well. For example, it is possible to compare the production risk and the service requirements of the hospital. Also, commercial risks would relate to increases in costs related to health issues such as personal protection equipment and the changes in the market conditions that suddenly make them scarce. Each process displayed aspects that met the needs of the hospital resource allocation problem, but a Portfolio Decision Analysis approach offers more aspects beneficial to our problem. Additionally, we explored the applications of a goal programming model. Likewise, the approach aligns well with the problem at hand by incorporating the allocation of resources based on multiple objectives with some sort of preference under a constrained environment. Next, we will outline the common steps for creating both models, followed by a discussion on the unique aspects of each model's format as a means of comparison.

III. Methodology

3.1 Overview

In this section, we describe the proposed process of structuring the problem and associated assumptions in determining both an appropriate Goal Programming (GP) model and a Portfolio Decision Analysis (PDA) model for the problem of optimizing the allocation of scarce resources. The methodology of both approaches will be outlined, with generic formulations. This chapter also provides insights and important considerations when comparing the two models. Similarly, it will discuss the results expected from each model and the potential interpretation of these results for decision makers concerned with this type of problem.

3.2 The Selected Methodology

Figure 1 depicts the steps that must be taken for the structuring, solving, and communicating of results of any complex optimization problem similar to the one we are approaching in this work. Notably, some of the steps, namely steps 1 through 5 and 8, are typically common to most of the existing optimization methodologies. This is also the case in the work presented, where steps 1 through 5 and 8 are going to support, in the same way, both the application of the GP model and the PDA model.

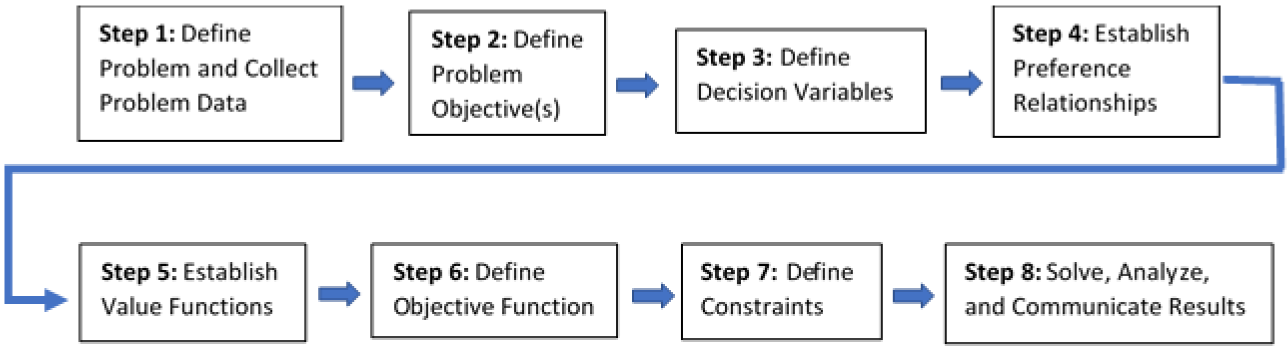


Figure 1. Optimization Methodology Steps

3.2.1 Define Problem and Collect Data

To set the stage for solving a problem of optimization, it is necessary first to formulate it in a manner reflecting the situation being modeled (Rockafellar, 1997). Therefore, determining a thorough definition of the problem is a vital step in beginning to formulate a model. Although problem definition and data collection are not necessarily the focus of this work, there are interesting and powerful methods for accomplishing these activities. Problem structuring methods are widely used in the literature and may scientifically support these activities. Mingers and Rosenhead (2002) compiled a substantial record of applications that describe a wide variety of use in both context and content. An illustration of defining the problem and collecting data comes from Oddoye et al.'s (2009) study of a Medical Assessment Unit (MAU) in the United Kingdom. The MAU acts as a buffer between the emergency department and the rest of the hospital, able to provide observation and treatment to the patient for 48 hours before either discharging them or transferring to a specialist department in the hospital. The problem was initiated by clinicians from the MAU who framed it as a resource problem with the hope of avoiding a bottleneck of transfers from emergency to specialist. The clinicians' concerns were categorized into several areas, of which the study and the data collection focused on one concerning resource level. The model was then developed using data from the MAU database over 4 years, after it was cleaned. Following the definition and structuring of the problem, the focus shifts to developing problem objectives.

3.2.2 Define Problem Objective(s)

Once the problem has been defined and researched, it is important to focus on the objective or, in some cases, objectives that one may want to consider when seeking potential solutions to the problem. Keeney (1992), when describing his Value-focused Thinking (VFT) approach, states that a decision maker's values are made explicit with objectives. He continues by writing that fundamental objectives, as opposed to means objectives, are the basis for any interest in the decision being considered and qualitatively state all that is of concern in the decision context. They also provide guidance for action and the foundation for any quantitative modeling or analyses that may follow. When formulating fundamental objectives, several properties must hold. The fundamental objective should be essential, controllable, complete, measurable, operational, concise, and understandable. If the objectives have these properties, the problem can be formulated in a manner that produces value to the decision maker. A complete description of fundamental objectives can be found in Keeney (1992). For instance, Oddoye et al. (2009) show how the value of delivering more efficient and effective care led to a focus on resource levels after meeting with the MAU clinicians. In their work, they produced four objectives that were considered fundamental in that study. These objectives were: (i) minimize patient delay, (ii) minimize extra number of doctors, (iii) minimize extra number of nurses, and (iv) minimize extra number of beds required, the last three objectives measured by hours of the day. With the objectives specified, the inputs to the model need to be discussed.

3.2.3 Define Decision Variables

Once the objectives have been defined, additional research should be conducted for the problem to determine what can be done to impact the achievement of these objectives, specifically the set of alternatives that are available for the decision maker to choose. This set of alternatives or their combination in strategies defines the problem decision context (Keeney, 1992). The manner to measure how much will be spent in adopting alternatives may be through a discrete measure, for example different suppliers of medical equipment, or may be through a continuous measure within a defined range like different quantities of hours to be worked by a doctor in an intensive care unit, ranging from a minimum of 5 hours to a maximum of 12 hours. The inputs, which indicate different manners of adopting the available alternatives will become the decision variables of the problem. The variation of these values will influence the performance achieved for each of the problem objectives, either aiding or hindering their realization. The decision variables often are inputs to other computed parameters that add additional insight or context to the problem. For instance, in Oddoye et al.'s (2009) study, the main decision variables are binary and relate to whether patients are seen by doctors and/or nurses during a given hour. They were categorized into 3 types: initial contact, ongoing contact, and discharge. These impacted other important variables to be calculated such as the number of doctors, nurses, or beds available, but not used during the hour, as well as the number of extra doctors, nurses, or beds required in that hour. Patient delay and starting hour of treatment could also be determined. In another example, Blake and Carter (2002) present a model that has integer decision variables that assign a certain number of patients to each doctor. Furthermore, Karakas et al. (Karakas, Koyuncu, Erol, & Kokangul, 2010) utilize a mixture of integer and binary decision variables related to cost in their formulation. There also exist models where the decision variables and inputs take on multiple variable types, as is the case with Chu et al. (Chu, Ho, Lee, & Lo, 2000) who that modeled the distribution of the nurse team work hours utilizing both continuous and binary variables.

3.2.4 Preference of Objectives

With the objectives now defined, the next step is concerned with preferences or priorities that may exist among the problem's objectives. This will determine the order they should be accomplished. This preference also helps to determine how the objective function of the optimization problem should be formulated. If there is a clear priority, there are different approaches that may be taken. We discuss later, specifically for each of the methods we are exploring in this work, suitable manners of encompassing different preferences for objectives when this is the case. Additionally, any dependencies between objectives should be noted, so they can be incorporated into the model later.

3.2.5 Value Functions

One important aspect that must be encompassed in any optimization model is the definition of the returns to scale on a measure of importance that may exist (Kirkwood, 1998). Businesses typically measure value in dollars, often net present value. This allows benefits or value to be converted to dollars. When benefits cannot be converted to dollars, or when this is not a convenient measure, it is possible to use normalized values. Normalized value uses a value function to convert the level on a measure to a normalized value instead of dollars or net present value as shown in Figure 2. The value model that is being maximized should be based on values carefully elicited from the decision maker. The value measures can be direct or proxy and natural or constructed, all dependent upon the amount of time and data available. A complete discussion about different types of attributes used for measuring values is presented by Keeney and Gregory (2005). According to Ghoushchi et al. (2019), the application of appropriate value functions can cover the preferences of the decision maker to a great extent and determine the final ranking more clearly and reliably for the decision maker.

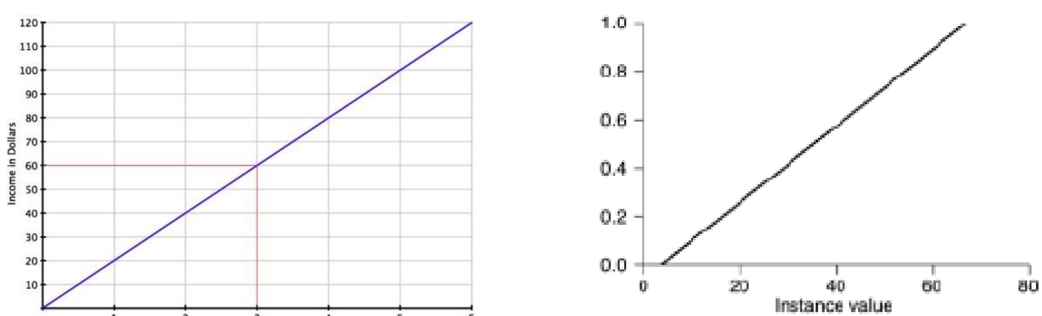


Figure 2. Linear Value Function in Dollars and Normalized.

Value functions can be linear or nonlinear. Either form begins with anchor points set to values of 0 and 1, which indicate the high and low levels while defining the preference order. A simple linear value function estimation method is a direct rating. Here the decision maker rates remaining attribute levels in terms of relative value such that relative spacing between impact levels reflects preferences of one level to another (Belton, 1986). Bisection is another method that can be used. In this mid-value splitting technique, the decision maker is asked to determine the halfway point between two levels in terms of value. This is done to the level of fidelity desired and is especially useful with unknown or continuous levels. Another technique is using the piecewise linear value function where the decision maker assesses relative value increments between each of the potential attribute levels. For example, the smallest value increase between levels is determined and all other increments are based in terms of that smallest value. Then, the actual value for each increment can be defined by setting the sum of all increments equal to 1. A piecewise value function can be a good alternative when other functions are incapable of representing the value function shape desired, such as a V-shape (Ghoushchi, Khazaeili, Amini, & Osgooei, 2019). Some numerical attributes like time, cost, or distance can take on infinite continuous levels. To capture this, a large number of impact levels may be defined and approximated by a piecewise function or a nonlinear function, like an exponential may be used. When a nonlinear value function is desired, Kim and Lin (2000) argue that an exponential function with varied parameters can generate a rich variety of shapes making it a suitable and admissible functional form. Liesio (2012) shows an example of the use of an exponential value functions in the selection of conservation sites. Kirkwood and Sarin (1980) present preference conditions that, if met, restrict the nonlinear value function to an exponential, logarithmic, or power form. Nonlinear functions may more accurately depict the decision makers preferences but add complexity to the model. Choices on whether a linear value function or nonlinear value function is used must find a balance between this tradeoff. A piecewise linear value function can also be utilized to estimate a nonlinear value function if required.

The most common calculation for total value in a portfolio is the additive model, which is the weighted sum of the value on each value measure (Parnell, 2007). Buck and Parnell explain that such a model is made up of five parts: a value hierarchy, which describes and organizes the benefits desired; measures that quantify each benefit; ranges for each of the measures, from worst acceptable (or available) to best possible (or available); value functions that describe how value accumulates as one goes from low to high scores in each measure; and swing weights that show the relative value of full-range swings in each of the different measures (Burk & Parnell, 2011). An important assumption for the additive value model is that the measures are mutually preferentially independent. This means that the assessment of the value function on one value measure does not depend on the scores of other value measures (Keeney & Raiffa, 1976). With the groundwork of the problem formulation laid, we now must define the objective function.

3.2.6 Define Objective Functions

An objective function, in a mathematical optimization problem, is the real-valued function whose value is to be either minimized or maximized over the set of feasible alternatives. For instance, the PDA problem's objective function seeks to maximize the value of a portfolio, while in a GP formulation, the objective function seeks to minimize any deviations that may exist among decision variables, target levels, and a given solution to the problem. While their objectives are quite distinct, both offer solutions to the resource allocation problem we are approaching in this work. We present specific comments about objective functions for both of the explored methods when discussing each one later in this chapter. Detailed comments about the next section, constraints for each method, are also presented later in the chapter.

3.2.7 Define Constraints

Another vital part to solving an optimization problem is determining what limitations must be obeyed in the problem and developing constraints to model those restrictions. These constraints can be based, for example, on the availability of resources, undesired upper and lower thresholds for the resources, or explicit conditions that the model must observe. These constraints may restrict the achievement of the objectives of the problem and sometimes limit the solution space. There are two types of constraints to be considered: (i) hard constraints and (ii) soft constraints. Hard constraints are "musts" and define the widest acceptable limits of the soft constraints, or "wants" which bracket the most desirable range of the constraint value (de Kluyver, 1978). The example that de Kluyver (1978) gives from advertising is that the desired range for ads, or soft constraint, is between 4 and 10, but the hard constraint is that there must be between 1 and 13 ads. Akplogan et al. (2013) use both hard and soft constraints in their integer linear program formulation to crop allocation. With this step, the model is formulated.

3.2.8 Solve, Analyze, Communicate

After the formulation of the optimization program, it needs to be solved using an appropriate solver, such as Microsoft Excel, Minitab, Matlab, etc. This will provide a solution that shows the mixture of decision variables that produce the best answer according to how the objective function was established. The decision maker can analyze the results to determine the feasibility of the solution, what factors influence this solution, and where shortfalls exist. Additionally, the analysis helps decide where adjustments can be made in the context of the problem and the organization overall to ensure that the decision maker's values align with the results. Furthermore, sensitivity analysis can be conducted to explore potential trade space and to see what effect any potential adjustments to the model inputs could produce.

3.3 Portfolio Decision Analysis

One of the most well-known and explored methods to optimizing the allocation of scarce resources is Portfolio Decision Analysis. This approach seeks to select, out of a group of potential alternatives, a subset or portfolio that is the best overall value, subject to limitations or constraints (Burk & Parnell, 2011). Each alternative has a cost associated with it and some potential benefit. Burk and Parnell (2011) give four reasons a portfolio problem requires decision analysis:

1. There are more alternatives than the budget can fund.
2. There are multiple and conflicting objectives.
3. There are major uncertainties.
4. There are interactions among the alternatives.

Difficulties in identifying alternatives or decisions include uncertain costs or overall budget, access to decision makers, requirements on completion time or multiple time periods, and multiple resource constraints.

As before, *Value-Focused Thinking* (Keeney R. L., 1992) recommends focusing on the values that the portfolio is meant to fulfill rather than on the alternatives that may be available. This produces objectives that mirror the values of the organization and, therefore, enhance the creation of desirable alternatives. Burk and Parnell (2011) recommend developing an additive value model to provide a numerical measure of overall value. Furthermore, they present a 15-step procedure for any portfolio decision analysis. Broadly, these steps break down into defining and framing the problem, working with the decision maker to determine values creating a quantitative model, and analyzing the results. The first seven steps all include interacting with the decision maker and the stakeholders. Montibeller and Franco (2011) detail the importance, as with goal programming, of working with the decision maker to define the decision problem, explaining that decision makers often have a compartmentalized view of the organization that may depend on their department affiliation. Kloeber (2011) mentions the following steps taken to build a quantification model during a pharmaceutical case study:

1. Define Objectives
2. Organize an Objectives Hierarchy
3. Define Measures
4. Define Value Functions
5. Assign Weights

These examples not only exhibit the steps to the process this work has laid out, but really acknowledge the importance of interacting with the decision maker and striving to accurately frame and structure the problem at hand.

3.3.1 PDA Model Objective Function and Constraints Formulations

Portfolio Decision Analysis seeks to maximize the value of the portfolio or decision. The PDA objective function strives to maximize the value associated with the objectives. These objectives are affected by a resource or budget constraint because not all decision opportunities can be pursued since resources are invariably scarce and may not be easily changed (Liesio, Salo, Keisler, & Morton, 2020). Toppila et al. (2007) use this method to allocate resources for telecommunications research and development investments. The value, in this case, is realized through sales. Therefore, the objective function maximizes expected sales by solving a mixed integer linear program. Topilla (2011) explains that although the model only shows budget constraints, it could support additional linear constraints such as mutual exclusivity of proposed activities. In another example, Kloeber (2011) applies a maximizing objective function to the ranking of drug discovery programs for a pharmaceutical company. Through much interaction with the decision makers, the value to the company is able to be transformed into metrics that are tied to the decision makers' objectives for the organization. Constraints can be introduced to model project interactions by including a project if and only if the interaction is triggered by the portfolio composition. Then the project's value and resource parameters can be used to indicate how the interaction effects the entire portfolio (Liesio, Salo, Keisler, & Morton, 2020). A third example outlines the allocation of local government resources utilizing a facilitated PDA approach (Montibeller & Franco, 2011). The facilitated approach helps support, in this case, the social aspect of government planning. This allows portfolio decision models to be built and analyzed by the decision makers who then deem which best captures, not only the resource allocation, but their objectives concerning value to society. Montibeller and Franco (2011) illustrate a basic case allowing for a value to cost ratio to be formed $(\frac{V(a_i)}{c_i})$. This simple and direct approach permits a rank order based on that value to cost ratio, then projects would be funded in that order until the budget could no longer support the cost of the next project on the list. While simple, this method does not guarantee an optimal solution. Montibeller and Franco (2011) instead show the two optimal models provided below for the decision of funding new start projects and continuing current projects. The new starts model features the value function, $V(a_i)$, and a binary variable, x_i, indicating the selection of the new project. The current project model features the value function, $V(a_i)$, and a proportional variable, $0 \leq y_i \leq 1$, indicating what proportion of the current project will be continued. Both have the overall budget as constraints.

New Start:

$$Max\ \sum_{i=1}^{N} V(a_i)x_i \qquad (1)$$

Subject to

$$\sum_{i=1}^{N} x_i c_i \leq Budget \qquad (2)$$

Current Project:

$$Max\ \sum_{i=1}^{N} V(a_i)y_i \qquad (3)$$

Subject to

$$\sum_{i=1}^{N} y_i c_i \leq Budget \qquad (4)$$

This formulation ensures that the maximum value to the organization will be realized by using as much of the budget as possible. Therefore, a project with a lower cost may overtake others on the value to cost ratio ranking because they fall under the remaining budget, thus providing more overall value.

3.4 Goal Programming

The Goal Programming (GP) approaches utilized by Lee (1972) and Schneiderjans (1995) seek to model a multi-criteria/multi-objective optimization problem and deals with decision situations with single or multiple goals and subgoals. The objectives state that which is of concern and, therefore, important regarding the decision; while the goals set a target value for the objective measure to be achieved. Furthermore, in GP, we want to achieve these goals as closely as possible with penalty for deviation from these target goal levels (Charnes & Cooper, 1976). As we reviewed in Chapter 2, GP is a fruitful approach (Lee, S, 1972; Blake & Carter, 2002; Kwak & Lee, 1997; Ataollahi et al, 2013) for this type of problem because:

1. There are multiple objectives that are critical and must be considered when competing for the same resources.

2. There is a level of risk associated with any allocation, even an optimal one, therefore a prioritized list of objectives is necessary.

3. Adaptability to changing situations allows for a quick update based on a dynamic environment.

3.4.1 Goal Programming Model Objective Function Formulation

Formulating the goal program objective function is related to the preferences discussion presented in section 3.2.4. Depending on the decision maker's preferences, each of the following GP methods will produce a different objective function. Here we discuss three variants (lexicographic, weighted, and Chebyshev) that seek to minimize the deviations from the goals, but each with a different focus.

In the lexicographic, or pre-emptive variant of goal programming the higher-level priority is infinitely more important than those in lower levels. Ignizio (1976) shows an algorithm that solves the lexicographic goal program as a series of linear programs. This traditional GP approach was used by Tan et al. (Tan, Elmekkawy, Peng, & Oppenheimer, 2007) to schedule elective surgeries. It was useful because their proposed model had very obvious and different priority levels and there was no tradeoff between criteria allowed. Similarly, Li et al. (Li, Rafaliya, Baki, & & Chaouch, 2017) created their own pre-emptive model to schedule elective surgeries and modeled four objectives each with its own ranked priority. A third example uses staff assignment and shows the flexibility of the lexicographic goal program. Rihm and Baumann (2015), first had requirements as the highest priority for one instance of the model, then used fairness as the highest priority in the second iteration and were able to show a more acceptable model that still had the same quality as the first. While this is a popular method, it is most useful when there exists a clear priority ordering amongst the goals to be achieved.

In situations where the decision maker has a clear order in which they wish to see goals satisfied, the lexicographic variant is desirable (Jones & Tamiz, 2010). This method makes the higher level priority infinitely more important than the lower level priority. Therefore, the minimization algorithm steps through one priority at a time, minimizing all deviational values associated with that priority. Once an optimal solution is determined for the first priority, this will set the feasible region for the next priority. The process is repeated one priority at a time until all deviations have been minimized. Suppose p_1 is the positive deviation and n_2 is a negative deviation for Priority 1 objective, n_3 is a negative deviation associated with Priority 2 objective, and p_4 and n_5 are deviations associated with Priority 3 objective. The objective function would be as follows:

$$Min\ a = [(p_1 + n_2), (n_3), (p_4 + n_5)] \qquad (5)$$

The steps of the minimizations would be as follows:

Step 1

$$Min\ Z_1 = p_1 + n_2 \qquad (6)$$

Subject to constraints of the model

Step 2

$$\boldsymbol{Min\ Z_2 = n_3} \qquad (7)$$

Subject to constraints of the model and results Z_1

Step 3

$$Min\ Z_3 = p_4 + n_5 \tag{8}$$

Subject to constraints of the model and results of Z_1 and $\boldsymbol{Z_2}$

The effects of using this structure will lead to an imbalance between goals. Furthermore, if the priority structure is modified, then it is likely that a completely different solution will be obtained.

If the decision maker is more interested in direct comparisons of the objectives, then a weighted, or non-pre-emptive, goal program can be employed. The goals are weighted by relative weights that present the decision maker preferences between different goals (Iskander, 2012). If there is no preference, then the objectives, or goals, can be equally ranked and assigned equal weights. With the previous study mentioned (Oddoye, Tamiz, Jones, & Schmidt, 2009), there was no existing priority order of the objectives and they were only interested in trade-offs between the objectives. In another goal programming model, Lee and Kwak (1999) detailed the process of how they established the goal priorities with the help of the organization's decision makers. In a third example, Prasad and Reddy (2018) presented a model with the weights generated in two different ways. They illustrated a percent normalization method as well as the use of an analytical hierarchy process. Their study shows that both methods produced similar results.

When the decision maker wishes to compare deviations and investigate tradeoffs between them, the weighted goal program variant is applicable (Jones & Tamiz, 2010). This trade off would allow the decision maker to see what could be gained in one objective at the expense of another. Since many decision makers will not be able to instantly define the weights, insight into these tradeoffs may influence their decisions in the weighting assignments. Any subsequent adjustments may then more accurately represent the decision maker's values. Using a weighted goal program, all unwanted deviations from all our goal target values are multiplied by weights and added together as a single sum to form the objective function. The assigned weights reflect the relative importance of meeting that goal. The objective is then to minimize this overall sum of deviations. The algebraic representation is shown below where *m* is the number of objectives, n_i are negative deviations, p_i are positive deviations, and u_i and v_i are their respective weights.

$$Min\ z = \sum_{i=1}^{m}(u_i n_i + v_i p_i) \qquad (9)$$

An issue that can arise in both lexicographic GP and weighted GP leading to erroneous modeling is that the deviations within a priority or the weighted deviations being summed may be measured in different units and, therefore, cannot be summed directly (Jones & Tamiz, 1996). If the units are not compatible, the summation is useless. In this case, the deviations would need to be multiplied by a normalization constant. Three commonly used normalization constants exist: percentage, zero-one, and Euclidean (Jones & Tamiz, 2010). Percentage normalization is described as turning each deviation into a percentage value away from its target level; therefore, converting to all values to the same units. Typically, these are divided by the target levels as opposed to the entire goal. In actuality, the objective function contributions are proportions, not percentages, but it is fundamentally the same. According to Jones and Tamiz (2010), one potential pitfall of this normalization method is that there can be a distortion if a subset of goals has the same units. If the concern focuses on percentage shortfall and not direct unit comparison, the method still holds. The zero-one normalization scales and maps all unwanted deviations onto a zero-one range with zero representing no deviation from the target value and one representing the worst possible deviation. This method is good in cases when each objective has clearly defined ranges and the entire feasible set is of potential interest to the decision maker. It also suffers from irrelevant alternatives with unbounded regions. Finally, the Euclidean normalization method calculates the Euclidean mean and uses it as the normalization constant. It is considered computationally robust, but because there is a lack of consideration of the target value, the optimal value of the achievement function has no obvious meaning. According to Jones and Tamiz (2010), the Euclidean normalization method is best reserved for cases where the percentage method and zero-one method are impractical. Ultimately, the choice of normalization scheme is dependent upon the individual problem situation and preferences of the decision maker. A normalized achievement function using the percentage method is shown below with positive and negative deviations represented as p and n respectively, and target values shown as tv.

$$Min\ z = \frac{p_1}{tv_1} + \frac{n_2}{tv_2} + \frac{n_3}{tv_3} + \frac{p_4}{tv_4} \tag{10}$$

Since we are minimizing the deviations, they act as penalties in the objective function. Only unwanted deviation variables should be given a positive weight and this weight gives the relative importance of the penalization. If a deviation, such as excess profit, were given a positive weight, a good solution would be unnecessarily penalized and lead to erroneous conclusions (Jones & Tamiz, 2010). The deviations are typically penalized using a direct linear relationship between penalty and distance from goal; however, this penalty can be modelled in multiple other ways. Jones and Tamiz (1995) discuss four such situations: an increase in penalty as further distance from goal, a decrease in penalty at further distance from goal, a discontinuity in preferences, and a non-linear preference structure. These methods add objectives at the point where the penalty changes creating a similar objective with a new target value and altered penalty, depending on the decision maker's preferences. It is possible for a nonlinear preference to arise. When such a preference occurs, it can be dealt with by a piecewise linear approximation as defined by Williams (1978). At this point, the previous methods of increasing or decreasing penalty can be implemented. Another method for nonlinear preference is the Sequential Unconstrained Maximization Technique which sets the penalty to grow quadratically as points move away from the feasible or desired region (Bradley, Hax, & Magnanti, 1977). When the solution is better than the goal or within an acceptable range the penalty expression equals zero and no penalty is incurred. A penalty scale factor can be applied to ensure near-feasible points receive a large enough penalty. Additionally, Bradley, Hax, and Magnanti (1977) describe the barrier method in which penalty terms are replaced by barrier terms. These terms become infinite as the variable approaches the infeasible or unwanted region. Cetin and Sarul (2009) used nonlinear goal programming to create a blood bank location model with a nonlinear objective. Although transformations could have been used to reduce computation time, this proved to be unnecessary, and their results are obtained by solutions of different starting points completed in a reasonable time. Attari et al. (Attari, Pasandide, Agaie, Taghi, & Niaki, 2017) present a case where nonlinear objectives and constraints are linearized before minimizing the deviations of the goal program. This transformation back into a linear goal program not only allowed them to solve the model using linear goal programming techniques, but also reduced the complexity. In a third example, a genetic algorithm is utilized to make the nonlinear GP more practical and easier to use (Deb, 2001). Deb used a non-dominated sorting genetic algorithm, in particular, and demonstrates its application and efficiency on five different test cases.

Another significant variant is Chebyshev goal programming. The effect of this method is to, as much as possible, provide a balance between the levels of the objectives and should be utilized when the requirements are defined in terms of balance and fairness (Romero, 2001). Gur and Eren (2018) present a model in which the goals are shown separately and there is no prioritization among the goals. Li, Liang, and Yu (2011) demonstrated the effectiveness of the Chebyshev method to take three performance criteria and optimize a car's suspension. This method was chosen because the three criteria are conflicting and non-commensurable; therefore, a balance was desired. Pinheiro et al. (Pinheiro, Landa-Silva, Laesanklang, & Constantino, 2019) describe a situation where the decision maker benefits from having a set of solutions representing a compromise between multiple objectives, giving them the option to choose their preferred solution. Chebyshev goal programming is used in this situation to obtain a balanced solution and it is described as an effective technique especially if the target goals are similarly difficult to obtain. Ghuran et al. (Ghufran, Khowaja, & Ahsan, 2015) characterized Chebyshev's method as a specific form of the weighted goal program.

They showed it as solving a set of single goal optimization problems at both the best and worst values of each objective. Then the best values are used as targets for the objectives and then minimized such that worst values from each objective are at a minimum. By utilizing this method, Ghuran et al. (2015) were able to convert their problem into a bounded variable mixed integer linear programming problem. In another example, Naeini et al. (Naeini, Khodamoradi, & Sabzian, 2014) compared a Chebyshev GP model with a weighted GP model in the optimization of expansion for sports facilities. Their conclusion showed that although the weighted model had more complete achievements in objectives, it also had more complete deviations in the objectives. Despite having fewer complete achievements, the Chebyshev model was far more balanced and was superior in providing a better-balanced allocation of the budget. Overall, their conclusion was that when balance among the multiple goals in important for the planner, the Chebyshev goal program is strongly recommended (Naeini, Khodamoradi, & Sabzian, 2014).

In the scenario where balance between the objectives is the dominant need, then the Chebyshev goal programming variant should be applied. Both the lexicographic and weighted variants seek to find solutions at the extreme points, due to the use of the ruthless optimization associated with the underlying properties, leading to an imbalance among the objectives (Jones & Tamiz, 2010). In the Chebyshev, or Minmax, variant, the maximum deviation among the weighted set of deviations is minimized rather than the sum of those deviations (Jones & Tamiz, 2003). A generic Chebyshev goal program would be as follows:

$$Min\ z = D \tag{11}$$

subject to

$$\frac{1}{k_i}[u_i n_i + v_i p_i] \leq D \quad i = 1, \ldots, m \tag{12}$$

$$f_i(x) + n_i - p_i = b_i \tag{13}$$

where m is the number of objectives in the model, $f_i(x)$ is the objective, b_i is the target value or goal value, p_i and n_i represent the positive and negative deviations, u_i and v_i are the respective weights assigned to these deviations, z is the achievement function, D is the maximum deviation to be minimized, and k_i is the normalization constant.

3.4.2 Goal Programming Constraints Formulation

Another vital part to solving an optimization problem is determining what the limitations are in the problem and developing constraints to model those restrictions. The constraints can be written as either equalities or inequalities to show the maximum (or in some cases minimum) resources to be used. These will be the hard constraints, indicating that they cannot be violated. A constraint that is a less than inequality indicates a limitation of some resource, while a greater than inequality indicates that a certain threshold needs to be reached. Another hard constraint that may need to be added is a non-negativity constraint. This constraint states that negative values for physical quantities cannot exist in any feasible solution. A generic example follows:

x_i: quantity of product i produced

R_i: quantity of raw material available to produce resource i

D_i: demand for product i

m: number of products being considered for production

Hard Constraints:

$$\sum_{i=1}^{m} x_i \leq R_i \text{ (Resource limitation)} \qquad (14)$$

$$\sum_{i=1}^{m} x_i \leq D_i \text{ (Threshold for supply)} \qquad (15)$$

$$x_i \geq 0 \text{ for all } i \quad 1{:}m \text{ (Non-negativity)} \qquad (16)$$

As shown in a cyclical nurse schedule goal program (Jenal, Ismail, Yeun, & Oughalime, 2011), the goals are incorporated into the model as constraints. These will be soft constraints and they will utilize deviational variables. These variables indicate possible deviations from below or above the target value on the right-hand side of the constraint. The inclusion of these variables allows the inequality constraints to be converted to equality constraints with the deviational variables acting as real slack variables. In Oddoye's example (2009), a deviational variable was introduced to measure the amount of time a patient has been delayed. This value can then be minimized, along with other deviational variables, in the objective function. In this particular case, the negative deviational variable was omitted since the ideal value of the delay is the same as the expected delay of 0. The generic equations above with deviational variables added become:

n_i: negative deviation from resource i goal

p_i: positive deviation from demand i goal

$$\sum_{i=1}^{m} x_i + n_i = R_i \text{ (Resource limitation)} \qquad (17)$$

$$\sum_{i=1}^{m} x_i + p_i = D_i \text{ (Threshold for supply)} \qquad (18)$$

$$x_i, n_i, p_i \geq 0 \text{ for all i 1:m (Non-negativity)} \qquad (19)$$

3.5 Comparing PDA and Goal Programming Approaches

Portfolio Decision Analysis and Goal Programming both seek to allocate scarce resources in an ideal manner, but by focusing on different aspects. As mentioned above, each features the same first five steps in the formulation process. Each must define the problem and collect data, define the problem objectives, define the decision variables, establish any preference relationships among the objectives, and establish value functions. The difference lies in how each method realizes the resource allocation. GP focuses on allocating resources based on the ideal state, as defined by the decision maker, and then minimizes the deviations from that state. PDA concentrates on what mix of resources generates the most value to the decision maker by maximizing each objective's value as defined by the value functions. GP utilizes a target value for objectives; however, this is not the case for PDA. Preferences among the objectives are set in GP through explicit priorities or through assigned objective weights while preferences for PDA are expressed through the decision maker's value functions and associated objective weights. The final step in the methodology is to solve, analyze and communicate. This can be accomplished in a similar manner for each and both approaches generate meaningful insights to the stakeholders, but those results are influenced by the manner with which they were achieved. Arevalo and Insua (2011) present a case for using the two methods in tandem. In their model for innovation management, they suggest using goal programming as a way to manipulate the problem and gain a better understanding; followed by utilizing value functions to maximize the satisfaction of the selected innovation projects. Barbati et al. (2018) argue that PDA may be a more robust method in handling multi-objective resource allocation problems with multiple criteria. By fixing certain levels of qualitative satisfaction to each objective, PDA was employed to make each of these levels become an objective to be maximized.

3.6 Summary

This chapter presented the selected methodology, showing and specifying the elements of the common steps in the formulation, as well as the unique aspects of Portfolio Decision Analysis and Goal Programming, detailing the variants of each method. A comparison of the approaches was also outlined. Next, our healthcare resource allocation during a pandemic problem will be formulated using PDA and GP. The subsequent analysis will provide further insight into the formulation of the models and another means of comparison for the two methods .

IV. Analysis and Results

4.1 Chapter Overview

In this section, we take the process outlined in Chapter 3 and apply it to our problem of healthcare resource allocation at a Military Treatment Facility (MTF) during a pandemic. The parameters and inputs will be notionally developed to depict a real-world application of the methodology. Next, we will apply the portfolio decision analysis approach, followed by the goal programming approach. Finally, both methods will be solved with discussion of the outputs and resulting analysis.

4.2 The Selected Methodology

Steps 1-5 of Figure 3 will be the same for both notional formulations in this Chapter. These steps will set the stage for the objective function and constraints associated with each approach.

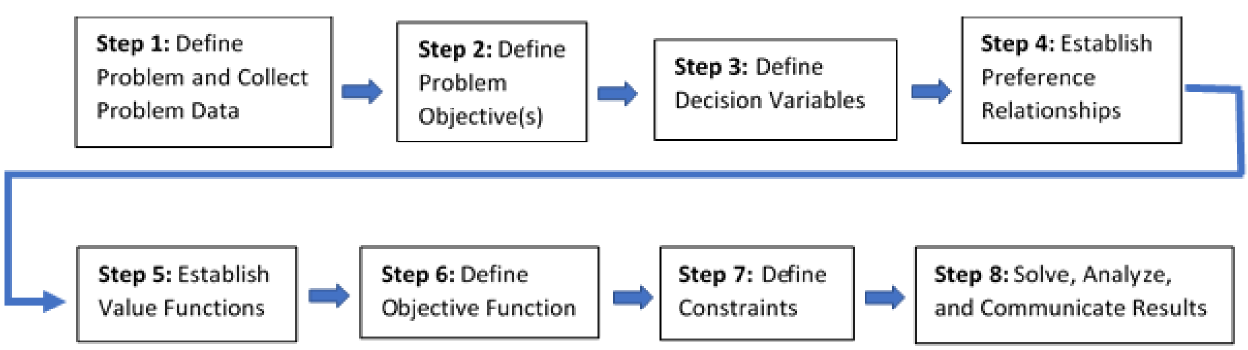


Figure 3. Optimization Methodology Steps Restated

4.2.1 Define Problem and Collect Data

In the case of a highly contagious and deadly pandemic, MTFs, much like civilian hospitals, face an influx of patients. This arrival creates many challenges for the hospital. First, the infected patients are highly contagious, so there needs to be an area in which they can be quarantined from non-pandemic patients while being treated. This requires the use of existing rooms, taking away from their intended purpose, or the creation of rooms. If new, temporary rooms are added, this would demand the need for more beds and medical equipment. Additionally, the increase in patients related to the pandemic requires more doctors and nurses to aid in their treatment. These personnel would likely need to be pulled from other departments within the MTF, leading to shortages in those departments. With the threat of the pandemic, additional personal protective equipment (PPE) would be essential. This would include specialized PPE (masks, gowns, goggles/face shields, and gloves) for any workers treating pandemic-related symptoms, as well as increased need for standard PPE (masks and gloves) for doctors and nurses anywhere else within the facility, whether treating patients or not. For the sake of this discussion, assume PPE refers to a package of PPE that encompasses all needed supplies for a single use. Because a pandemic would not be limited to just the local area, PPE and cleaning supplies will likely be limited due to massive demand and disruptions to supply chains. Two primary concerns would likely arise out of this problem with its cascading effects: treating patients and MTF personnel safety. These broad concerns lie in competition with one another and MTF decision makers will need to wisely address these issues based on the responsibilities and values of the organization.

The data for this problem would mostly stem from internal databases. Available data would range from current supplies, to hospital bed requirements and equipment available, to staffing levels. Additionally, data could be collected from other hospitals or MTFs that are deeper into the crisis. In this study, we consider that much of the data used to formulate the basis of the portfolio decision analysis or goal program could be based on decision maker and staff experience. For example, as experts in the field, they may be able to provide their judgment on how short-staffed a department can be, yet still be operational. The upside to this framework being provided, is that adjustments can be made in real-time and inputs can be updated quickly as new things are learned about the situation.

4.2.2 Define Problem Objectives

As an MTF, one of the primary values would likely be the treatment of patients. In this situation, that falls into two different categories. The first category is treating individuals suffering from symptoms of the pandemic. Due to its highly contagious and deadly nature, these patients would be considered vulnerable and in need of timely medical attention. The second category of patients would be those coming to the MTF for a non-pandemic related reason, thus falling under the scope of normal hospital operations. Those individuals could be further categorized as emergent, non-emergent, and routine and would require varying levels of care and timeliness.

A probable second value of the MTF decision maker is that of safety of the hospital personnel. This concern, while primarily a humanitarian desire to keep them safe, is secondarily a business concern since the doctors and nurses are already in high demand.

Any reason they are unable to work further complicates the resource limitations. This value of personnel safety again can be categorized in two different ways. The first is physical safety of the workers. They are interacting with patients all day who are either showing pandemic symptoms or at the facility for another reason, but still potential transmitters of the illness. Both situations, although to different degrees, put the MTF personnel at risk of contracting the virus. The second category is wellness of the worker. As mentioned in Chapter 2, healthcare workers can suffer physical and mental exhaustion and may develop psychological distress, thus limiting their availability and effectiveness.

Suppose these two MTF or decision maker values generate four related objectives. The first two fall under patient treatment and the third and fourth fall under MTF personnel safety. The objectives are to maximize the following:

1. Pandemic related patient treatment
2. Patients treated under normal MTF operations
3. MTF personnel physical safety
4. MTF personnel mental wellness

These objectives conflict with each other and compete for the same limited resources. They meet the properties outlined by Keeney (1992) in Chapter 3. Other values of the decision maker may exist and lead to the creation of additional objectives, such as cost/profit, patient wait times, treatment times, staff utilization, or ethical considerations. However, for the purpose of this example, we will model these four. Furthermore, at this point, the objectives are in no particular order as far as preference or priority. That discussion comes later in the Chapter. First, we must examine the MTF's controllable inputs.

4.2.3 Define Decision Variables

With the objectives defined, we must determine what can be done to impact their achievement. In this case, the MTF leadership should establish what is within their control that can comprise the set of alternatives based on the decision context. Suppose that the decisionmaker identifies four primary decision variables that directly affect the realization of the objectives. These decisions are the (i) number of beds to utilize, (ii) the number of ventilators to utilize, (iii) the amount of personal protection equipment (PPE) to utilize, and (iv) the number of doctors to schedule. The achievement of each objective, in this case study, depends on the variation of one or more of these variables. Furthermore, the decision maker determines which variables effect which objectives as shown in Table 1.

Table 1. Decision Variables by Objective

	Beds	Vents	PPE	Doctors
Objective 1 – Pandemic-related patient treatment	X	X	X	X
Objective 2 – Patients treated under normal MTF operations	X	X	X	X
Objective 3 – MTF personnel physical safety			X	
Objective 4 – MTF personnel mental wellness				X

Henceforth, the decision variables will be defined as follows:

B_i *is beds for Objective i*

V_i *is ventilators for Objective i*

P_i *is PPE for Objective i*

D_i *is doctors for Objective i*

The achievement of Objective 1, the treatment of pandemic patients, depends on the MTF's ability to admit that patient providing them with a bed and a doctor. Additionally, for the doctor to treat that patient, the doctor will need access to treatment resources and the required PPE. Therefore, Objective 1 is measured by the number of beds, ventilators, PPE, and doctors available to treat these patients. Likewise, the achievement of Objective 2, non-pandemic patient treatment, relies on the same types of resources, and thus will be measured in the same manner. Objective 3, MTF personnel physical safety, is primarily dependent upon their ability to protect themselves from the virus. To ensure the PPE provided is most effective, this objective is measured by the surplus PPE available for use, allowing personnel to utilize it as directed and not rely on re-use, homemade, or personally procured PPE. Objective 4, the mental wellness of MTF personnel, is related the amount of time off for personnel to care for themselves. This is measured by the total number of doctors working. If all doctors are utilized, then there are no days off. While in Objectives 1-3, more resources being utilized is considered ideal, Objective 4 is measured in a way that makes less doctor utilization ideal. With the objectives formed and the decision variables effecting those objectives defined, it is now time for the decision maker to consider the preference of the objectives.

4.2.4 Preference of Objectives

The next task at hand for the MTF decision maker is to determine whether a preference or priority amongst the objectives exists. One could argue that the decision maker would find it difficult to say that one objective is an obviously higher priority than another. At the same time, a balance between each objective is not necessarily ideal either. Therefore, it is best to assign weights to the objectives. This enables the decision maker to have direct comparisons of the objectives by establishing a preference and relative importance to each other.

There are multiple ways to go about assigning weights to the objectives. In Chapter 3, an example of the Analytical Hierarchy Process (AHP) was referenced from Prasad and Reddy (2018). This can be accomplished by simply providing pairwise comparisons to the decision maker and noting their preferences. Suppose the MTF decision maker decides that treating the patients suffering from the pandemic virus is twice as important as treating the standard patients. Next, the decision maker indicates that the relative importance of physical safety of the personnel lies somewhere between the two treatment categories. Finally, the decision maker estimates that the physical safety of the personnel is roughly three times as important as the mental wellness of the personnel. The resulting weights are displayed in Table 2.

Table 2. Objective weights

Objective	Weight
Pandemic-related patient treatment	40%
MTF personnel physical safety	30%
Patients treated under normal MTF operations	20%
MTF personnel mental wellness	10%

4.2.5 Value Functions

The next step in the formulation process is to determine how to measure value in the model. Since the objectives created by the MTF are not monetary, it is best to use normalized values and value functions. Suppose the MTF decision maker wants to use the simplest and quickest measure of value, as time for the decision is at a premium due to the pandemic. This equates to the value functions being linear and based ultimately on the ideal numbers of each decision variable (to be determined later). This means that each unit of the decision variable amount yields the same value. As an example, the value function for beds in objective 1 would be as shown in Equation 20. The graph of that normalized function is shown by Figure 4.

$$V(B_1) = \frac{1}{B_1(ideal)} * B_1 \tag{20}$$

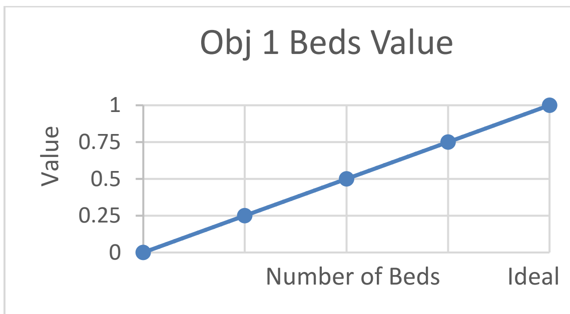


Figure 4. Sample Linear Value Function

In the portfolio decision analysis method, each unit of a decision variable attributed to that objective would add the same value based upon Equation 20. With the goal programming approach, each unit of deviation would result in the same loss of value for that objective. These value functions, through the use of an additive value function model applying the weights associated with each objective, will help determine the overall value of the objective function.

4.2.6 Define Objective Function

Both model approaches will seek the optimal decision variable values to satisfy their objective function over the set of feasible alternatives. The portfolio decision analysis model will maximize the value gained across the weighted objectives based on the value functions. The goal programming model will aim to minimize the deviation from the objective targets. Both objective functions will be formally discussed and formulated in their respective sections below as will method specific constraints, but those constraints common to both models are discussed next.

4.2.7 Define Constraints

The MTF and its objectives are subject to resource constraints, hence the problem at hand. Many of these constraints are common to the problem overall and not dependent on the model. Suppose the MTF is a 300-bed facility during normal operations. Of those, around 45 are dedicated to the Intensive Care Unit (ICU) and are accompanied by 20 ventilators. Furthermore, the MTF has on hand 300 PPE packs equating to one set per potential standard patient. Finally, there are 50 doctors that work at the facility. Of these 50 doctors, ideally only 40 (80%) are on duty any particular day, allowing for a day off every 5 days. Additionally, each one of these resources has an associated cost that is applied to the budget. For the purpose of this discussion, we assume the doctors have no additional monetary cost. Their cost is in time and will be captured by noting how many are on duty at one time. All resource levels and associated costs to buy and/or operate are shown in Table 3.

Table 3. Cost per Resource

Resource	Standard Operations Available	Cost per Resource
Beds	300	$5000
Ventilators	20	$40000
PPE Packs	300	$2500
Doctors	50	

With the introduction of the pandemic, there is a sudden need for increases in all these resources. Suppose all are available for purchase, except doctors. There will be a hard constraint of 50 doctors. A survey of other hospitals dealing with the pandemic suggest an additional 60 beds, 30 ventilators and 180 PPE packs are required for a hospital of this size. Those requirements are outlined in Table 4. Due to limitations in the supply chain and increased demand, presume only a limited amount of these resources can be purchased. Those limitations are shown in Table 5.

Table 4. Standard and Pandemic Resource Requirements

Resource	Standard Operations Available	Pandemic Requirements	Cost per Resource
Beds	300	60	$5000
Ventilators	20	30	$40000
PPE Packs	300	180	$2500
Doctors	50		

Table 5. Resource Purchase Constraints

Resource	Standard Operations Available	Pandemic Requirements	Available for Purchase	Total Available	Cost per Resource
Beds	300	60	30	330	$5000
Ventilators	20	30	20	40	$40000
PPE Packs	300	180	300	600	$2500
Doctors	50				

Another limitation that is required to be considered as a constraint in the explored model is the budget availability. We may assume any desired value to be considered by the model as the available total budget, defined as B_T, to be used during the crisis scenario we are considering in this work. All of these hard constraints are modeled below.

$$\sum_{i=1}^{2} B_i \leq 330 \tag{21}$$

$$\sum_{i=1}^{2} V_i \leq 40 \tag{22}$$

$$\sum_{i=1}^{3} P_i \leq 600 \tag{23}$$

$$\sum_{i=1}^{2} D_i \leq 50 \tag{24}$$

$$\sum_{i=1}^{3} (B_i) * 5000 + (V_i) * 40000 + (P_i) * 2500 \leq B_T \tag{25}$$

Other constraints are needed to model the interdependence among the objectives. For instance, it does not make sense to have too many ventilators available, without enough beds. This is prevented by Equations 26 and 27. Also, PPE is not needed for doctors if there are no beds for patients with Equations 28 and 29 protecting against that. Finally, there is a ratio of doctors per number of beds that can be developed. Equations 30 and 31 apply that ratio. Due to the differences in types of treatment required, Objectives 1 and 2 have different constraints associated with them. Those constraints are listed next.

$$V_1 \geq 0.3 * B_1 \tag{26}$$

$$V_2 \geq 0.045 * B_2 \tag{27}$$

$$P_1 \leq 3.1 * B_1 \tag{28}$$

$$P_2 \leq 1.2 * B_2 \tag{29}$$

$$D_1 \leq (1/3) * B_1 \tag{30}$$

$$D_2 \leq (0.14) * B_2 \tag{31}$$

In addition to the constraints, the MTF decision maker also establishes the ideal decision variable values that would lead to a completely fulfilled objective. Objectives 1 and 2 are based on projected needs, Objective 3 is a 25% surplus of PPE, and Objective 4 is set such that doctors would receive a day off every 5 days. Those resources are listed in Table 6.

Table 6. Ideal Decision Variable Values per Objective

	Beds	Ventilators	PPE	Doctors
Objective 1	60	30	180	20
Objective 2	300	20	300	40
Objective 3	-	-	120	-
Objective 4	-	-	-	40

Thus far, we have discussed steps and parts of the formulation of the problem common to both models. Now the focus will turn to aspects of the model specific to each approach.

4.3 Portfolio Decision Analysis

Recall that a portfolio decision analysis model seeks to maximize the value to the decision maker for the determined objectives which are subject to resource and budget constraints. In this case study, the desire is the determine a mixture of resource allocation that maximizes the value of the objectives laid out above. The model objective function is shown as Equation 32. There are multiple ways to build the model-specific constraints in relation to the value functions. This can be accomplished through a direct computation based on the decision variables as demonstrated in Equations 33, 35, 37, and 39 or through a measure of the deviation from the ideal normalized value (1) as shown in Equation 34, 36, 38, and 40.

$$Max\ a = \sum_{i=1}^{3}\left(V(B_i)\right) * w_1 + \left(V(V_i)\right) * w_2 + \left(V(P_i)\right) * w_3 + \left(V(D_i)\right) * w_4 \qquad (32)$$

Subject to

$$V(B_i) = \frac{1}{B_i(ideal)} * B_i,\ where\ i = 1, 2 \qquad (33)$$

$$V(B_i) + n_{B_i} = 1,\ where\ i = 1, 2 \qquad (34)$$

$$V(V_i) = \frac{1}{V_i(ideal)} * V_i,\ where\ i = 1, 2 \qquad (35)$$

$$V(V_i) + n_{V_i} = 1,\ where\ i = 1, 2 \qquad (36)$$

$$V(P_i) = \frac{1}{P_i(ideal)} * P_i,\ where\ i = 1, 2, 3 \qquad (37)$$

$$V(P_i) + n_{P_i} = 1,\ where\ i = 1, 2, 3 \qquad (38)$$

$$V(D_i) = \frac{1}{D_i(ideal)} * D_i,\ where\ i = 1, 2 \qquad (39)$$

$$V(D_i) + n_{D_i} = 1,\ where\ i = 1, 2 \qquad (40)$$

$$D_4 = D_1 + D_2 \tag{41}$$

$$V(D_4) = 1 + (D_4(ideal) - D_4) * \frac{1}{D_4(ideal)} \tag{42}$$

$$V(D_4) - p_{D_4} = 1 \tag{43}$$

$$B_i, V_i, P_i, D_i, \geq 0 \; integer\ values \tag{44}$$

$$0 \leq n_{B_i}, n_{V_i}, n_{P_i}, n_{D_i}, p_{D_4} \leq 1 \tag{45}$$

where,

$n_{B_i}, n_{V_i}, n_{P_i}, n_{D_i}$ *are negative deviational variables*

w_1, w_2, w_3, w_4 *are assigned objective weights*

Using the formulated objective function and constraints shown here as well as the constraints from 4.2.7, the portfolio decision analysis model is now ready to be solved. Analysis of this model will follow the formulation of the goal programming model.

4.4 Goal Programming Model

A key part of creating the goal programming model is determining whether a preference or priority amongst the objectives exists. That determination will lead us to choose a particular variant a goal programming; either lexicographic, weighted, or Chebyshev. Since there is no clear priority, the lexicographic variant of goal programming would not be the ideal choice. Alternatively, the Chebyshev method is best applied to as means to provide a balance between objectives when the requirements are defined in terms of balance and fairness. In our problem, the objectives, like the condition of the patients themselves, should be treated like a triage. They all have importance but should not necessarily have balanced levels of resources applied to them. Thus, the Chebyshev method is also not the preferred choice. This leaves the weighted goal program. The weighted variant is best when the decision maker is interested in direct comparisons of the objectives. It establishes a preference between the objectives and allows the decision maker to determine their relative importance to each other.

In this case, the weights have already been determined by the decision maker and the ideal levels or targets for each objective have been set. The goal programming model objective function, Equation 46, will then minimize the weighted, normalized overall sum of deviations from each objective.

$$Min\ z = w_1\left(\frac{n_{B_1}}{B_1(ideal)} + \frac{n_{V_1}}{V_1(ideal)} + \frac{n_{P_1}}{P_1(ideal)} + \frac{n_{D_1}}{D_1(ideal)}\right) + w_2\left(\frac{n_{B_2}}{B_2(ideal)} + \frac{n_{V_2}}{V_2(ideal)} + \frac{n_{P_2}}{P_2(ideal)} + \frac{n_{D_2}}{D_2(ideal)}\right) + w_3\left(\frac{n_{P_3}}{P_3(ideal)}\right) + w_4\left(\frac{p_{D_4}}{D_4(ideal)}\right) \quad (46)$$

Subject to

$$B_i + n_{B_i} - p_{B_i} = B_i(ideal), where\ i = 1, 2 \quad (47)$$

$$V_i + n_{V_i} - p_{V_i} = V_i(ideal), where\ i = 1, 2 \quad (48)$$

$$P_i + n_{P_i} - p_{P_i} = P_i(ideal), where\ i = 1, 2, 3 \quad (49)$$

$$D_i + n_{D_i} - p_{D_i} = D_i(ideal), where\ i = 1, 2 \quad (50)$$

$$D_4 = D_1 + D_2 \quad (51)$$

$$D_4 + n_{D_4} - p_{D_4} = D_4(ideal) \quad (52)$$

$$B_i, V_i, P_i, D_i, n_{B_i}, n_{V_i}, n_{P_i}, n_{D_i}, n_{B_i}, n_{V_i}, n_{P_i}, n_{D_i}, p_{D_4} \geq 0 \; integer\ values \quad (53)$$

Using the formulated objective function and constraints shown here as well as the constraints from 4.2.7, the goal programming model is now ready to be solved.

4.5 Solution and Analysis

If there were no budget restrictions at all, the hospital standard operations would require \$3.05M to be held. The additional pandemic requirements amount sums to \$1.7M. This means to fulfill all requirements modeled in this case, a total budget equal to \$4.75M would be necessary. However, having all the required budget availability is not the common situation in the healthcare resource allocation reality, especially when facing an unexpected pandemic. To emphasize how the proposed models would allocate a lower than ideal amount of budget, we start to analyze our results by conditioning the total budget availability at \$4.5M.

Considering the total budget availability of \$4.5M, we observe that the initial results provided by both models, shown in Tables 7 and 8, are very similar. Each allocates the same number of beds, 292, ventilators, 40, and PPE packages 576. Both methods also utilize the entire \$4.5M budget. The difference is in the use of doctors.

Table 7. PDA Results

PDA	Beds	Vents	PPE	Docs
Objective 1	60	20	180	20
Objective 2	232	20	276	20
Objective 3	-	-	120	-
Objective 4	-	-	-	**40**
Total	292	40	576	**40**
Cost: $4.5M	$1.46	$1.6	$1.44	

Table 8. Goal Program Results

GP	Beds	Vents	PPE	Docs
Objective 1	60	20	180	20
Objective 2	232	20	276	30
Objective 3	-	-	120	-
Objective 4	-	-	-	**50**
Total	292	40	576	**50**
Cost: $4.5M	$1.46	$1.6	$1.44	

These results were expected because the PDA model prioritizes the maximization of value and the GP model prioritizes minimization in deviation. Therefore, we observe that the strictly linear value function for the PDA approach generates more value by not exceeding the 40 doctors limit for Objective 4, the MTF personnel mental wellness. Alternately, the linear function related to the weighted deviations for the GP approach result in an additional 10 doctors being added to Objective 2, treatment of non-pandemic patients, at the expense of deviation from Objective 4. Since Objective 2 has a higher weight, the deviation penalty is greater than that of Objective 4.

Due to the objective function used in the PDA model, resources that increase the total value of the portfolio, or total resources allocated, at the lowest rates will receive the lowest priority to be allocated. This is directly reflected by the number of each type of resource allocated. In this case, because we are considering linear value functions, the value added per objective by each resource was 1 divided by the ideal amount for each resource. That value is then multiplied by the objective's weight and is independent of the doctors already allocated. For example, the value per doctor in Objective 1 is $\frac{1}{20\ (ideal)} \times 1.4\ (weight) = 0.07$, while the value per doctor in Objective 2 is $\frac{1}{40\ (ideal)} \times 1.2\ (weight) = 0.03$. Therefore, the PDA model will generate more value per doctor assigned to Objective 1 than Objective 2. Hence, Objective 1 is fully realized before Objective 2. Likewise, doctors assigned above the ideal level of 40 (or -10 from the maximum of 50) in Objective 4 have a value of $\frac{-1}{10\ (ideal)} \times 1.1\ (weight) = -0.11$. By trying to maximize value, the PDA model will avoid breaking the threshold of 40 doctors because each doctor above that level has a negative value that exceeds any positive value gained from the other objectives. The same holds true with the allocation of ventilators. Both Objective 1 and Objective 2 are allocated 20 ventilators despite the fact that Objective 1 has an ideal level of 30 ventilators and is considered the preferred objective given its weighting. Again, this outcome is due to the linear value function. The weighted value of Objective 1 ventilators, using the same formula as described with doctor allocation, is 0.047 while the weighted valued of Objective 2 ventilators is 0.06. Hence, Objective 2 ventilators are allocated before Objective 1 ventilators. The same concept holds true for all resource allocations in the PDA model based on the linear value functions and other hard resource and budget constraints. Table 9 shows the weighted value per resource for all objectives. In general, the PDA model will allocate the highest-valued resources first while also considering cost per resource. An alternate way to view Table 9 is which objective will get which resource first. As an example, PPE is allocated to Objective 3 first, then to Objective 1, and finally to Objective 2.

Table 9. PDA Values per Resource

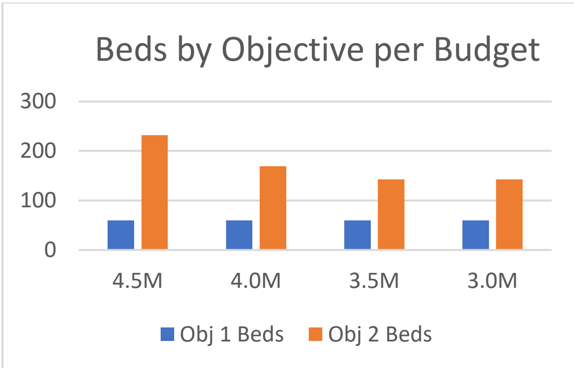
PDA	Beds	Vents	PPE	Doctors
Objective 1	0.023	0.047	0.008	0.070
Objective 2	0.004	0.060	0.004	0.030
Objective 3	-	-	0.011	-
Objective 4	-	-	-	**-0.110**

Likewise, the objective function used in the GP model allocates resources such that the resource with the highest weighted deviation is allocated first. In this approach, each resource has a linear deviation based on the objective's ideal allocation. For example, the doctors in Objective 1 have a weighted deviation of 0.07 (1/20 x 1.4) per doctor, independent of how many doctors have already been allocated to that objective. Doctors in Objective 2 have a weighted deviation of 0.03 (1/40 x 1.2) per doctor. Since the objective function is seeking to minimize deviation, the GP model will allocate, in this case, Objective 1 doctors before Objective 2 doctors because they have a higher deviation per resource. Unlike the PDA model, the GP model allocates all 50 doctors, essentially ignoring Objective 4. This occurs because the weighted deviation for Objective 4 doctors is 0.0275 (1/40 x 1.1), just marginally below that of Objective 2. Therefore, to minimize deviation, the model allocates all the doctors it can to Objective 2 at the expense of Objective 4. As with the PDA model, the GP model allocates 20 ventilators to both Objective 1 and Objective 2. Similarly, the weighted deviation for each ventilator in Objective 1 is 0.047 while the weighted deviation per ventilator in Objective 2 is 0.06. So, even though Objective 1's achievement is more preferred, the weighted deviation is higher per ventilator for Objective 2 causing the model to allocate ventilators to Objective 2 first in order to minimize deviation. Table 10 shows the weighted deviations per resource. As with the PDA model, the GP model will allocate the highest deviation resource first.

Table 10. GP Deviations per Resource

GP	Beds	Vents	PPE	Doctors
Objective 1	0.023	0.047	0.008	0.070
Objective 2	0.004	0.060	0.004	0.030
Objective 3	-	-	0.011	-
Objective 4	-	-	-	**0.0275**

One type of analysis that may be done here is regarding the available budget fluctuation. It may be the case that the decision maker is interested to understand what would be allocated at higher or lower budget availabilities according to the model. For example, what occurs when that budget is less? As expected, the models take resources, in the form of beds, from Objective 2 first until it levels out at $3.5M. The same is true for PPE, except the models continue to take from PPE as the budget drops. This is due to beds and PPE for Objective 2 having the lowest value generated for the PDA model and the lowest deviation per unit for the GP model. Ventilators remain steady for the highest two budgets, then a few of each are taken from Objectives 1 and 2 to meet the $3.5M budget. At the $3M mark, the models both take half the ventilators remaining from Objective 2 in order to meet the reduced budget. Interestingly, the PDA model remains constant in the allocation of doctors, however, the GP model reduces the number of doctors allocated to Objective 2 as the budget decreases even though the doctors have no cost associated with them. This occurs due to the doctor to bed ratio constraint introduced earlier. With the model being forced to utilized fewer beds, there becomes less need for doctors to be assigned.



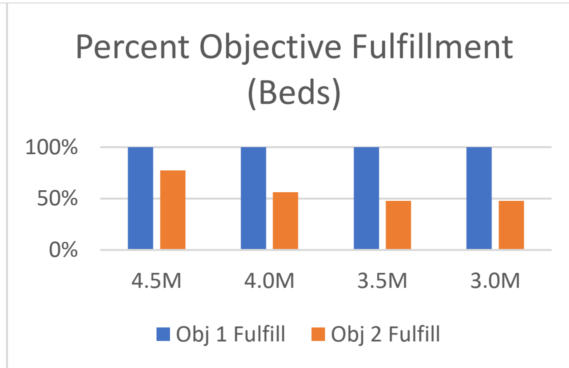
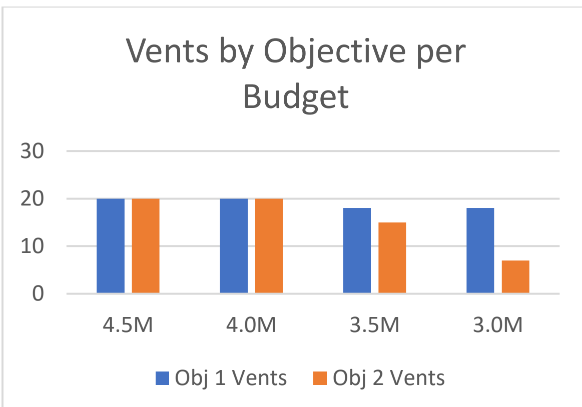


Figure 5. Beds by Obj per Budget

Figure 6. Percent Bed Fulfillment per Obj



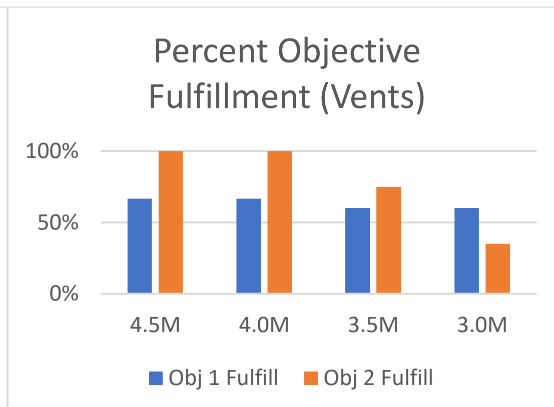
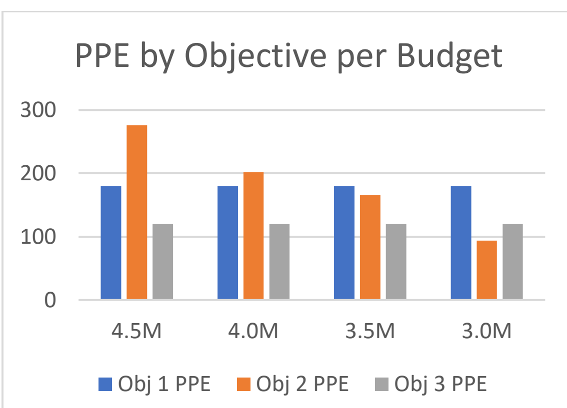


Figure 7. Vents by Obj per Budget

Figure 8. Percent Vent Fulfillment per Obj



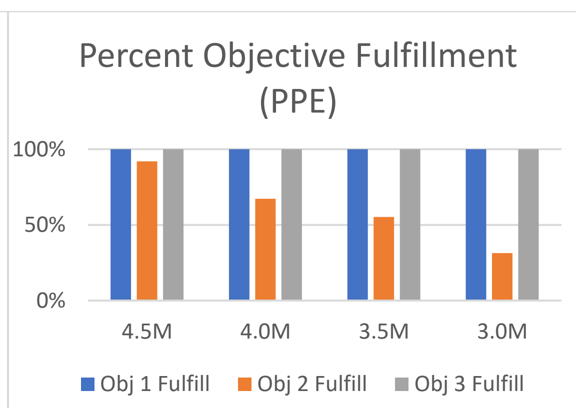
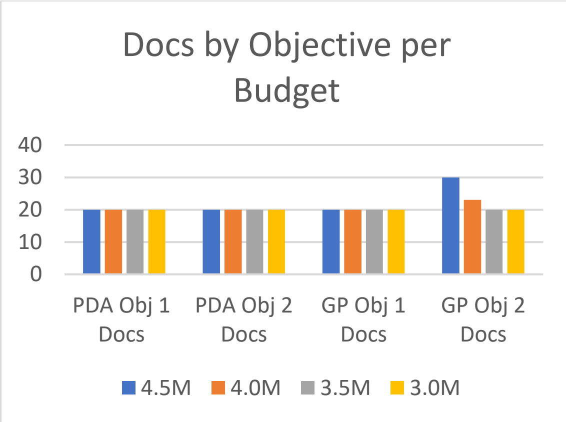


Figure 9. PPE by Obj per Budget

Figure 10. Percent PPE Fulfillment per Obj



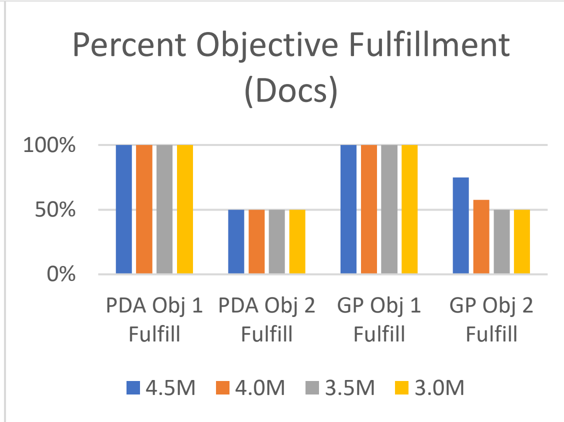


Figure 11. Docs by Obj per Budget

Figure 12. Percent Doc Fulfillment by Obj

Another useful analysis to be conducted is tradeoff analysis. This analysis provides the decision maker with some information on what is being accomplished given the current inputs to the model. The initial model solution and analysis concerning the budget can offer insight into how likely the objectives are to be met and to what extent. Moreover, the tradeoff discussion can influence their decisions on which objective they may be willing to accept additional risk to achieve a better result in another objective. First, suppose instead of meeting 100% of the ideal beds for Objective 1, that 90% was sufficient. This means that only 54 beds were needed. These beds could then be applied to Objective 2; however, assuming the $4.5M budget, this only results in an increase of Objective 2 fulfillment from 73% to 75%. As before, the results hold for both the PDA model and the GP model with the exception of how the doctors are allocated. With the doctor to bed ratio constraint in place, both models take 2 doctors from Objective 1 and allocate them to Objective 2. Alternatively, if the decision maker deemed the surplus in PPE associated with Objective 3 was not as vital, that part of the budget could be used to increase the Objective 2 beds to 90% (only limited by the number of beds available) and still have budget remaining to purchase 20 more packs of PPE. With this insight, the decision maker can determine the reduced amount of PPE they are willing to purchase and the added percentage of normal MTF operations that can now be open that best suits the needs of the MTF. A summary is displayed in the tables below.

Table 11. Scenario 1 PDA Results

Obj 1 90%	Beds	Vents	PPE	Doctors
Objective 1	54	20	167	18
Objective 2	240	20	288	22
Objective 3	-	-	117	-
Objective 4	-	-	-	40
Total	294	40	572	40

Table 12. Scenario 1 GP Results

Obj 1 90%	Beds	Vents	PPE	Doctors
Objective 1	54	20	167	18
Objective 2	240	20	288	32
Objective 3	-	-	117	-
Objective 4	-	-	-	50
Total	294	40	572	50

Table 13. Scenario 2 PDA Results

No Surplus PPE	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	270	20	300	20
Objective 3	-	-	20	-
Objective 4	-	-	-	40
Total	330	40	500	40

Table 14. Scenario 2 GP Results

No Surplus PPE	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	270	20	300	30
Objective 3	-	-	20	-
Objective 4	-	-	-	50
Total	330	40	500	50

4.5.1 Analysis of Non-linear Value Functions

A vital part of the formulation of both the PDA and GP models is the determination of the value function. This function will determine the relative value or deviation associated with one unit of a resource. In the formulation and analysis above, a linear value function was used meaning each unit of a resource within an objective accounted for the same value or deviation regardless of how many resources had already been allocated. A linear value function was used initially for our case due to its simplicity and ease of implementation. It may be of interest to the decision maker to create a different, perhaps more accurate representation of their value preferences. One such method of creating a value function is by using a bisection approach to create a piecewise linear value function. With this method, the decision maker took the lowest (worst) level to be 0, the highest level (best) to be 1 and then determined what level of resources would be the midpoint between those levels and provide them with 0.5 value. The same process would then be used to determine the 0.25 and 0.75 values. One example of the result of this process, doctors allocated for Objective 2, is shown in Table 15. With 0 doctors allocated as the worst and 40 doctors allocated as the best, the decision maker deemed the mid-value of those to be 15 doctors. They continued by determining 8 and 25 to be the number of doctors allocated to provide a value of 0.25 and 0.75, respectively. The graph of this value function is shown in Figure 13.

Table 15. Obj 2 Piecewise Value Function

Doctors Allocated	Value
0	0
8	0.25
15	0.50
25	0.75
40	1

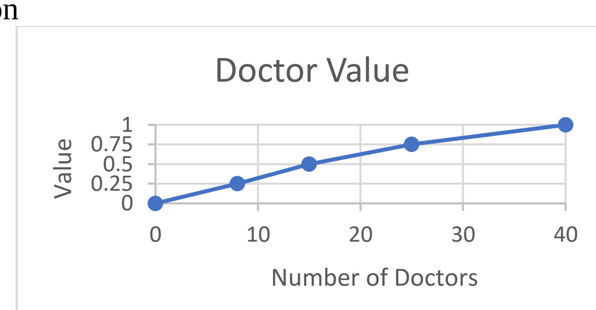


Figure 13. Obj 2 Piecewise Value Function

What this function shows is that the decision maker views the allocation of the first 15 doctors more important than the allocation of the next 25 doctors for this objective. This can be seen in the higher slope of the function for the lower allocation ranges. Now, instead of a linear function across the entire range of levels, the value of the allocation is determined by the function associated with the range that number falls within. Therefore, an allocation in the range of 0-8 will have a higher per resource value than that of an allocation in the range of 15-25. The same process for determining the value function ranges and piecewise functions is used for all resources within each objective. Next, we repeat the previous analysis with these updated value functions.

In order to have comparable analysis, we consider an initial budget of $4.5M. Notably, the GP model using piecewise value functions, yields the same result as the linear models. The only difference is that now, the new value function creates a large enough penalty for exceeding 40 doctors in Objective 4, that the model remains at 40. The weighted piecewise deviation for doctors in Objective 4, 0.11, now exceeds the weighted piecewise deviation in Objective 2, 0.03. This indicates that the decision maker thinks that keeping the total number of doctors at 40 for Objective 4 is more than three times as important than adding a 21st doctor to treat non-pandemic patients in Objective 2. In the PDA model, the introduction of piecewise value functions made changes to many resource allocations from the initial linear value functions. In particular, the model added more beds and PPE to Objective 2 at the expense of 4 vents in Objective 2. This shows that in the PDA model, the value gained from the 20 extra beds and 24 extra PPE packages in Objective 2 outweighs the value of the next 4 ventilators in that objective. Based on the hard constraints of the model, to add another ventilator, 6 fewer beds and 5 fewer PPE packages would be allocated. The calculated value gained by the next ventilator, the 17th in Objective 2, would be 0.0625 while the value lost from the reduction in beds and PPE would be 0.0665, a small, but critical loss of 0.004 in value. Although both models are using the same piecewise functions, the PDA model while maximizing the value produces slightly different results than the GP model which is minimizing the penalized deviations from the target levels.

Table 16. Piecewise Value Function Results

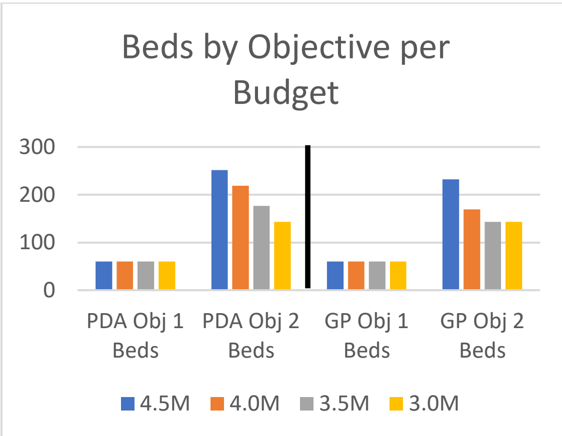
PDA	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	252	16	300	20
Objective 3	-	-	120	-
Objective 4	-	-	-	40
Total	312	36	600	40
Cost- 4.5M	$1.56	$1.44	$1.5	

Table 17. Piecewise Value Function Results

GP	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	232	20	276	20
Objective 3	-	-	120	-
Objective 4	-	-	-	40
Total	292	40	576	40
Cost- 4.5M	$1.46	$1.6	$1.44	

Once more, in order to have a way to compare the two approaches, we show analysis based on the available budget as we did with the linear value functions. Both models mirror each other in their allocation of resources to Objective 1 and Objective 4. For Objective 2, the PDA model has a steady decline in beds as the budget declines, whereas the GP model has a sharp drop in beds allocated as soon as the budget drops. The opposite is true regarding the allocation of ventilators. As soon as the budget is reduced, ventilators drop in the PDA model, while in the GP model it takes a greater reduction in the budget to stop allocating ventilators to Objective 2. Both models end up allocating the same number of beds and ventilators in Objective 2 at the lowest analyzed budget. This indicates that the PDA model values beds more than ventilators while the GP model prefers ventilators to beds in Objective 2. In the allocation of PPE for Objective 2, the GP approach consistently distributes fewer than does the PDA approach suggesting that PPE generates more value to the PDA model. That holds true for Objective 3 as well, until the budget reaches the $3M level, then there is noticeably less PPE allocated to

Objective 3, whereas the GP model always allocates the maximum PPE resources to Objective 3.



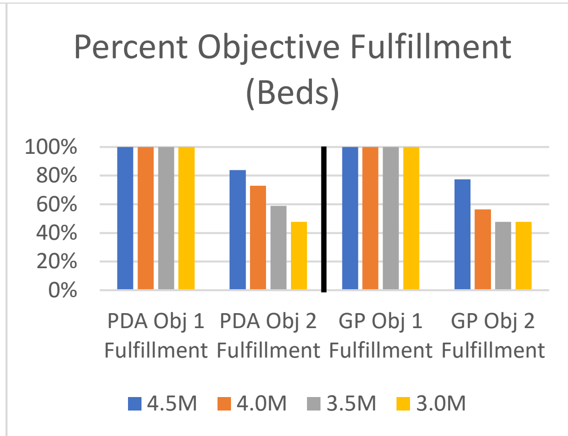
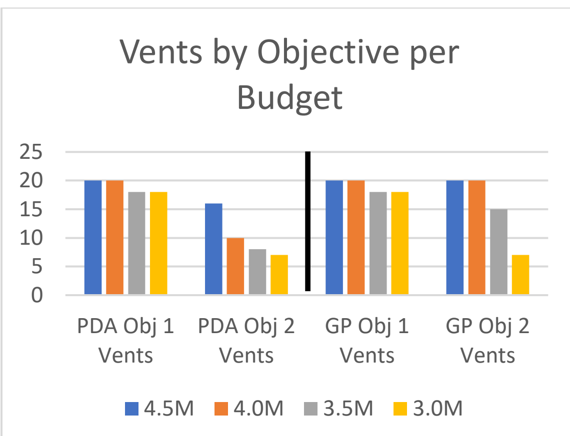


Figure 14. Beds by Obj per Budget

Figure 15. Percent Bed Fulfillment per Obj



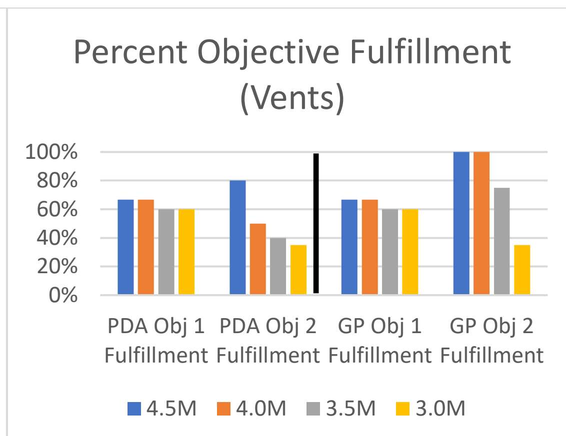


Figure 16. Vents by Obj per Budget

Figure 17. Percent Vent Fulfillment per Obj

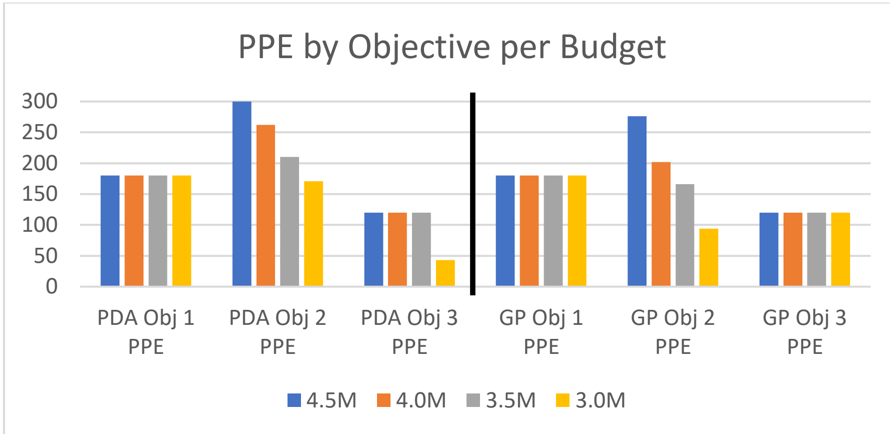


Figure 18. PPE by Obj per Budget

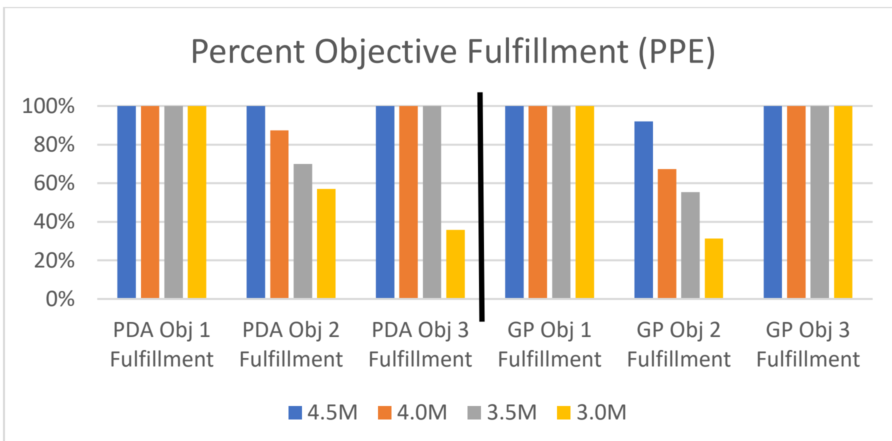


Figure 19. Percent PPE Fulfillment per Obj

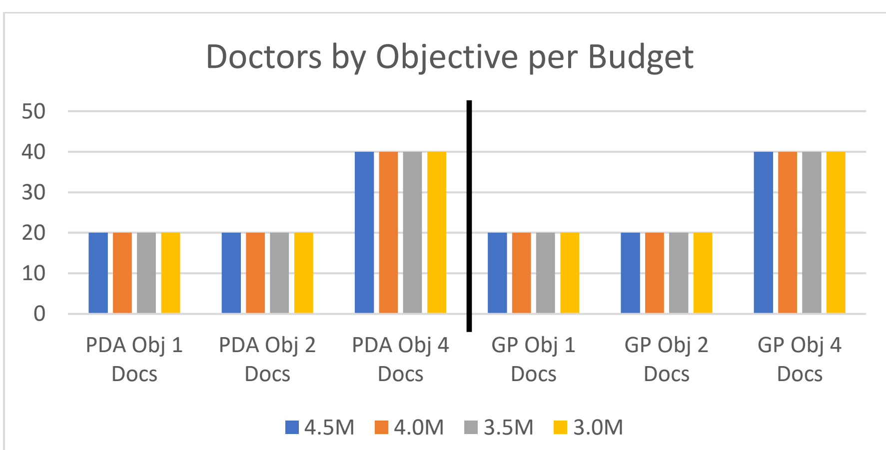


Figure 20. Docs by Obj per Budget

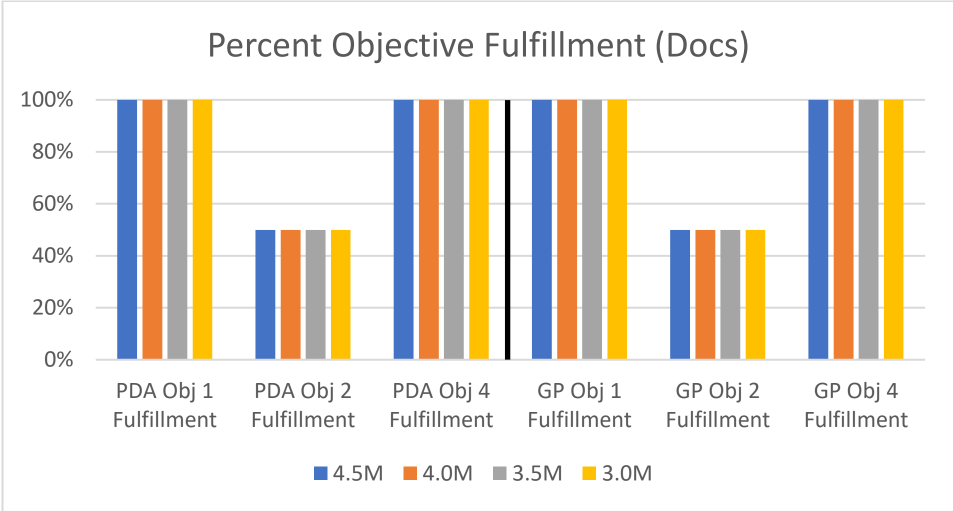


Figure 21. Percent Docs Fulfillment per Obj

As with the linear value function, performing tradeoff analysis provides the decision maker with information about what is being accomplished given the current inputs to the model and can influence decisions on where within the model they may be willing to accept risk. We examine the scenario where the decision maker is willing to accept 90% achievement in Objective 1. In the PDA model, shown in Table 18, this equates to a gain of 2 ventilators and 2 doctors for Objective 2 and results in a 10% and 5% increase in fulfillment of those two resources, respectively. In the GP model, Table 19, Objective 2 is allocated an additional 8 beds, 9 PPE packages and 2 doctors leading to a 3%, 3%, and 5% increase in fulfillment, respectively. With this information, the decision maker can determine whether such a tradeoff is beneficial or necessary. In our other scenario, the decision maker would like to know the impact if Objective 3, measured by surplus PPE, is not required. The result in the PDA model, detailed in Table 20, essentially is an additional 4 ventilators toward Objective 2 in exchange for 60 surplus PPE packages giving that objective 100% of required ventilators while reducing Objective 3 to 50% fulfillment. The GP approach, shown in Table 21, allocates 38 more beds and 24 more PPE packages to Objective 2 in this scenario, reducing surplus PPE to 20 packages. As a result, Objective 2 now has 90% of the required beds and 100% of the required PPE packages leaving the surplus PPE for Objective 3 at 20% fulfillment. With this insight, the MTF decision maker understands the impact of each scenario on the overall allocation and can determine what actions may be best for the MTF's needs.

Table 18. PDA Piecewise Results

Obj 1 90%	Beds	Vents	PPE	Doctors
Objective 1	54	20	167	18
Objective 2	250	18	300	22
Objective 3	-	-	117	-
Objective 4	-	-	-	40
Total	304	38	584	40

Table 19. GP Piecewise Results

Obj 1 90%	Beds	Vents	PPE	Doctors
Objective 1	54	20	167	18
Objective 2	240	20	285	22
Objective 3	-	-	120	-
Objective 4	-	-	-	40
Total	294	40	572	40

Table 20. PDA Piecewise Results

No Surplus PPE	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	250	20	300	20
Objective 3	-	-	60	-
Objective 4	-	-	-	40
Total	310	40	540	40

Table 21. GP Piecewise Results

No Surplus PPE	Beds	Vents	PPE	Doctors
Objective 1	60	20	180	20
Objective 2	270	20	300	20
Objective 3	-	-	20	-
Objective 4	-	-	-	40
Total	330	40	500	40

4.6 Summary

This chapter presented a hypothetical case study in which we described how the steps in the proposed methodology are accomplished in relation to our problem. Both a PDA and GP model were formulated, solved, and analyzed. Initially, we explored linear value functions and discussed the results from the models using this function. It was shown how PDA and GP models selected the next resource to include in the allocation. Further analysis useful to the decision maker, namely budget fluctuation analysis and tradeoff analysis, was conducted to illustrate potential insights into the model and the problem itself that could be discovered. Next, we adopted piecewise linear value functions and explored their effect on the models. It was shown how the allocations differed between value function types and between PDA and GP approaches, further emphasizing how the models behaved and how the risk attitude of the decision makers could be encompassed in the methodology. Finally, the benefits of additional analysis were reiterated through budget and tradeoff analysis.

V. Conclusions and Recommendations

5.1 Chapter Overview

In this chapter, we first provide a summary, then explain conclusions derived from this research. Finally, we highlight the limitations of the proposed methodology and we propose suggestions for potential future work.

5.2 Summary of Research

In the first chapter of this research, the background of the problem is explored, and the problem statement is outlined. The decision maker must decide the best course of action to allocate critical, but scarce resources in the hopes of achieving multiple, conflicting objective under multiple resource constraints. Additionally, research objectives are stated and the path to those objectives is laid out.

In Chapter 2, this document provides a literature review of the resource allocation problem in the healthcare environment, focusing specifically on hospital or MTF resource allocation problem. It continues by reviewing the scientific literature about PDA and GP, two of the most explored methods supporting resource allocation, and discusses important similarities and differences between the two methods.

In Chapter 3, we presented the methodology proposed in this work allowing for the comparison of these two methods seeking to optimize resource allocation on health organizations. We explain the steps in the proposed methodology that overlap both approaches and detail the unique steps for both types of formulation. The steps of this process provide a framework with which the decision maker can aim to develop an optimal allocation of resources based on the organization's values and goals. This chapter also provides a glimpse of the analysis to come that may be performed to provide insights for the decision maker.

Chapter 4 presents a hypothetical case study where the proposed methodology is applied using both the PDA and GP approach. After the formulations of these model, analysis is provided based on the results of each method along with a description of key differences between PDA and GP. Insights into the benefits for the decision maker based on the analysis of each model are explored in performing a budget analysis and the tradeoff analysis.

5.3 Conclusions

This application showed the merits of both models. PDA allows for the decision maker to decide what values are important to the organization and then maximizes that value generation via the objective function which is driven by the value function. The GP approach allows for the decision maker to set target level that would be ideal for each objective and then minimizes any deviation from that goal subject to penalty based on the value function. Both, using the framework provided, allow for as little or as much fidelity as required based on the situation. Each model can be easily updated to account for the dynamic environment or as a result of the budget and tradeoff analysis findings. The flexibility and adaptability of these models is especially useful in our problem. The method chosen should reflect what best suits the decision maker preferences, thus producing the most accurate results and organization buy-in.

5.4 Limitations of the Proposed Methodology

One limitation of this research is that we have investigated only two value functions, one of which was a linear value function. Another limitation in this proposed methodology is the omission of uncertainty. All resource constraints and demands were deterministic in nature. Additionally, more analysis could be accomplished to ensure an efficient allocation of resources based on value per cost. Finally, this study presents a hypothetical case, whereas the use of actual MTF data would represent a more accurate application.

5.5 Recommendations for Future Research

While research into resource allocation, specifically in the healthcare industry, has been studied extensively, this work identified several potential areas of future research. The first area would be to further explore the use of non-linear value functions. As Kim and Lin (2000) argued, an exponential value function can generate a rich variety of shapes that may more fully capture the decision maker's values. This can make the model more complex, so, depending on the size of the problem, that is a consideration in exploring this topic.

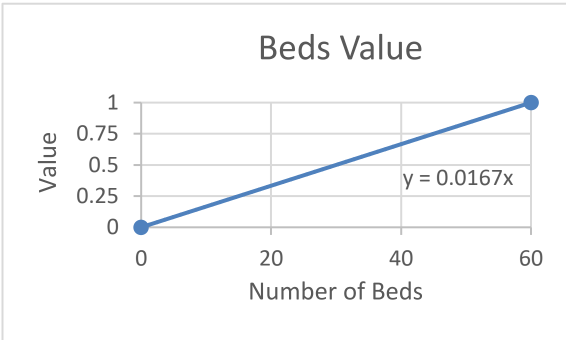
A second suggestion of future research is to encompass uncertainties in the formulation and use a different approach such as a stochastic PDA. The problem that we addressed would likely face uncertainty, especially an unprecedented situation like a pandemic. Such an approach would be interesting way to attempt to capture the reality of the real-world problem.

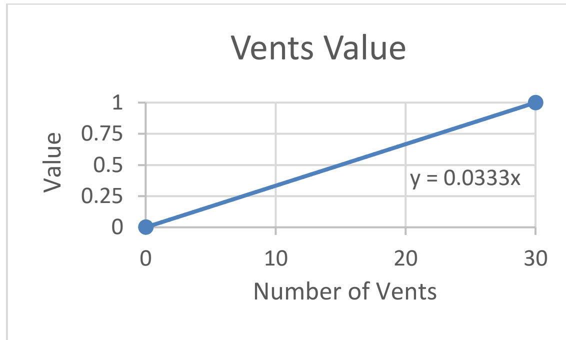
Another suggestion would be to investigate a value to cost analysis. This would help to ensure an efficient allocation of resources and allow for the creation of a Pareto frontier, providing further insight to the decision maker. Tradeoffs could then be considered to determine if any weak Pareto or strong Pareto improvements exist. If not, there will be no resource allocation that will improve one objective without weakening another objective.

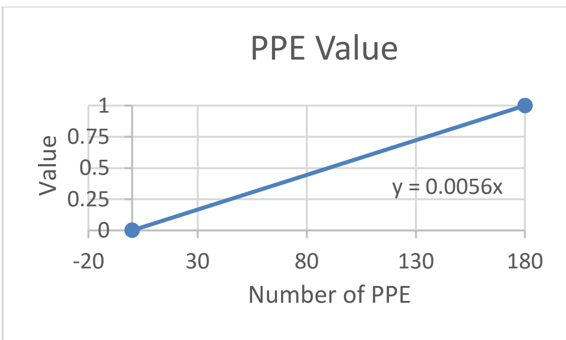
A final suggestion a future application of this research would be to use real data from a Military Treatment Facility post pandemic as a verification of the model. The MTF would have a better idea of the course of the pandemic and what challenges are faced at the different stages of the pandemic cycle. Additionally, the use of post-pandemic data would allow for preparation and training in the event of another crisis or similar situation.

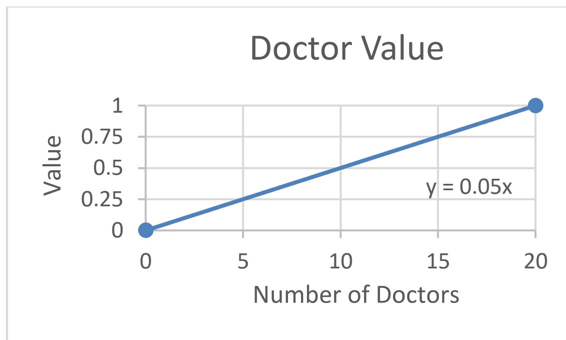
Appendix A. Linear Value Functions

Objective 1

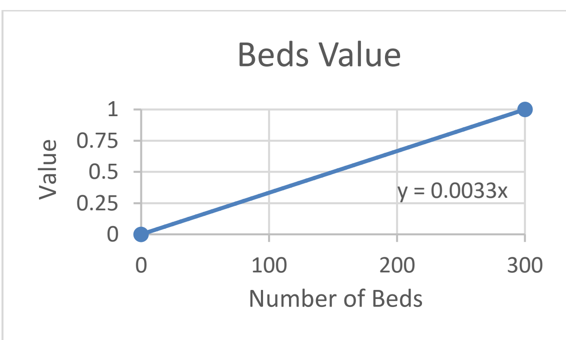


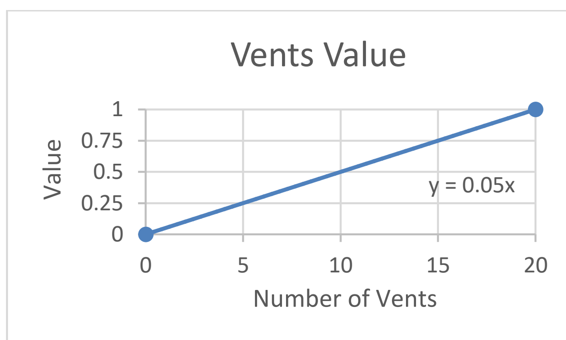


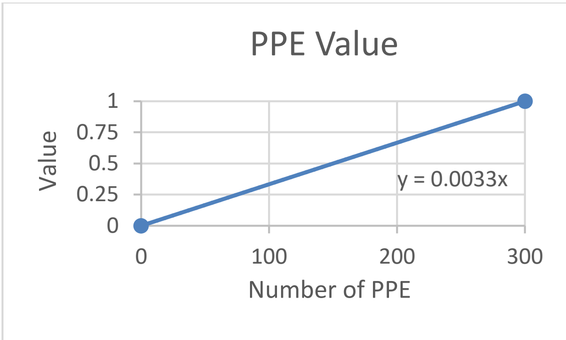


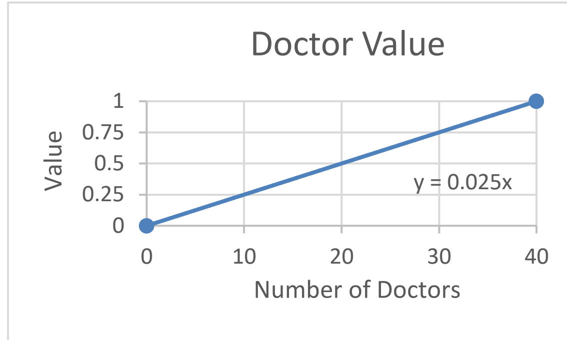


Objective 2

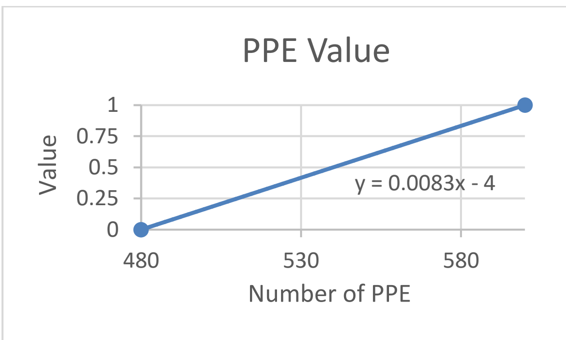




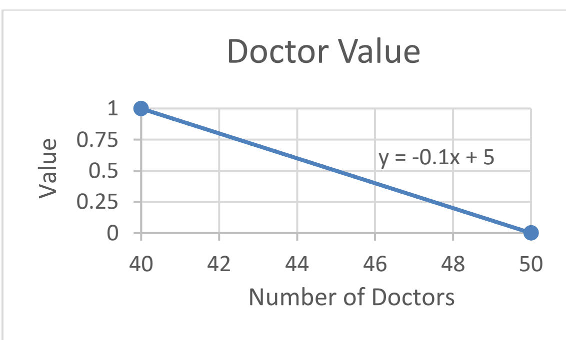




Objective 3



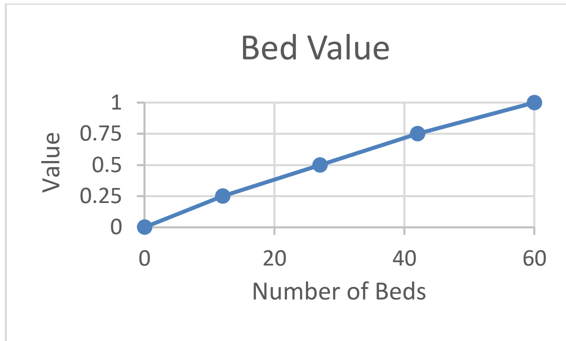
Objective 4

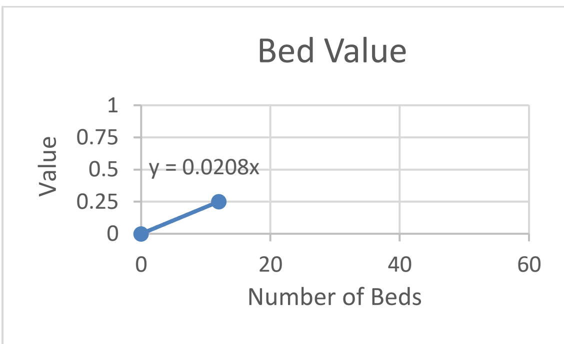


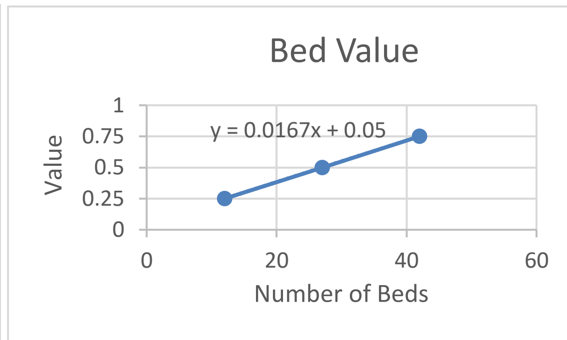
Appendix B. Piecewise Value Functions

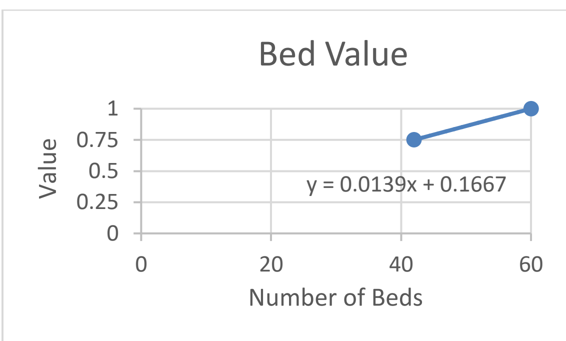
Objective 1 Beds

Beds Used	Value
0	0
12	0.25
27	0.5
42	0.75
60	1



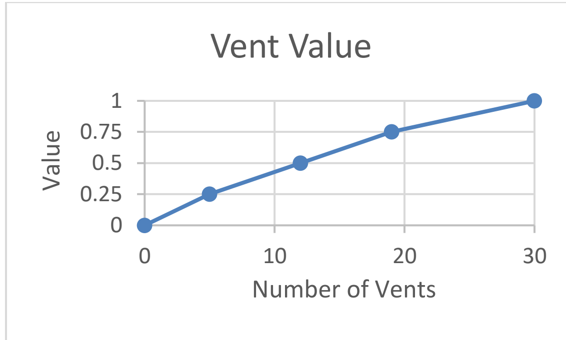


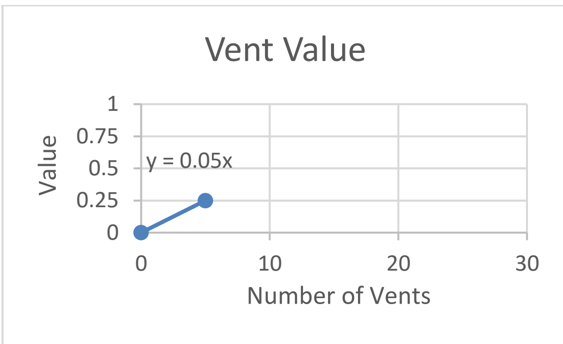


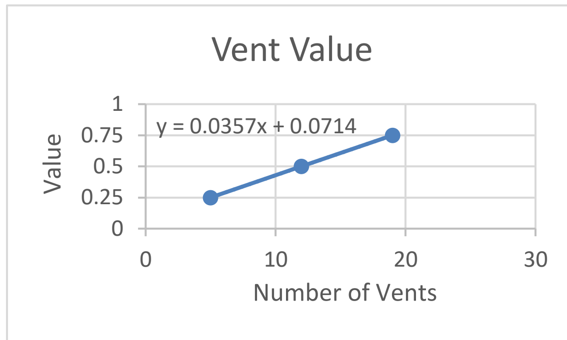


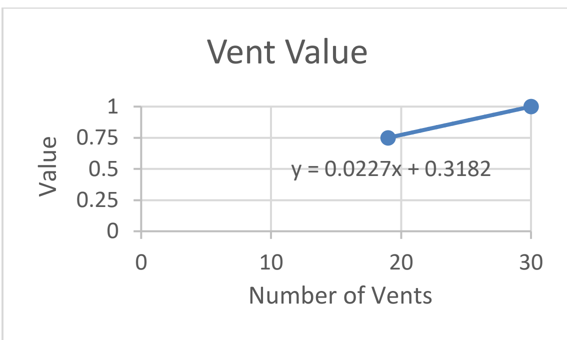
Objective 1 Vents

Vents Used	Value
0	0
5	0.25
12	0.5
19	0.75
30	1



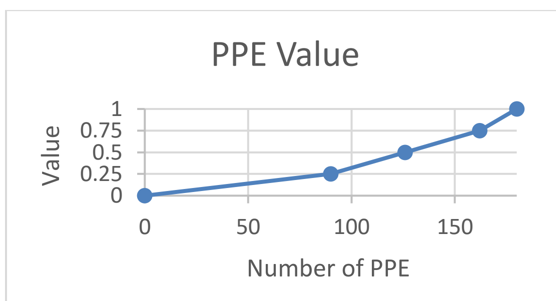


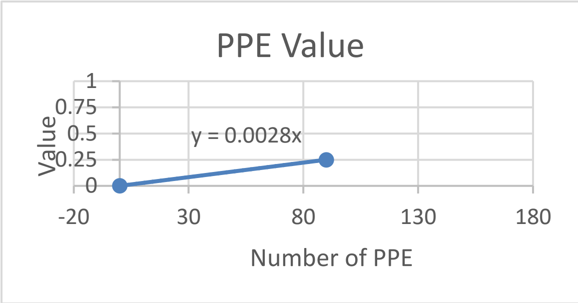


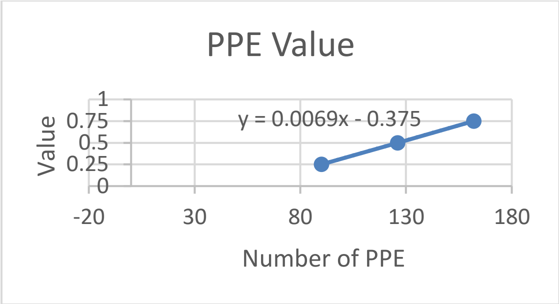


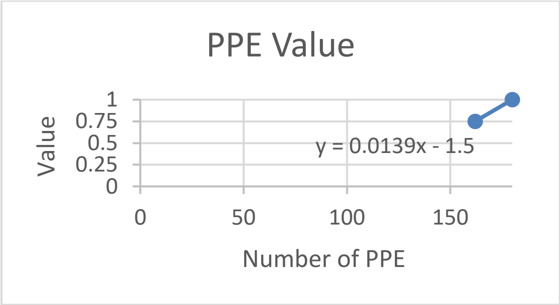
Objective 1 PPE

PPE Used	Value
0	0
90	0.25
126	0.5
162	0.75
180	1



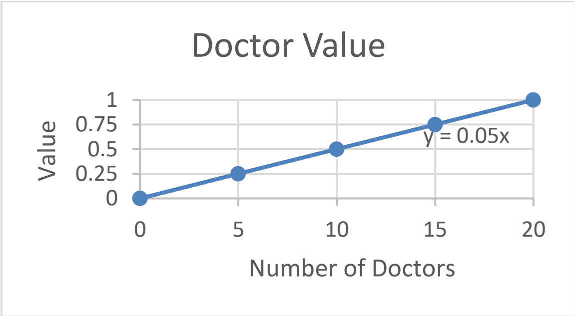






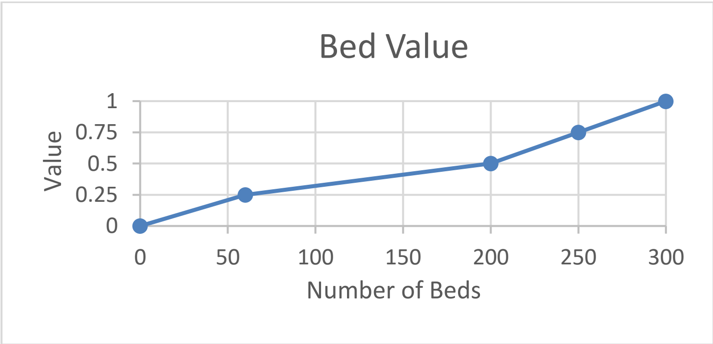
Objective 1 Doctors

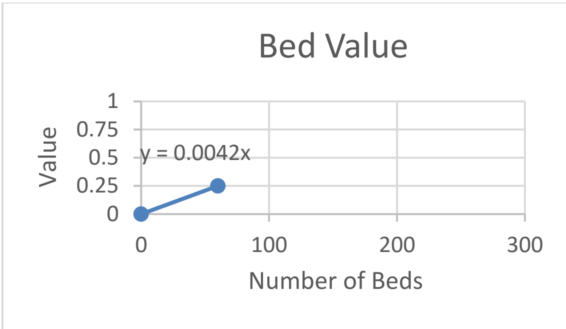
Doctors Used	Value
0	0
5	0.25
10	0.5
15	0.75
20	1

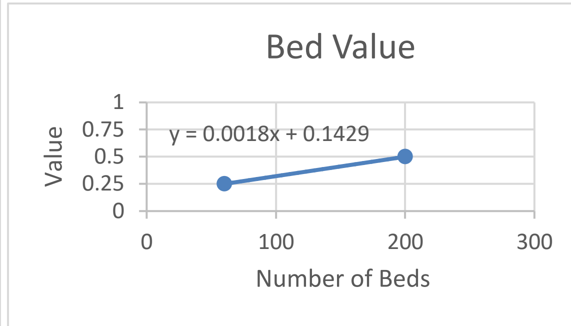


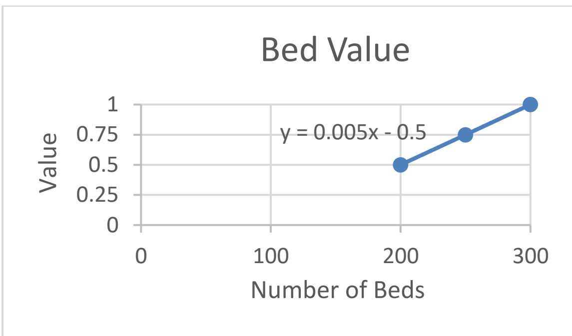
Objective 2 Beds

Beds Used	Value
0	0
60	0.25
200	0.5
250	0.75
300	1



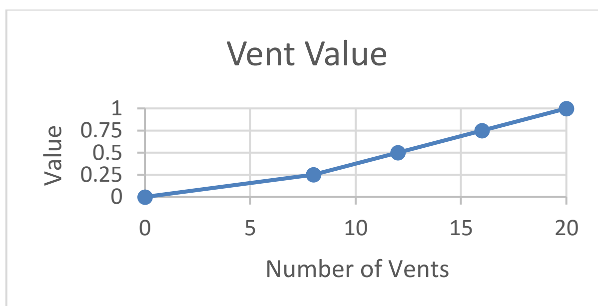


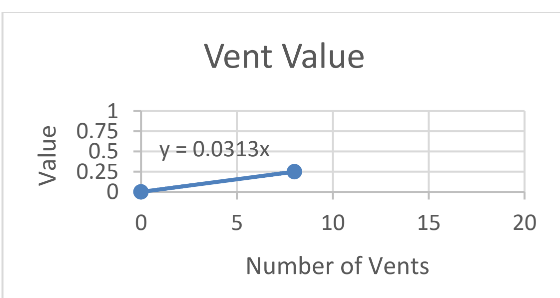


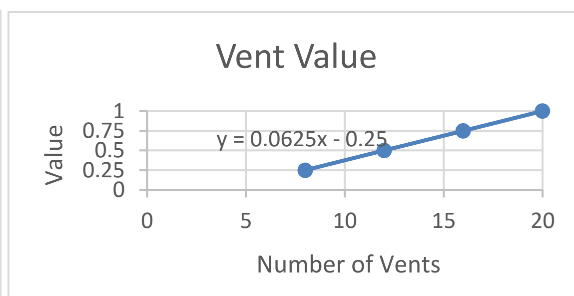


Objective 2 Vents

Vents Used	Value
0	0
8	0.25
12	0.5
16	0.75
20	1

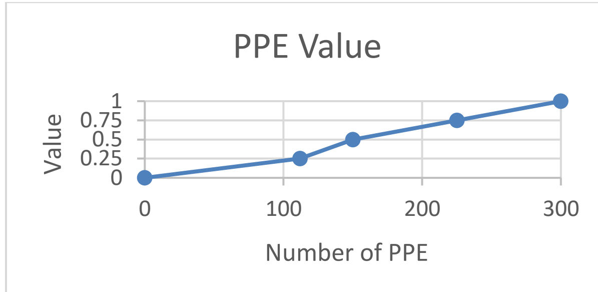


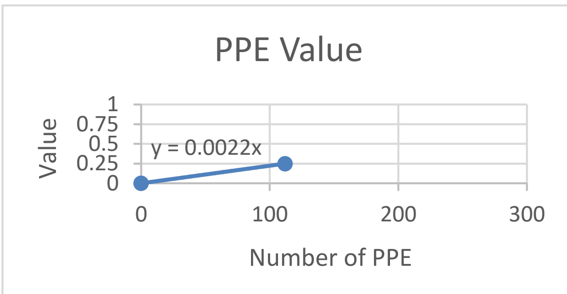


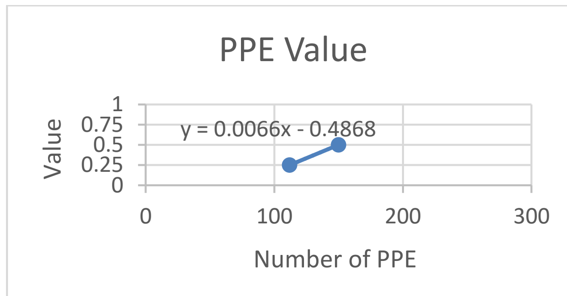


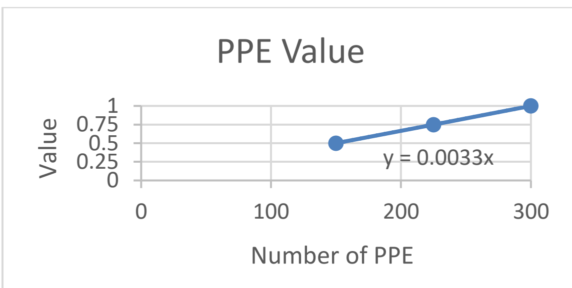
Objective 2 PPE

PPE Used	Value
0	0
112	0.25
150	0.5
225	0.75
300	1



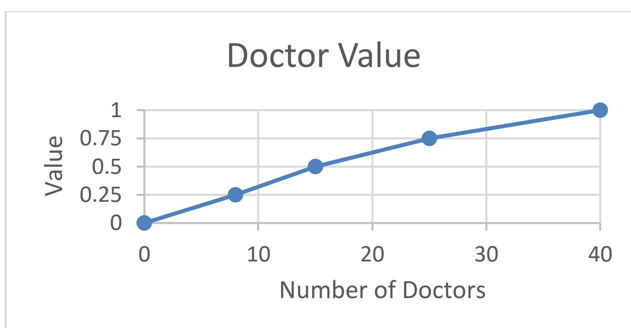


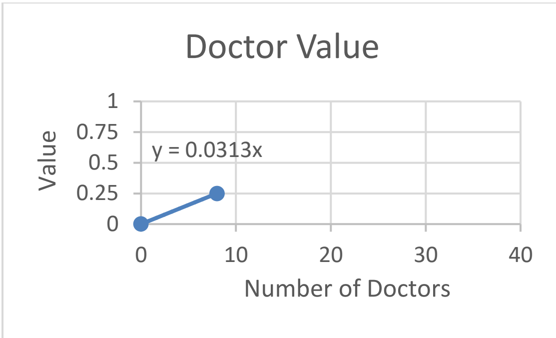


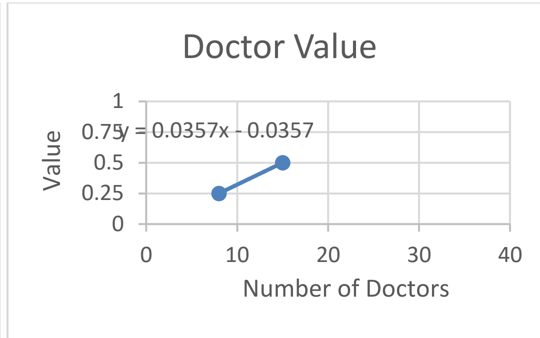


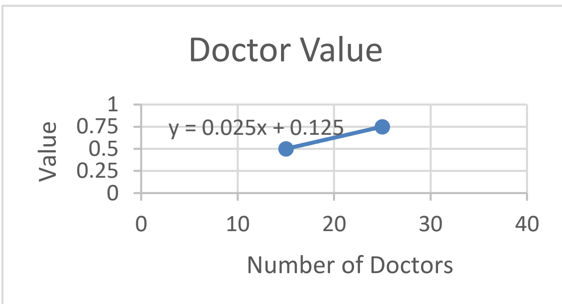
Objective 2 Doctors

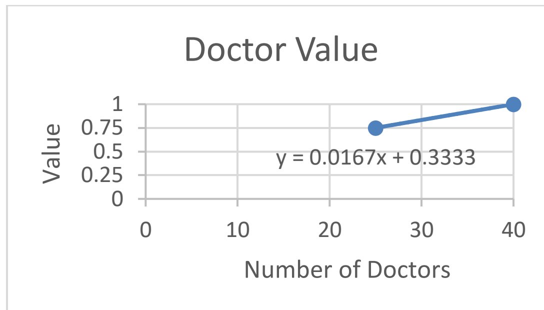
Doctors Used	Value
0	0
8	0.25
15	0.5
25	0.75
40	1





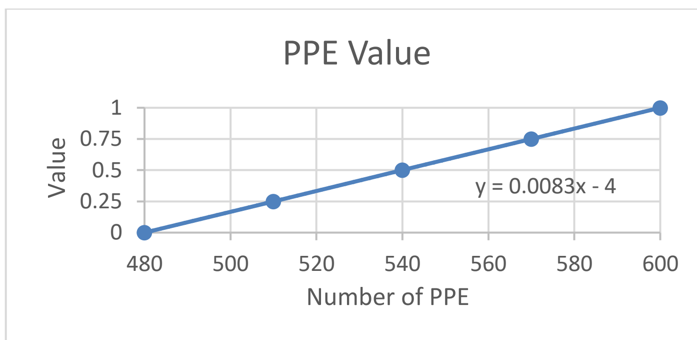






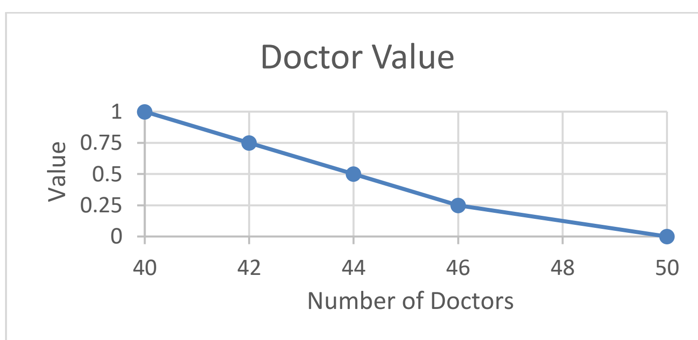
Objective 3 PPE

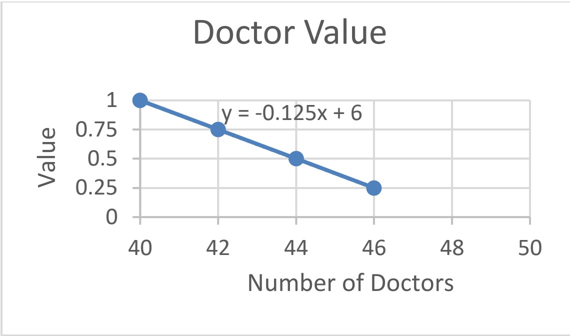
PPE Used	Value
480	0
510	0.25
540	0.5
570	0.75
600	1



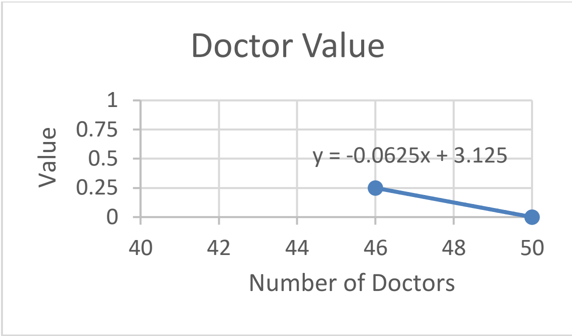
Objective 4 Doctors

Doctors Used	Value
50	0
46	0.25
44	0.5
42	0.75
40	1





Doctor Value
y = -0.125x + 6
1
0.75
0.5
0.25
0
Value
40
42
44
46
48
50
Number of Doctors



Doctor Value
y = -0.0625x + 3.125
1
0.75
0.5
0.25
0
Value
40
42
44
46
48
50
Number of Doctors

Bibliography

Akplogan, M., De Givry, S., Metivier, J. P., Quesnel, G., Joannon, A., & Garcia, F. (2013). Solving the Crop Allocation Problem Using Hard and Soft Constraints. *RAIRO-Operations Research*, 151-172.

Arevalo, G., & Insua, D. R. (2011). A Framework for Innovation Management. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio Decision Analysis* (pp. 167-185). New York: Springer.

Ataollahi, F., Bahrami, M. A., Abesi, M., & Mobasheri, F. (2013). A Goal Programming Model for Reallocation of Hospitals' Inpatient Beds. *Middle-East Journal of Scientific Research*, 1537-1543. doi:10.5829/idosi.mejsr.2013.18.11.12449

Attari, M. Y., Pasandide, S. H., Agaie, A., Taghi, S., & Niaki, A. (2017). Presenting a stochastic multi choice goal programming model for reducing wastages and shortages of blood products at hospitals . *Journal of Industrial and Systems Engineering*, 81-96.

Barasa, E. W. (2015). Setting healthcare priorities in hospitals: a review of empirical studies. *Health Policy and Planning*, 386–396. doi:https://doi-org.afit.idm.oclc.org/10.1093/heapol/czu010

Barbati, M., Greco, S., Kadziński, M., & & Słowiński, R. (2018). Optimization of multiple satisfaction levels in portfolio decision analysis. *Omega*, 192-204.

Belton, V. (1986). A comparison of the analytic hierarchy process and a simple multi-attribute value function. *European journal of operational research*, 7-21.

Bengoz, A. (2012). Using VFT as a Constraint for Goal Programming Models: A Case Study for Turkish Air Force Flying Hour Program. Air Force Institute of Technology.

Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal 48*, 28-43.

Blake, J. T., & Carter, M. W. (2002). A goal programming approach to strategic resource allocation in acute care hospitals. *European Journal of Operations Research*, 541-561.

Blake, J. T., & Carter, M. W. (2002). A goal programming approach to strategic resource allocation in acute care hospitals. *European Journal of Operational Research*, 541-561. doi:https://doi.org/10.1016/S0377-2217(01)00219-3

Blake, J. T., & Donald, J. (2002). Mount Sinai Hospital Uses Integer Programming to Allocate Operating Room Time. *INFORMS Journal of Applied Analytics*, 1-87.

Bodina, A., Pavan, A., & S., C. (2017). Resource allocation criteria in a hospital. *J Prev Med Hyg*, E184-E189.

Bradley, S. P., Hax, A. C., & Magnanti, T. L. (1977). Non-Linear Programming. In S. P. Bradley, A. C. Hax, & T. L. Magnanti, *Applied Mathematical Programming* (pp. 410-464). Reading: Addison-Wesley Publishing Company.

Burk, R. C., & Parnell, G. S. (2011). Portfolio Decision Analysis: Lessons from Military Applications. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio Decision Analysis: Improved Methods for Resource Allocation* (pp. 333-357). New York: Springer.

Carmassi, C., Foghi, C., Dell-Oste, V., Cordone, A., Bertollini, C. A., Bui, E., & Dell-Osso, L. (2020). PTSD symptoms in healthcare workers facing the three coronavirus outbreaks: What can we expect after the COVID-19 pandemic. *Psychiatry Research*. doi:https://doi.org/10.1016/j.psychres.2020.113312

Center for Disease Control and Prevention. (2018, August 30). *vhf:ebola:healthcare-us:ppe.* Retrieved from Center for Disease Control and Prevention Web site: https://www.cdc.gov/vhf/ebola/healthcare-us/ppe/guidance.html

Çetin, E., & Sarul, L. S. (2009). A Blood Bank Location Model: A Multiobjective Approach. *European Journal of Pure and Applied Mathematics*, 112-124.

Charnes, A., & Cooper, W. W. (1976). *Goal Programming and Multiple Objective Optimizations (Part 1).* Austin: University of Texas Center for Cybernetic Studies.

Charnes, A., Cooper, W. W., & Ferguson, R. O. (1955). Optimal estimation of executive compensation by linear programming. *Management Science*, 138-151.

Chauhan, R. C. (2018). Marauding terrorist attack (MTA): prehospital considerations. *Emergency Medicine Journal*, 389-395.

Chu, S. C., Ho, M. P., Lee, K. K., & Lo, H. P. (2000). Nurses allocation models for maternal and child health services. *Journal of the Operational Research Society*, 1193-1204.

Cox, C. (2020). 'Healthcare Heroes': problems with media focus on heroism from healthcare workers during the COVID-19 pandemic. *Journal of Medical Ethics, 46*(8), 510:513.

Crown, W., Buyukkaramikli, N., Sir, M. Y., Thokala, P., Morton, A., Marshall, D. A., . . . Pasupathy, K. S. (2018). Application of Constrained Optimization Methods in Health Services Research: Report 2 of the ISPOR Optimization Methods Emerging Good Practices Task Force. 1019-1028. doi:10.1016/j.jval.2018.05.003.

de Kluyver, C. A. (1978). Hard and Soft Constraints in Media Scheduling. *Journal of Advertising Research*, 27-31.

Deb, K. (2001). Non-linear Goal Programming Using Multi-Objective Genetic Algorithms. *Journal of the Operational Research Society*, 291-302.

Department of Defense. (2006, August). *damir:documents:*. Retrieved from DOD Acquisition website: https://www.acq.osd.mil/damir/documents/DAES_2006_RISK_GUIDE.pdf

Dexter, F., Blake, J. T., Penning, D. H., Sloan, B., Chung, P., & Lubarsky, D. A. (2002). Use of Linear Programming to Estimate Impact of Changes in a Hospital's Operating Room Time Allocation on Perioperative Variable Costs. *Anesthesiology*, 718-724. doi:https://doi.org/10.1097/00000542-200203000-00031

Diaz Anadon, L., Chan, G., & Lee, A. (2014). Transforming U.S. Energy Innovation. In L. Diaz Anadon, M. Bunn, & V. & Narayanamurti, *Expanding and better targeting U.S. investment in energy innovation: an analytical approach* (pp. 36-80). New York: Cambridge University Press. doi:10.1017/CBO9781107338890

Emanuel, E. J. (2020). Fair Allocation of Scarce Medical Resources in the Time of Covid-19. *The New England Journal of Medicine*, 2049-2055. doi:10.1056/NEJMsb2005114

Ghoushchi, S. J., Khazaeili, M., Amini, A., & Osgooei, E. (2019). Multi-criteria sustainable supplier selection using piecewise linear value function and fuzzy best-worst method. *Journal of Intelligent & Fuzzy Systems* , 2309-2325.

Ghufran, S., Khowaja, S., & Ahsan, M. (2015). Optimum multivariate stratified double sampling design: Chebyshev's Goal Programming approach. *Journal of Applied Statistics*, 1032-1042.

Grant, E. W. (1987). An Application of Linear Programming in Hospital Resource Allocation. *Journal of Health Care Marketing*, 69-72.

Gunpinar, S., & Centeno, G. (2015). Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals. *Computers & Operations Research*, 129-141. doi:https://doi.org/10.1016/j.cor.2014.08.017

Gur, S., & Eren, T. (2018). Scheduling and Planning in Service Systems with Goal Programming: Literature Review. *Mathematics*.

HealthLeaders Media Staff. (2009). Nurses Protest H1N1 Respirator Mask Shortage. *Health Leaders*.

Ignizio, J. P. (1976). *Goal Programming and Extensions.* Lexington: Lexington Books.

ILO, FAO, IFAD, WHO. (2020, October 13). *World Health Organization News*. Retrieved from Impact of COVID-19 on people's livelihoods, their health and our food systems: https://www.who.int/news/item/13-10-2020-impact-of-covid-19-on-people's-livelihoods-their-health-and-our-food-systems

Incident Command Center . (2020). *COVID-19 Phase I.* Wright Patterson Air Force Base: 88th Air Base Wing.

Iskander, M. G. (2012). A Suggested Approach for Solving Weighted Goal Programming Problem. *American Journal of Computational and Applied Mathematics*, 55-57.

Jenal, R., Ismail, W. R., Yeun, L. C., & Oughalime, A. (2011). A Cyclical Nurse Schedule Using Goal Programming . *Journal of Mathematical and Fundamental Sciences*, 151-164.

Jones, D. F., & Tamiz, M. (1995). Expanding the Flexibility of Goal Programming via Preference Modelling Techniques. *Omega*, 41-48.

Jones, D. F., & Tamiz, M. (1996). An Example of Good Modelling Practice in Goal Programming: Means for Overcoming Incommensurability. *Advances in Multiple Objective and Goal Programming : Proceedings of the Second International Conference on Multi-Objective Programming and Goal Programming* (pp. 29-37). Torremolinos: Lecture Notes in Economics and Mathematical Systems.

Jones, D., & Tamiz, M. (2003). Goal Programming in the Period 1990–2000. In M. Ehrgott, & X. Gandibleux (Eds.), *Multiple Criteria Optimization: State of the Art Annotated Bibliographic Surveys* (pp. 129-170). Boston: Springer.

Jones, D., & Tamiz, M. (2010). Formulating Goal Programmes. In D. Jones, & M. Tamiz, *Practical Goal Programming* (pp. 23-51). New York: Springer.

Kaiser, R. (1999). Using Capital Markets' Value Cycles in Allocating to Real Estate vs. Stocks or Bonds. *Using Capital Markets' Value Cycles in Allocating to Real Estate vs. Stocks or Bonds, Journal of Real Estate Portfolio Management*, 1-22. doi:10.1080/10835547.1999.12089563

Karakas, E., Koyuncu, M., Erol, R., & Kokangul, A. (2010). Fuzzy programming for optimal product mix decisions based on expanded ABC approach. *International Journal of Production Research*, 729-744.

Keeney, R. L. (1992). *Value Focused Thinking.* Cambridge: Harvard University Press.

Keeney, R. L., & Raiffa, H. (1976). *Decision making with multiple objectives: preferences and value.* New York: Wiley.

Kim, K.-J., & Lin, D. K. (2000). Simultaneous optimization of mechanical properties of steel by maximizing exponential desirability functions. *Applied Statistics*, 311-325.

Kirkwood, C. W. (1998). Strategic decision making: multiobjective decision analysis with spreadsheets. *Journal of the Operations Research Society*, 96-97.

Kirkwood, C. W., & Sarin, R. K. (1980). Preference Conditions for Multiattribute Value Functions. *Operations Research*, 225-232.

Kleinmuntz, D. N. (2007). *20 Resource Allocation Decisions.* Cambridge: Cambridge University Press.

Kloeber, J. (2011). Current and Cutting Edge Methods of Portfolio Decision Analysis in Pharmaceutical R&D. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio Decision Analysis: Improved Methods for Resource Allocation* (pp. 283-331). New York: Springer.

Kurth, M., Keisler, J. M., Bates, M. E., Bridges, T. S., Summers, J., & Linkov, I. (2017). A portfolio decision analysis approach to support energy research and development resource allocation. *Energy Policy*, 128-135. doi:https://doi.org/10.1016/j.enpol.2017.02.030

Kurth, M., Keisler, J. M., Bates, M. E., Bridges, T. S., Summers, J., & Linkov, I. (2017). A portfolio decision analysis approach to support energy research and development resource allocation. *Energy Policy*, 128-135.

Kwak, N. K., & Lee, C. (1997). A Linear Goal Programming Model for Human Resource Allocation in a Health-Care Organization. *Journal of Medical Systems*, 129-140.

Kwak, N. K., & Lee, C. (1997). A Linear Goal Programming Model for Human Resource Allocation in a Health-Care Organization. *Journal of Medical Systems volume*, 129-140. doi:https://doi.org/10.1023/A:1022850505219

Lahtinen, T. J., Hämäläinen, R. P., & Liesio, J. (2017). Portfolio Decision Analysis Methods in Environmental Decision Making. *Environmental Modelling and Software*, 73-86.

Lee, C., & Kwak, N. K. (1999). Information resource planning for a health-care system using an AHP-based goal programming method. *Journal of the Operational Research Society*, 1191-1198. doi:10.1057/palgrave.jors.2600821

Lee, S. M. (1972). An aggregative resource allocation model for hospital administration. *Socio-Economic Planning Sciences*, 381-395. doi:https://doi.org/10.1016/0038-0121(73)90005-0

Lee, S. M. (1972). *Goal programming for decision analysis in government.* Philadelphia: Auerback.

Lee, S. M., & Jerro, A. J. (1974). Capital budgeting for multiple objectives. *Financial Management 3*, 58-66.

Li, C., Liang, M., & Yu, Q. (2011). Multi-objective Optimization of Vehicle Passive Suspension with a Two-Terminal Mass Using Chebyshev Goal Programming. *World Academy of Science, Engineering and Technology*, 633-638.

Li, X., Rafaliya, N., Baki, M. F., & & Chaouch, B. A. (2017). Scheduling elective surgeries: the tradeoff among bed capacity, waiting patients and operating room utilization using goal programming. *Health Care Management Science*, 33-54.

Liesio, J. (2012). Measurable multiattribute value functions for portfolio decision analysis. *Decision Analysis*, 1-20.

Liesio, J., Salo, A., Keisler, J. M., & Morton, A. (2020). Portfolio decision analysis: Recent developments and future prospects. *European Journal of Operational Research*, 1-20.

Marino, D. Q. (2019). A proposal for a new index to evaluate hospital resource allocation: The case of Italian NHS rationalisation. *European Research on Management and Business Economics*, 23-29. doi:https://doi.org/10.1016/j.iedeen.2018.10.001

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 77-91.

Military Health System. (2021, February 16). *About the Military Health System*. Retrieved from Health.mil: https://www.health.mil/About-MHS

Mingers, J., & Rosenhead, J. (2002). Problem structuring methods in action. *European Journal of Operations Research*, 530-554.

Montibeller, G., & Franco, L. A. (2011). Resource Allocation in Local Government with Facilitated Portfolio Decision Analysis. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio Decision Analysis: Improved Methods for Resource Allocation* (pp. 259-281). New York: Springer.

Mottley, C. M., & Newton, R. D. (1959). The selection of projects for industrial research. *Operations Research 7*, 689-827.

Mulholland, M. W., & Abrahamse, P. B. (2005). Linear Programming to Optimize Performance in a Department of Surgery. *Journal of the American College of Surgeons*, 861-868. doi:https://doi.org/10.1016/j.jamcollsurg.2005.01.001

Naeini, A. B., Khodamoradi, S., & Sabzian, H. (2014). Comparison of Two Goal Programming Models for Budget Allocation Problem - A Case Study. *International Journal of Economy, Management and Social Sciences*, 749-754.

National Conference of State Legislatures. (2020, May 21). *research:labor-and-employment:covid-19-essential-workers-in-the-states*. Retrieved from National Conference of State Legislatures website: https://www.ncsl.org/research/labor-and-employment/covid-19-essential-workers-in-the-states.aspx

Oddoye, J., Tamiz, M., Jones, D., & Schmidt, P. (2009). Combining Simulation and Goal Programming for Healthcare Planning in a Medical Assessment Unit. *European Journal of Operations Research*, 250-261.

Ohio Department of Health. (2020, May 1). *wps:portal:gov:covid-19:checklists:english-checklists/healthcare-procedures-hospitals-covid-19-checklist*. Retrieved from Ohio Department of Health website: https://coronavirus.ohio.gov/wps/portal/gov/covid-19/checklists/english-checklists/healthcare-procedures-hospitals-covid-19-checklist

Parnell, G. S. (2007). Value Focused Thinking. In A. G. Loerch, & L. B. Rainey (Eds.), *Methods for Conducting Military Operational Analysis* (pp. 619-655). Military Operations Research Society.

Pearson, S., & Littlejohns, P. (2007). Reallocating resources: how should the National Institute for Health and Clinical Excellence guide disinvestment efforts in the National Health Service? *Journal of Health Services Research & Policy*, 160-165.

Phua, J., Weng, L., Ling, L., Egi, M., Lim, C.-M., Divatia, J. V., . . . Du, B. (2020, May 1). Intensive care management of coronavirus disease 2019 (COVID-19): challenges and recommendations. *The Lancet: Respiratory Medicine, 8*(5). doi:https://doi.org/10.1016/S2213-2600(20)30161-2

Pinheiro, R., Landa-Silva, D., Laesanklang, W., & Constantino, A. (2019). An Efficient Application of Goal Programming to Tackle Multiobjective Problems with Recurring Fitness Landscapes. In G. Parlier, F. Liberatore, M. Demange, G. Parlier, F. Liberatore, & M. Demange (Eds.), *Operations Research and Enterprise Systems* (pp. 134-152). Springer, Cham. doi:10.1007/978-3-030-16035-7_8

Prasad, A., & Reddy, R. Y. (2018). Comparison of two weighted goal programming models for financial management of a health care system. *International Journal of Statistics and Applied Mathematics*, 363-369.

Rawls, C. G. (2012). Pre-positioning and dynamic delivery planning for short-term response following a natural disaster. *Socio-Economic Planning Sciences*, 46-54. doi:https://doi-org.afit.idm.oclc.org/10.1016/j.seps.2011.10.002

Rihm, T., & Baumann, P. (2015). Improving Fairness in Staff Assignment: An Approach for Lexicographic Goal Programming. *Institute of Electrical and Electronics Engineers (IEEE)*, 1247-1251.

Rockafellar, R. T. (1997). *Fundamentals of Optimization Problem Formulation.* Retrieved from University of Washington Depts of Mathematics and Applied Mathematics: https://sites.math.washington.edu/~burke/crs/515/notes/nt_2.pdf

Romero, C. (2001). Extended lexicographic goal programming: a unifying approach. *Omega*, 63-71.

Salo, A., Keisler, J., & Morton, A. (Eds.). (2011). *Portfolio Decision Analysis: Improved Methods for Resource Allocation.* New York: Springer.

Schneiderjans, M. J. (1995). *Goal Programming: Methodology and Applications.* New York: Springer Science+Business Media.

Schwartz, S. L., & Vertinsky, I. (1977). Multi-Attribute Investment Decisions: A Study of R & D Project Selection. *Management Science*, 285-301. doi:https://www.jstor.org/stable/2630823

SCRC SME. (2005). Supply Chain Disruptions: Minimize the Effects. *Supply Chain Resource Cooperative*.

Sherlaw, W., & Raude, J. (2013). Why the French did not choose to panic: a dynamic. *Sociology of Health & Illness*, 332-344. doi:10.1111/j.1467-9566.2012.01525.x

Tan, Y., Elmekkawy, T., Peng, Q., & Oppenheimer, L. (2007). Mathematical Programming for the Scheduling of Elective Patients in the Operating Room Department. *Proceedings of the Canadian Engineering Education Association (CEEA)*.

Tao, Y., Henry, K., Zou, Q., & Zhong, X. (2014). Methods for measuring horizontal equity in. *Health Economics*, 4-10. doi:10.1186/s13561-014-0010-x

Topilla, A., Liesio, J., & Salo, A. (2011). A Resource Allocation Model for R&D Investments: A Case Study in Telecommunication Standardization. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio Decision Analysis: Improved Methods for Resource Allocation* (pp. 241-258). New York: Springer.

U.S. Department of Labor. (2020, March). *Publications: OSHA3990.* Retrieved from Occupational Safety and Health Administration: https://www.osha.gov/Publications/OSHA3990.pdf

Varghese, L., Ezat Wan Puteh, S., Schecroun, N., Jahis, R., Van Vlaenderen, I., & Standaert, B. A. (2020). Applying a Constrained Optimization Portfolio Model to Aid Prioritization of Public Health Interventions in Malaysia. *Value in Health Regional Issues*, 172-180. doi:https://doi.org/10.1016/j.vhri.2019.11.001

Williams, H. (1978). Non-Linear Models. In H. Williams, *Model Building in Mathematical* (pp. 126-143). Chichester: John Wiley & Sons, Ltd. (UK).

WilmerHale. (2020, April 8). *en:insights:client-alerts:20200408-federal-government-identifies-15-products-as-scarce-materials-subject-to-compelled-production-and-distribution-under-the-defense-production-act*. Retrieved from WilmerHale website: https://www.wilmerhale.com/en/insights/client-alerts/20200408-federal-government-identifies-15-products-as-scarce-materials-subject-to-compelled-production-and-distribution-under-the-defense-production-act

Wolfe, I., Garrett, J., Carter, B., & Lantos, J. (2020). Children's Hospital ICU Resource Allocation in an Adult Pandemic. *Pediatrics*. doi:10.1542/peds.2020-1140

World Health Organization. (2020). *csr:resources:publications:ppe_en.* Retrieved from World Health Organization website: https://www.who.int/csr/resources/publications/ppe_en.pdf?ua=1

Xu, J. L. (2006). Power Portfolio Optimization in Deregulated Electricity Markets With Risk Management. *IEEE Transactions on Power Systems*, 1653-1662. doi:10.1109/TPWRS.2006.879272

Zhang, B., Murali, P., Dessouky, M. M., & Belson, D. (2009). A mixed integer programming approach for allocating operating room capacity. *Journal of the Operational Research Society*, 663-673. doi:https://doi.org/10.1057/palgrave.jors.2602596

Vita

Captain Donald B. Hale attended Shepherd University for his undergraduate studies earning Bachelor of Science degrees in both Business Administration and Mathematics in 2007. Donald commissioned into the United States Air Force through Officer Training School in February 2013.

Captain Hale's first assignment was to Air Combat Command's 53rd Wing at Eglin AFB, Florida, conducting Electronic Warfare operational testing where he served as a Lead Operational Analyst and Project Manager. He logged 99 hours as a Flight Test Engineer on EC-130H, C-130J, and B-52 test missions. While here, he also earned a Master of Science degree in Industrial Engineering from New Mexico State University.

In 2016, he was assigned to the National Air and Space Intelligence Center in the Plans and Programs division at Wright-Patterson AFB, Ohio. He served as the Deputy Chief of Customer Experience where he led analysis on requirements and production to support warfighter, acquisition, and policy customers to inform Wing decisions.

In August 2019, Captain Hale entered the Air Force Institute of Technology's Graduate School of Engineering and Management also at Wright-Patterson AFB. Upon earning a Master of Science degree in Operations Research, he moved to support the Defense Threat Reduction Agency's mission at Fort Belvoir, Virginia.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
25-03-2021	Master's Thesis	September 2019 – March 2021

TITLE AND SUBTITLE	
Allocation of Scarce Healthcare Resources in a Military Treatment Facility During a Pandemic: A Comparison of Goal Programming and Portfolio Decision Analysis Methods	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Hale, Donald B., Captain, USAF	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/ENS) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865	AFIT-ENS-MS-21-M-165
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)** **N/A**
Intentionally left blank	**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRUBTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
In a pandemic, healthcare decisionmakers face the challenge of allocating critical, but scarce healthcare resources in a dynamic, uncertain environment. Their decisions will not only affect the patients coming to the hospital for treatment, but also the Military Treatment Facility's personnel responsible. The decisionmaker must decide how to allocate these resources to achieve multiple, conflicting objectives under multiple constraints. In response, we propose a methodology for the implementation of both Portfolio Decision Analysis and Goal Programming. The steps of this methodology provide a framework with which the decisionmaker can develop optimal allocation of resources. This framework was then applied to a notional case study using both a linear value function and a piecewise value function to show the effect of non-linear value functions on each method. Complementary analysis was conducted to illustrate insights into the model and the problem itself. This application showed the merits of both models. Both, using the framework provided, allow for as much fidelity as required by the situation. Each model can be updated to account for the dynamic environment or based on analysis performed. The flexibility and adaptability of these models is especially useful in our problem.

15. SUBJECT TERMS
Portfolio Decision Analysis, Goal Programming, Optimization

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Lt Col Marcelo Zawadzki, AFIT/ENS
U	U	U	UU	116	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 255-3636, ext 4303; Marcelo.Zawadzki.BR@afit.edu

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18