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Optimization Models and System Dynamics Simulations to Improve Military Manpower Systems

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Optimization Models and System Dynamics Simulations to Improve Military Manpower Systems

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Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2015

Dedicated, with deep admiration and gratitude, to my amazing wife, Jenny.

Acknowledgements

I would like to thank the many people who have made, not just the writing of this dissertation, but the entire Ph.D. graduate experience possible, possible. The very most important to thank is my wife, Jenny. I cannot call her a supporter – that implies a cheerleader, one who provides encouragement, one who remains on the sidelines. Over the last five plus years, Jenny decided to roll up her sleeves, to enter the arena with me, to work with me, to sweat it out, and to make sacrifices to help us complete this project. I am overwhelmed to think about how lucky I am to have such an amazing friend, smart and wise confidant, hardworking teammate, and lovely wife.

My children have also made sacrifices that helped contribute to this project. I pray us you get older, as you meet your own challenges in your life; you are comfortable coming to your mother and me to talk and to help you reflect on them. The experiences your mom and I have gone thru to finish this dissertation, and the other challenges we have faced in our lives, might provide a couple of ideas to help you meet your goals. Patrick, Brendan, Sarah, Matthew, your mom and I love you all so much.

I would like to thank my parents and my brother and sisters as well. Not for helping with this project, but for helping shape and mold me into the person I am today. I don't know enough about developmental psychology, but I am pretty certain the values we were raised with and how we were taught to treat each other, have had a great impact on me. Mom and Dad, thank you for being so willing to help Jenny and me, sometimes at the drop of a hat. I am amazed by the support and love you continue to give us and our children.

It is very common today for people to say to service members "Thank you for your service." Well, I want to thank the United States Army for providing me the amazing opportunity to study, to learn, to do research, and to work towards this degree. It is an unheard of opportunity and one that I will benefit from for the rest of my life. I am so grateful, not just for this opportunity, but for all of the experiences I have had in the Army and all the incredible people I have met.

I want to thank the men and women, and their families, of our Armed Services. It is impossible to begin to describe the sacrifices of our Soldiers, Sailors, Airmen, and Marines and their families. Thank you to all who have served and continue to serve.

I would like to thank Professor Lasdon. Thank you for being an amazing coach, mentor, and friend. Your everlasting patience, never ending encouragement, and sage advice made all the difference. I have grown and developed so much under your watchful eye and I am grateful for your willingness to help and support me. From the bottom of my heart, thank you.

Professor Anderson, I treasured the afternoons sitting in your office talking about system dynamics, how it applied to my research, and an endless list of other topics. You introduced me to a discipline that I did not know anything about that ended up being an essential part of this project.

My committee members were great sources of advice and support. Professor Matwiczak, thank you for your detailed coaching on my writing and helping me to think about how a multi objective decision model could be beneficial to this research. I really believe that the addition of this type of model made the difference. Professor Fulton and Pat McMurry, thank you so much for introducing me to the Army Medical Department and providing me with an area of research. Professor Bagchi, thank you for your support of this research.

Thank you to my fellow students, especially Vivek Vasudeva. Thanks for being my graduate school Ranger Buddy.

I would like to thank the United States Military Academy for the opportunity to study and teach. Thank you to the Department of Behavioral Sciences and Leadership for giving me the opportunity to study at Texas and for the opportunity to teach cadets. I am so grateful for the opportunity to teach operations management, as well as leadership, organizational change, and strategy classes. The experience has opened my eyes to a world where quantitative analysis and organizational behavior coexist and it has changed my way of thinking.

Doctor Mike Kwinn – if it was not for you, I would not have had the opportunity to study at the University of Texas. My family fell in love with living in Austin and made incredible friends here. I cannot thank you enough for your support and for your coaching over the years. I know the only thanks you really want is for me to do the same, to help open doors for others, and I will try to live up to your example.

Jenny, it all begins and ends with you. Thank you so much for loving me completely.

Optimization Models and System Dynamics Simulations to Improve Military Manpower Systems

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The University of Texas at Austin, 2015

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Manpower policy decisions are an extension of traditional operations management problems. Manpower policies strive to place the appropriate and accurate numbers of the correct types of people in the right jobs at the necessary time. Managers create inventory by hiring new workers, either in entry level or more senior positions. Over time, managers promote workers to satisfy demand for more advanced positions. Managers face the challenge of determining the number of people to hire into entry level positions, the number of people already in the work force to promote to more senior level positions, and in some open systems when and how many experienced employees to hire into these senior positions.

This dissertation studies and develops three different methods and approaches to provide improved decision support to a healthcare organization's manpower system. Our research goal is to design models of the organization's manpower system to improve human resource operations. The healthcare system of interest is the United States Army's Medical Department (AMEDD). The research will be arranged in three sections. We explore current practices and build improved optimization manpower system models.

We use multi objective decision analysis techniques to enhance the optimization models. Lastly, we construct a system dynamics simulation model of the manpower system to address the limitations in the optimization models.

There are three main contributions of this dissertation to the operations management literature. First, the development of improved manpower optimization models can be extended to other manpower systems. Second, we develop a technique to assess the manpower system value based on a series of value scoring transformation functions and weighting the over two hundred sub objectives in the optimization manpower system's objective function. This application of multiple objective decision analysis makes it possible to compare different manpower systems. The system dynamics simulation of a military manpower system is new to the operations management literature as is how we use the system dynamics simulation to update optimization model parameters to construct a more realistic manpower system model.

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1. Introduction

Manpower policy decisions are an extension of traditional operations management problems. Manpower policies strive to place the appropriate and accurate numbers of the correct types of people in the right jobs at the necessary time. Managers create inventory by hiring new workers, either in entry level or more senior positions. Over time, managers promote workers to satisfy demand for more advanced positions. Managers face the challenge of determining the number of people to hire into entry level positions and the number of people already in the work force to promote to senior level positions.

Current hiring and promotion decisions not only affect the present day work force structure, but also influence the work force structure's future well-being. If organizations try to save resources by hiring fewer entry level workers, this upstream policy will have an effect in the future, downstream, when the organization is trying to meet senior level position requirements. Manpower policies may promote workers to eliminate shortages in senior level positions. But promotion policies may also prohibit mass or large scale promotions where all or many members of the workforce are promoted and there is no system to ensure that only qualified individuals are selected for promotion. An additional complicating manner is determining how people will transition from one specialty in the workforce to another. Individuals may wish to execute these transitions because of personal career objectives or the transition may be management imposed to meet demand in particular specialties.

This dissertation will explore and develop operations management techniques that can be used to better construct, manage, and measure the performance of manpower systems. We begin with an examination of how manpower decisions are currently made in the United States Army's Medical Department (AMEDD), which promotes, sustains, and enhances Soldier health, trains, develops, and equips a medical force that supports full spectrum operations, and delivers health services to over 550,000 Soldiers and their families.[1] AMEDD is responsible for managing the strength and skill sets of its 15,000 officers serving in six different career management fields to fulfill its mission today and to be prepared to meet future requirements. AMEDD manpower managers and analysts currently use a suite of nonlinear goal programming optimization models to manage the hiring of new officers, promotion rates for eligible officers, and how to transition officers from one specialty to another. One model exists for each of the six career management fields or corps. Though these models are sophisticated and in use by the Army today, AMEDD manpower models are fragmented. They lack the ability to provide overall, AMEDD level policy solutions because the current models do not consider the interactions that do exist between the six corps. The models are also unable to account for and model AMEDD manpower objectives.

We construct an alternative manpower decision support tool to the current one. Our alternative model is a linear goal programming optimization model that integrates the six AMEDD career management fields. We are able to combine the six career management fields because our model incorporates career management field interdependencies. Specifically, we look at how manpower requirements can be optimally assigned to improve the work force structure. Our model is a "global" AMEDD model. It provides AMEDD decision makers a total AMEDD manpower policy – optimizing accession, promotions, and transfers while minimizing the mismatch

[1] U.S. Army Medical Department Army Medicine http://www.armymedicine.army.mil/about/mission.html

between the AMEDD officer inventory and officer requirements and individual corps requirements as well.

The modeling advancements to the current optimization tool are then leveraged as we build a linear goal programming model which adds a time index to the models described above. This allows us to start with the current, on hand inventory in the AMEDD manpower system, and determine hiring, promotions, and transfers in each year to meet desired targets either in several years and/or a final year. Our linear program determines the optimal manpower policy to manage the officers in the manpower system. Our solution is able to reduce the total number of officer inventory and officer inventory targets or requirements from 1,155 deviations to only 175 deviations from the officer inventory targets.

During our research of manpower systems, we identified challenges faced by comparing and aggregating six separate manpower systems. It was difficult to compare deviations between the number of required officers and the number of officers on hand. It was difficult to quantify the impact of a shortage of or an excess of officers on the performance of the entire manpower system. The optimization model could identify an optimal manpower policy that would optimize the six components of the manpower system, but would do so at the expense of the overall well-being of the manpower system.

We used multi objective decision analysis techniques to weigh the over 200 hundred objectives, far more than we could assess by asking the decision maker questions like "How much do you prefer Objective *A* to Objective *B*?" These techniques also transformed deviations from officer targets into value scores. This allows decision makers to quantify the cost of not meeting the officer requirements and allows decision makers to compare the cost of not meeting requirements in specific career fields and officer ranks.

The multi objective decision analysis techniques are improvements to the current model, but the flow of officers in the manpower system is influenced by constant continuation rates that model the percentage of officers that stay in the manpower system from one year to the next. The assumption that officers will not change their retention behavior is faulty. We identified a need to build a model of the manpower system that updated the officer continuation rates. The updated model would take the current estimates of officer continuation rates and model how these continuation rates would evolve over time.

There are three main contributions of this dissertation to the operations management literature. First, the development of improved manpower optimization models can and will improve AMEDD manpower planning. It also can be extended to other manpower systems, both in the military and other areas. Second, we develop a technique to assess the manpower system value based on a series of value scoring transformation functions and weighting the over two hundred sub objectives in the optimization manpower system's objective function. This application of multiple objective decision analysis makes it possible to compare different manpower systems. The system dynamics simulation of a military manpower system is not new to the operations management literature. But, our integration of an optimization model and a system dynamics simulation is unique. The pairing of the models allows us to use the system dynamics simulation to update optimization model parameters to construct a more realistic manpower system model.

This dissertation has the following structure. In Chapter 2, we explore the literature of manpower systems. We demonstrate that military manpower systems because of their ordered, hierarchical structure are excellent manpower systems to model. We explore some popular modeling techniques. In Chapter 3, we describe the manpower system that is the subject of this research – the Army Medical Department officer corps. This manpower system consists of over 15,000 officers in 89 different carrier fields. In Chapter 3, we explore the current nonlinear goal programming models that are used to model a component of the manpower system.

In Chapter 4, we study these models more closely and make several improvements to them. First, we are able to transform the nonlinear goal programming models to linear goal programming models. We complete this transformation for the six models that are used to manage the six divisions of the AMEDD manpower system by adding a time index. Second, we are able to combine these six models to model the entire AMEDD manpower system with a single linear goal programming model. In Chapter 5, we develop an optimal manpower policy for the actual inventory of officers in the manpower system. The linear programming techniques discussed in Chapter 4 are critical in Chapter 5 because the size of the optimization problem grows as we consider the manpower system over an extended planning horizon.

The creation of a global model from the six AMEDD division models creates some challenges. In order to balance the well-being and value of the six divisions as well as the AMEDD manpower system as whole, in Chapter 6 we present a value hierarchy of the manpower system. This value hierarchy allows us to assign a series of weights to the objective function components that measure the fitness of the six divisions and the overall system. This fitness is measured by transforming the number of deviations from the officer targets to a value score. In Chapter 7, we convert the linear goal programming models that minimized the deviations from inventory targets to linear programs that maximize the value score of the manpower system based on the multi objective decision analysis developments in Chapter 6.

The final modeling effort, the creation of a system dynamics model, is discussed in Chapter 8. We show how our system dynamics model is equivalent to the optimization models and then take advantage of system dynamics software tools to conduct additional analysis of the AMEDD manpower system.

2. Literature Review

Traditional operations management methods focus on how managers oversee, design, and redesign business operations in the production of goods and/or services in efficient and effective manners. Comprehensive management methods explicitly consider human resource systems as part of these business operations. When employers maintain large work forces and there is an excess of employee inventory, there is the potential for inefficiencies to emerge. There are too many people with only so much work to go around and labor costs are inflated. When there are shortages in employee inventory, there are fewer employees available to complete the necessary work; employee satisfaction, production, and task performance all suffer.

Large organizations are by their nature complex, multifaceted, and complicated. Corporations, firms, education systems, nonprofit organizations and military forces all face the challenge of motivating their employees to accomplish stated organizational goals. Operations management (OM) provides managers many tools - optimization, decision analysis, simulation, forecasting, to help make these goals attainable. These OM models help managers make decisions, create policies, and manage the implementation of these policies in resource constrained environments. Organizations are fueled by resources and human capital may be the most important of these resources.

OM models have been applied to the study of manpower planning models to produce the appropriate and accurate numbers of the correct types of people in the right jobs at the necessary time (Grinold & Marshall, 1977). Manpower planning models are built to demonstrate the effect of manpower systems on organizational and system performance. These models help us understand the relationships between the structure of a work force and the organization's bottom line.

Decision makers face the difficult problem of determining and selecting the objective of their manpower systems. They must determine what characteristics and attributes a good manpower policy exhibits. Goal programming is a technique designed for problems with multiple objectives where managers and analysts must consider multiple criteria when determining what type of manpower policy to adopt (Henry & Ravindrian, 2005). A traditional or straightforward objective (for example profit maximization) does not accurately capture the multiple objectives and goals of a manpower system. Additionally, many of the manpower system constraints are flexible and there can be instances where solutions violate some, if not all, of the constraints. If the constraints were considered strict, there may not exist a feasible solution (Price & Piskor, 1972).

Charnes, Cooper, and Ferguson introduced the concept of goal programming in a 1955 paper where they sought to estimate executive salaries. Salaries were based on executive performance on a set of attributes, but individual salaries were constrained. Employees were not allowed to receive more compensation than more senior employees and salary targets were established for each employee level. Charnes, Cooper, and Ferguson defined the optimal salary policy to be the policy that minimized the sum of the differences between actual individual employee compensation and salary target (Charnes, Cooper, & Ferguson, 1955).

Gass developed a goal programming model for military manpower planning models in 1988. He considered each military grade; essentially an employee level in the framework used by Charnes, Cooper, and Ferguson, and minimized the deviation between the number of soldiers in the workforce inventory and the requirements for soldiers of that grade. The objective function consisted of the weighted sum of deviations from requirements in each grade (Gass, Collins, Meinhardt, Lemon, & Gillette, 1988).

The military is an excellent candidate for manpower planning models. The military consists of a workforce that fits neatly into Grinold and Marshall's manpower taxonomy:

a. the workforce is compartmentalized into different jobs, occupational specialties, and grades.

b. members have similar career paths; soldiers enter at the bottom of the grade or rank structure

c. the workforce members have similar skills, ages, and evaluation systems.

There are two predominant types of manpower systems. A push manpower system exists when the system promotes workers according to a policy schedule or organization norm. Members of the workforce are promoted regardless if there is a demand for an employee of the next higher level or position. In a pull system, employees are promoted only when there is an opening in a higher level position and an employee is promoted to meet the higher level position demand (De Feyter, 2007). De Feyet explains that in practice, the two can combine to make a third system.

Military organizations have implemented manpower planning models for quite some time. In 1957, in a letter to the editors of *Operations Research*, Abrahams reported on the work of British scientists who used mathematical programming models to study the integration of aircraft mission sortie schedules, maintenance operations, and the availability of pilots. Abrahams also describes a think tank that tackled the problem of manpower and utilization problems in Britain's' Royal Air Force (Abrams, 1957).

Today, military operations researchers and systems analysts use manpower planning models to manage the accessions of new soldiers and the number of soldiers to promote from one grade to another. Gass's work in this area has had a great impact on the models used in practice by the United States Army to manage its personnel. His review of the types of manpower planning models in use includes transition rate (Markovian) models, network flow models, and goal programming models. His models describe people going from one state to another during their life cycle in the manpower system. Individuals get hired, get trained, take on new jobs, get retrained in new specialties, receive advanced level training in their current specialty, get promoted, get fired, retire, or die. Gass provides an aggregation of individuals by using classifications for them. Sample classes are specialty, number of years in service, grade and rank. A combination of these classifications corresponds to a state. Each service member can occupy only one state but it is possible to flow from one state to another (Gass, 1991).

Gass's models determine how many people are in each state, $X(g,s,y,t)$, the number of individuals of grade g, in specialty s, with y years of service in time period t. These problems become quite large based on the time horizon of the model and the number of different specialties in the military. For example, in the U.S. Army alone, there are over 200 military occupational specialties for enlisted soldiers. Enlisted soldiers can serve in one of nine rank positions and they can retire at 20 years of service.

Network flow models are natural fits to model manpower systems. Network flow models are powerful tools because they help us describe the flow of personnel from one state to another. These models provide managers with decision support for manpower planning models because they represent the flow of personnel from one inventory state to another with arcs in a network and we use nodes to represent different personnel states, combinations of (g,s,y,t) (Gass, 1991). Price attributed the benefit of formulating manpower planning models as network flow models because of the existence of advanced computer codes that can solve large scale network flow models very quickly (Price, W., 1978). Network flow modes in manpower planning models have the form of the minimum cost flow network problem. The networks arcs represent the flow of personnel. Source nodes have a supply equal to the initial personnel inventories and sink nodes are demand nodes with demands equal to future personnel inventory requirements. Transshipment or intermediate nodes have zero demand and help the network model maintain personnel balances and grade and military specialty inventory goals. Conservation of flow equations where the number of people in the state at the start of a period, plus the number of people that enter the state during that period (either through a new hire, a promotion, a transfer from another specialty, or a person that progresses from one year to the next in the army) minus the number of people that exit the state during that period, (either through separation from the system, promotion out of the current grade, or continuation in the service) must equal the number of people in that state at the end of the period. Because of the diversity of the type of officers that flow through the system, these problems are very similar to multi-commodity network distribution models (Geoffrion, 1971).

Besides making decisions about long range planning models, at times the Army has to make single time period decisions. One problem analysts face is to designate mid-career level officers into new career fields to meet end strength requirements while maximizing overall utility of officers (Shrimpton & Newman, 2005). After ten years of service, Army officers have the opportunity to choose whether they would like to continue their career in their basic branch or to transition to a new career field. Basic branches consist of the jobs we normally associate with the Army; infantry, artillery, aviation are a few examples. Career fields consist of the types of jobs that the Army needs to have for officers at higher grades but there is no need from them in lower grades. Examples are operations research systems analyst, public affairs officers, and foreign area officers.

Army analysts developed a network flow model, specifically a variant of the assignment problem, to solve this problem. There exists one node for each officer and one node for each career field. There exists an arc from an individual officer node to a career field if an officer has selected the career field as one of his or her top three preferences. A weight is assigned to each arc that represents both officer *i's* preference for career field *j* and the Army's assessment of how well a match officer *i* is serving in career field *j*. Each officer node has a supply of one and each career field node has an upper and lower bound on the number of offices that can be assigned to that career field. The model ensures that all officers are assigned and conservation of flow is maintained by including a sink node whose demand is equal to the number of officers that need to be assigned.

Manpower planning models are also used to determine the worth or value of potential human resource policies. An example of this type of study is an investigation of whether the practice of providing financial bonuses to individuals agreeing to continue their service is an effective retention tool (Coates, Silvernail, Fulton, & Ivanitskaya, 2011). Armacost and Lowe developed a linear programming formulation with a statistical classification algorithm to improve the assignment of graduating cadets at the United States Air Force Academy to their initial career fields (Armacost and Lowe, 205). Their model assigned cadets to available jobs and maximized the cumulative cadet preference for the job they were assigned to.

The military's manpower models have been extended to other manpower systems that also are closed, compartmentalized systems where potential employees have little to no opportunities to join the work force anywhere but at the bottom of the pay scale. Because of this limit to lateral entry, closed manpower systems, like the military, must recruit, train, and grow their personnel to meet future manpower requirements. The academic workforce at research universities can be modeled in this manner. It is a manpower system with multiple classes, where individuals primarily enter at the assistant professor level and the organization grows most (but definitely not all) of its full professors. (Hall, 2009) Popular optimization models have assigned nurses to work schedules and pilot crews to airline schedules (Anbil, Gelman, Patty, & Tanga, 1991).

Khoong recognized two types of scenarios where manpower models can be extremely useful (Khoong, 1999). The first scenario is to solve what he called steady state or day to day business problems. An example of a steady state problem is how many people to hire, promote, fire on a regular basis. The second type of scenario helps the organization develop the policies that are required to meet new organizational goals. An example of this might be if the new goal is to increase the operating strength of a grade or if there is going to be a new specialty added then these developmental models will help describe policies to help the organization meet these goals. When the goals are attained then the organization shifts back to steady state models. This example demonstrates how manpower planning models can be used to provide decision support for many different scenarios and planning horizons.

Cashbaugh (2007) wrote that many military manpower planning decision support tools do not recognize a problem before it is too late and the military finds it difficult to recover from mismanaged manpower policies (Cashbaugh, 2007). By developing a new optimization model that will consider the entire AMEDD system, we can improve the overall operating strength of the AMEDD officer system and begin to explore new models and methodologies that can be extended from this global AMEDD model to make further advancements in the AMEDD and Army manpower systems. With our system dynamics simulation, we can forecast what challenges the manpower system will face and how it will affect critical modeling parameters. We can use our understanding of the effect on these critical parameters to update our optimization model that develops optimal manpower policies. Essentially, we can create the optimal manpower policy not for a projection of the past system performance, but the optimal policy our projection for how we believe the manpower system could behave in the future.

System dynamics models have been used in the past to model both civilian and military manpower systems. Mutingi and Mbohwa constructed a system dynamics model to develop corporate manpower policies for recruitment and training. They also augment their system dynamics model with an optimization approach, how to best meet dynamic demand constraints and develop training and recruitment policies, while considering system costs.

Mutingi (2012) constructed a system dynamics model to formulate policies to manage a manpower system when the manpower system is involved in new product development. Mutingi recognizes that the management of the work force is a critical variable that contributes not only to the success of the product development, but to the firm itself.

Researchers have also used system dynamics to model military manpower systems. Cavana et. al. (2004) studied the electronic technicians career field in the New Zealand Army. Specifically, their system dynamic study researches the causal factors of poor retention and tried to identify potential policies that would improve retention. Their detailed description of the complex manpower system using causal loop diagrams and their ability to use these diagrams to facilitate workshops demonstrate the ability of a system dynamics point of view to help develop policy, even for the most complicated systems.

Garza et. al. (2014) studied how manpower system dynamic models can help enhance our understanding of these complex systems. System dynamic models, unlike traditional manpower optimization models, can produce multiple values, multiple indicators about the well being and performance of a system. These system dynamic models are focused on the behavior of the members of the manpower system and are able to monitor how personnel levels change, vary, and fluctuate over time.

3. AMEDD Nonlinear Manpower Models

Since 2010, the Army Medical Department Personnel Proponency Directorate (PPD) has used a suite of nonlinear optimization models to optimize AMEDD manpower policies. These models, one for each of the six corps or career management fields, produce an optimal or target work force structure. The policy is optimal in that it minimizes the sum of deviations between specified targets and the number of company grade officers and all senior grades. It does this separately for each corps (McMurry, et al., 2010) and (Fulton & McMurry, 2014). The target workforce structure is the optimal distribution of the officer corps over the officers thirty year life cycle. The target workforce structure not only specifies how many officers should serve in each rank and in each specialty, but how the officers are optimally distributed over the thirty year life cycle. This is a vital component of managing the officer manpower system. It is essential to achieve the optimal distribution of officers over the thirty year life cycle.

If officers are not distributed optimally in each of the officer ranks, than the optimal number of officers would not be eligible for promotions and it would be impossible to achieve the optimal number of officers in successive ranks. In other words, these models present a work force structure that minimizes the total mismatch between officer inventory and officer demand. These optimal policies specify the number of officers in each specialty to hire, the number of officers to promote, and when and how many officers to transfer from feeder specialties to specialties that do not accept new hires into their ranks. Army Medical Department PPD analysts solve these nonlinear programs in spreadsheets using add-in mathematical programming solvers. Specifically, they use Microsoft Excel spreadsheets and the Solver® tool to identify optimal manpower policies.

This chapter explores the manpower planning models developed in 2010 and we present the formulation of all six corps or career management fields in the mathematical programming software, General Algebraic Modeling System (GAMS). This conversion to a more sophisticated software platform allows us to analyze the size of the nonlinear programs and provides a base of comparison to compare the linear programs developed in Chapter 4. Chapter 5 also includes the how analysts develop an approximate or surrogate global manpower planning solution based on the six individual corps models and an analysis of this solution. Again, this analysis provides a base line for the models developed and described in Chapter 4.

3.1 Current Corps Manning Models

In this section, McMurry's model is presented in detail because it serves as a building block for subsequent modeling developments. McMurry describes a nonlinear goal programming model. He and Fulton present their latest model in a paper to appear in *Interfaces* article and implement the transformation of the nonlinear program to a linear program developed in this research. They do not discuss the concept of constructing a global model of the six AMEDD corps and considering the multi corps interdependencies. The nonlinear model determines the optimal promotion rate to promote officers from state (a,y,g) to state $(a,y,g+1)$; see definitions of the indices (a,y,g) below. The model then calculates the number of officers in state $(a,y,g+1)$ multiplying the optimal promotion rate by the number of officers in state (a,y,g). The model also calculates the optimal transfer rate from donor specialties to recipient specialties. The model also calculates the optimal number of officers to hire each year. After modeling the global AMEDD manpower system that includes all six AMEDD corps, an equivalent linear program is developed that has the structure of a network flow model with gain and side constraints in Chapter 4(Jensen, 2003).

3.1.1 Sets used in the Current Corps Manpower Models

A = officer area of concentration or specialties with index $a \in A$, a = 1, 2, 89

Y = an officer's number of years of service with index $y \in Y$, y = 1, 2, 30

G = an officer's grade with index $g \in G$, g = O-1, O-2, O-6

Corps = an officer's career field, $corps \in Corps$, *corps* = Army Medical Specialist Corps (AMSC), Dental Corps (DC), Medical Corps (MC), Medical Service Corps (MSC), Nurse Corps (NC), and Veterinary Corps (VC)

Company Grade (G) = subset of set G, junior officers that serve in the grade of O-1, O-2, and O-3. Company grade officer inventories and requirements are both aggregated in the model, while field grade ranks are all considered separately.

3.1.2 Parameters

Force development and Total Army Analysis are the Army procedures and systems utilized to "define military capabilities, design force structures to provide these capabilities" (2013-2014 How the Army Runs: A Senior Leader Reference Handbook, 2013-2014). The Office of the Secretary of Defense and Joint Staff publish guidance about what capabilities the Army must provide the nation and the joint force (the United States Army, the United States Air Force, the United States, Navy, and the United States Marine Corps). The United States Congress authorizes the Army to maintain prescribed end strength, a specific number of authorized soldiers. The Army is then responsible to determine how many soldiers it requires to provide these capabilities. The total number of soldiers is distributed among the Army's career fields and AMEDD determines the budgeted end strength by specialty and grade, based on the overall end strength of the Army and the capabilities AMEDD must provide the Army.

Additional model parameters are listed and described in Table 1 below.

Parameter	Description
bes_{ag}	The number of officers by grade and specialty AMEDD requires to complete its mission
c_{ayg}	historical continuation rate, the percentage of officers remaining in the system from one year to the next, for officers by grade by year by AOC
p_{ayg}	historical continuation rate for officers by grade by year by AOC not selected for promotion
pos_weight_g	weights for positive deviations between inventory and requirements for officers of grade *g*
neg_weight_g	weights for negative deviations between inventory and requirements for officers of grade *g*
pos_weight_co_grade	weights for positive deviations between inventory and requirements for company grade officers
neg_weight_co_grade	weights for negative deviations between inventory and requirements for company grade officers

Table 1 AMEDD Manpower System Parameters

Two sets of rate parameters describe whether or not an officer will remain in the Army year to year. The first set of rates, c_{ayg}, tells us the percentage of officers of a particular state that will continue to serve in the Army from one year to the next. This rate is applied to officers who have been promoted at every opportunity. A second rate applies to officers that have been previously passed over for promotion. The second rate matrix, p_{ayg}, tells us the percentage of these officers who have been passed over for promotion (non-selected) that will continue to serve in the army from one year to the next. The model keeps track of those officers who were ever passed over for promotion until they choose to exit the manpower system. A limitation of the model is that we do not model officers passed over for promotion who compete for future promotions. These two matrices allow us to show how officers will flow or continue through our network model.

A set of weights, pos_weight_g, $negs\_weight_g$, *pos_weight_co_grade, neg_weight_co_grade*, are used in the objective function to multiply deviations between inventory and targets for each grade. These weights allow decision makers to input their preferences on which deviations in which grade are more detrimental to the work force structure.

3.1.3 Decision Variables

$hires_{ayg}$ - number of officers hired into state (*a,y,g*)

$promrate_{ayg}$ – promotion rate, percentage of officers promoted into state (*a,y,g*) from state (a,y-1,g-1)

$passover\_rate_{ayg}$ – non select for promotion rate, passed over rate, percentage of officers not selected for promotion into state (*a,y,g*) from state (a,y-1,g-1)

$promrate\_DC_{yg}$ - promotion rate, percentage of Dental Corps officers promoted into state (*a,y,g*); rate is independent of Dental Corps specialty. All Dental Corps officers, regardless of specialty, are promoted at an identical, corps rate.

$passover\_rate\_DC_{yg}$ - non select for promotion rate, passed over rate, percentage of Dental Corps officers not promoted into state (*a,y,g*); rate is independent of Dental Corps specialty

$promrate\_MC_{yg}$ - promotion rate, percentage of Medical Corps officers promoted into state (*a,y,g*); rate is independent of Medical Corps specialty

$passover\_rate\_MC_{yg}$ - non select for promotion rate, passed over rate, percentage of Medical Corps officers not promoted into state (*a,y,g*); rate is independent of Medical Corps specialty *transrate*$_{aa'yg}$ – percentage of officers that transfer from a donor area of concentration to a receiving area of concentration per year per grade where $a \neq a'$

inventory$_{ayg}$ - number of officers in state (*a,y,g*)

inventory_passedover$_{ayg}$ - number of officers who have not been selected for promotion, but remain in the manpower system in state (*a,y,g*)

pos$_{cg}$ - positive deviations, representing excesses or surpluses, of officers when compared to targets or requirements for corps *c* and grade *g*

neg$_{cg}$ - negative deviations, representing shortages, of officers when compared to targets or requirements for corps *c* and grade *g*

pos_co_grade$_{c}$ - positive deviations, representing excesses or surpluses, of the number of company grade officers in corps *c* compared to total number of budgeted end strength for company grade officers

neg_co_grade$_{c}$ - negative deviations, representing shortages, of the number of company grade officers in corps *c* compared to total number of budgeted end strength for company grade officers

There are two types of decision variables in the current AMEDD models. The first types are the variables that represent the actual levers that the manpower manager and analysts can control to achieve the optimal work force structure. The model finds the optimal number of officers to hire, the optimal rate at which to promote eligible officers, and the optimal rate at which to pass over officers that are eligible for promotion. The number of officers to hire and the percentage of officers to promote in the Army Medical Specialist, Medical Services, Nurses, and Veterinary Corps are indexed (*a,y,g*) and the percentage of officers passed over for promotion is the complement of the percentage of officers chosen for promotion. Officers in the Dental Corps and the Medical Corps are promoted at the same rate from grade *g* to grade *g+1* regardless of specialty. Therefore, we create separate decision variables to represent these rates and they are indexed simply (*y, g*). The model also finds the percentage of officers in an inventory state that should be transferred to a specialty that does not hire new officers and relies on transfers from feeder or donor AOCs to create inventory. This decision variable has the index (*a, a', y, g*) because it determines the percentage of officers in specialty *a* that will be transferred to *a*', in year *y*, of grade *g*, where $a \neq a'$.

The second type of decision variables is what we call inventory control decision variables. The model keeps tally of all officers that have been promoted in the regular, usual manner by an inventory control decision variable for each inventory state. The decision variable $inventory_{ayg}$ tells us how many officers are in each state (a,y,g). Officers that have been passed over for promotion are also kept track of with the decision variable $inventory\_passedover_{ayg}$. The last type of inventory control decision variables describes the mismatch between the officer inventory for corps *c* and grade *g* and the $target_{cg}$. The model keeps track of surpluses and shortages in the usual goal programming manner. For each target, we have a positive and negative deviation variable. Positive deviation variables measure how many officers we are in excess of the grade target and the negative deviation variables measure how many officers we are lacking compared to the grade target. None of the decision variables are restricted to be integers. Thus this model requires the results to be rounded when the decision variables are related to the number of officers to hire or the number of officers in an inventory state. Generally, the values are large enough so that rounding causes only small errors.

3.1.4 Constraints

The number of officers in each corps is capped by the corps target, the upper bound on the total allowable corps inventory. The corps target is the sum of the target for each grade in corps *c*. The corps targets consist of the budgeted end strength and additional officer requirements.

$$\sum_{A(c)yg} (inventory_{ayg} + inventory\_passedover_{ayg}) \leq \sum_{A(c)g} target_{ag} \; where\ A(c) is\ the\ set\ of\ all\ a, areas\ of\ concentration\ in\ corps\ c$$

Equation 1 Corps Inventory Upper Bound

The number of officers is also bounded from below. AMEDD must field enough officers in each specialty to meet the requirements specified by the specialty's budgeted end strength. Regardless of rank, the number of officers in the inventory of specialty a must be sufficient to fill or match all of the required positions as stated by the specialty's budgeted end strength.

$$\sum_{ayg} inventory_{ayg} + inventory\_\_passedover_{ayg} \geq \sum_{g} bes_{ag} \;\; \forall a$$

Equation 2 Area of Concentration Lower Bound

Just over half (48 of the 89 areas of concentration) do not hire new officers into their specialty. These recipient areas of concentration receive their officers from donor areas of concentration. As an example, all dentists enter the Dental Corps in the specialty 63A, General Dentist. After a few years as a general dentist, officers must transfer to one of the nine, more advanced, more specialized Dental Corps areas of concentration, such as Orthodontist or Comprehensive Dentist. Officers will transfer from donor specialties, like 63A, General Dentist, to the other 48 AOCs to populate the ranks of the recipient AOCs. The optimal manpower policy must meet minimum transfer requirements to insure the recipient AOCs are manned sufficiently and in accordance with AMEDD policy. Equation 3 is a nonlinear constraint because both $transrate_{a,a',y,g}$ and $inventory_{a,y-1,g}$, are decision variables.

$$transrate_{aa'yg} * inventory_{ay-1g} \geq mintransfers_{aa'y}$$

Equation 3 Minimum Number of Transfers

A series of conservation of flow constraints ensure the flow of officers from one state to another is only decremented by the officers that choose to leave the Army. These constraints allow us to account for all officers in state (a, y, g). After officers enter the manpower system by being new hires, from year to year, there are four possible paths an officer can take from his current state (a,y,g). First, officers in state (a,y,g) may continue in the manpower system in the current area of concentration, in the current grade, and transition from state ($a,y,$g) to state ($a,y+1,$g). Second, officers may transfer from state (a,y,g) to state ($a',y+1,g$) where a is a donor area of concentration and a' is a recipient area of concentration. Third, officers may be promoted from state (a,y,g) to state ($a,y+1,g+1$). Fourth, officers may choose to transition out of the manpower system.

We have a series of constraints, three in all, that will help us maintain and conserve this flow. These constraints enforce the conditions that no inventory is created outside the initial hiring of officers and no inventory is destroyed unless it is by officer attrition. They also allow us to assign values to our inventory variables, the number of officers in each state (a,y,g). First, the number of officers that do transfer each year from specialty a has to be less than or equal to the number of officers in specialty a. The following constraint enforces this.

$$\sum_{\mathrm{R(a)}} transrate_{aa'yg} \leq 1$$
$$where\ \mathrm{R(a)}\ are\ all\ the\ AOCs\ that\ AOC\ \mathrm{a}\ can\ transfer\ to, \forall(y,g)$$
$$pairs\ where\ transfers\ are\ eligible\ to\ occur$$

Equation 4 Conservation of Transferring Officers

The second conservation of flow equation conserves the flow of all officers that have been promoted on time, at each opportunity for advancement. The number of officers in each inventory state (*a,y,g*) has five components. The first is the number of officers hired into state (*a,y,g*), which are defined only for states which allow hires. The second is the sum of the number of officers that transfer into state (*a,y,g*) from states (*a',y-1,g*) and (*a',y-1,g-1*) where *a'* are the AOCs that feed into AOC *a*. The third component is the sum of the number of officers that transferred out of states (*a,y-1,g*) and (*a,y-1,g-1*) to the AOCS that receive officers from AOC *a*. The fourth component is the officers that are promoted into state (*a,y,g*). The last component is the fraction of officers that advanced or continued into that state because they were in inventory state (*a,y-1,g*) in the previous year. A similar constraint keeps track of all officers that have been passed over for promotion, $inventory\_passedover_{ayg}$. We see in Equation 5 two nonlinear terms created by the product of transfer rates and the amount of inventory in a state and the cross product of promotion rates and the amount of inventory in a state.

$$inventory_{ayg} = hires_{ayg} + c_{ayg} * (inventory_{ay-1g} - \sum_{a'} transrate_{aa'yg} * inventory_{ay-1g} + \sum_{a'} transrate\_a'ayg * inventory_{a'y-1g})) + promrate_{ayg} * (inventory_{ay-1g-1} - + \sum_{a'} transrate_{aa'yg} * inventory_{ay-1g-1} + \sum_{a'} transrate\_a'ayg * inventory_{a'y-1g-1})) \ \forall\ (a,y,g), a \neq a'$$

Equation 5 Conservation of Flow of Officers

The following constraint sets the passed over rates as the compliment of the promotion rates.

$$passover_{rate_{ayg}} = 1 - promrate_{ayg}$$
$$passover\_rate\_DC_{yg} = 1 - promrate\_DC_{yg}$$
$$passover\_rate\_DC_{yg} = 1 - promrate\_DC_{yg}$$
$$for\ all\ (y, g)\ pairs\ that\ are\ feasible\ promotion\ (y, g)\ combinations$$

Equation 6 Set Passover Rates

There are two goal programming constraints in the model to calculate the mismatch between inventory and field grad office requirements and the mismatch between inventory and company grade officer requirements. The field grade deviations will be calculated for each grade individually. The company grade deviations will be calculated aggregately, with all O-1s, O-2s, and O-3s pooled together.

$$\sum_{a'y} inventory_{ayg} + inventory\_passedover_{a'yg} \quad - pos_{cg} + neg_{cg}$$
$$= target_{cg}\ where\ a'is\ the\ subset\ of\ all\ AOCs\ in\ corps\ c, c \in C\ and\ g\ \text{is}\ O-4, O-5, O-6$$

Equation 7 Calculating Field Grade Inventory Deviations from Requirements

$$\sum_{a'yg'} inventory_{ayg} + inventory_{\ passedover_{a'yg}} \quad - poscograde_c = negcograde_c$$
$$= company\ grade\ officer\ targets_c\ where\ a'is\ the\ subset\ of\ all\ AOCs\ in\ corps\ c, where\ g'\ \text{is} O-1, O-2, O-3, and\ \forall c \in C$$

Equation 8 Calculating Company Grade Officer Aggregate Deviations

The current AMEDD models also have a series of constraints that help maintain the sparsity of many of the decision variable matrices. For example, the AMEDD policy is that new officers are hired only into grades O-1s, O-2s, and O-3s. So the following constraint restricts all incidents of $hires_{ayg}$ where g = O-4, O-5, O-6 to zero, essentially enforcing the AMEDD hiring policy. For a = 1 to 89, y = 1 to 30, and three grades, there are a total of 8,010 constraints of this type.

$$\sum_{ay} hires_{ayg} = 0 \; for \; all \; g = O-4, O-5, O-6$$

Equation 9 Restricting New Hires to O-1s, O-2s, and O-3s

Additional constraints restrict new hires to the appropriate states. For example, AOC 65A hires O-2's and 65B hires O-1s. Other constraints maintain the sparsity of the promotion rate and passed over rate decision variable matrices. In Chapter 4, an improvement to this formulation is introduced.

3.1.5 Objective Function

The objective of these corps goal programming models is to minimize the number of deviations per grade from the targeted number of officers, the officer demand, and the officer inventory in each grade, the officer supply. The model groups all specialties together to compile a corps level grade deviation. Company grade officers, the three most junior grades, are grouped together and treated as one category. So the objective function has four components – the deviation from the O-4, O-5, and O-6 targets and the deviation from the aggregate company grade officer target. The objective function can also include weights and allow decision makers to weigh deviations. For example it might be more important for AMEDD to minimize the deviations between the number of more senior officers and the target levels for senior officers than more junior officer positions.

$$Minimize\ Objective\ Function = \sum_{c,g}\left(pos\_weight_g * pos_{cg} + neg\_weight_g * neg_{cg}\right) + \sum_c \left(pos\_weight\_co\_grade * pos\_co\_grade_c + neg\_weight\_co\_grade * neg\_co\_grade_c\right)$$

Equation 10 Objective Function

3.2 Corps Manning Nonlinear Models Results

The individual corps models were solved as part of this research to provide a baseline that we can use to assess the linear models we develop. The models were solved in GAMS Version 23.7 using the CONOPT solver on a Dell Studio 1537 with 4GB of RAM Intel Core 2 Duo CPU running Windows Vista. CONOPT is only able to find a locally optimal solution and we cannot be sure it is a globally optimal solution. Table 2 shows us the results from the six individual corps models. Three of the corps (Medical Services Corps, the Veterinarian Corps, and the Nurses Corps) have a perfect match between the total inventory of officers and the targets. The Army Medical Specialist Corps has a negligible deviation. The Dental Corps and Medical Corps have sizeable deviations between their actual inventory and their targeted workforce.

	AMSC		DC		MC	
	Excesses	Shortages	Excesses	Shortages	Excesses	Shortages
Company Grade Officers	0	0	152	0	0	204
Majors, O-4s	0	0		0	0	0
Lieutenant Colonels, O-5s	0	0		77.8	164.6	0
Colonels, O-6s	5.3	0		74.2	83.3	0

	MSC		NC		VC	
	Excesses	Shortages	Excesses	Shortages	Excesses	Shortages
Company Grade Officers	0	0	0	0	0	0
Majors, O-4s	0	0	0	0	0	0
Lieutenant Colonels, O-5s	0	0	0	0	0	0
Colonels, O-6s	0	0	0	0	0	0

Table 2 Current AMEDD Manning Model Results

We need to study the structure of the two corps that have large inventory – requirement mismatches. These two career management fields do not have the pyramid like requirements structure that the other fields have, see Figure 1. For example, the Dental Corps requires more O-6 Colonels than it does O-3 Captains. The Medical Corps does not have a requirements distribution that is weighted as heavily on the higher ranks as does the Dental Corps but there is another AMEDD policy that imposes a constraint on the manpower solution.

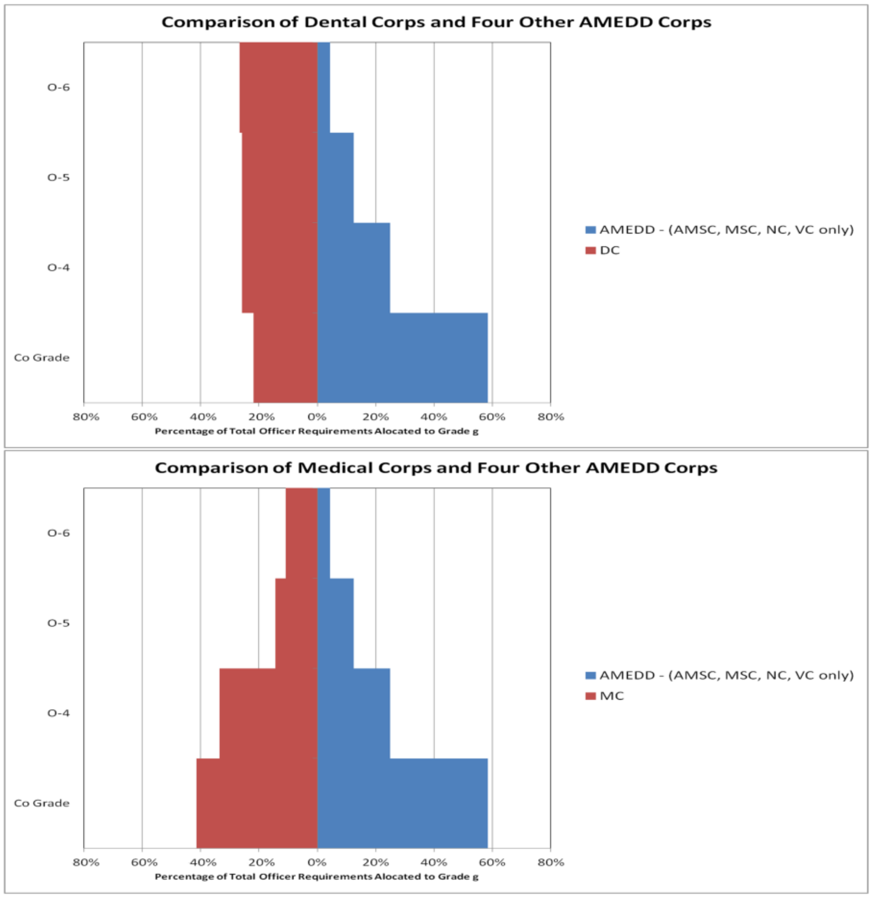


Figure 1 Distribution of Dental /Medical Corps and Other AMEDD Targets

AMEDD promotes higher percentages of its officers in the Dental and Medical Corps than they do in the other career management fields. The difference between the upper bound on promotion rates and lower bound is much smaller in these highly specialized and highly transferable to the civilian medical force fields than it is in the other career management fields. For example, the promotion rate to Colonel in the Medical Corps must fall between 75% and 76%. In the Medical Services Corps, the promotion rate to Colonel must fall between 40% and 60%. The tight ranges in the Medical and Dental Corps contribute to these fields being unable to remove the inventory- requirements mismatch. The optimizer has less flexibility in the Medical and Dental Corps models to pass officers over for promotion to remove excess officers.

3.3 A "*GLOBAL*" AMEDD POLICY

If each of these six independently derived policies is implemented, they become an ad hoc, unintentional, global AMEDD manpower policy. The solution ignores joint or coupling constraints that apply to AMEDD totals across all corps. There are many ways to measure the merit of a global AMEDD policy. One way is to calculate the mismatch between AMEDD global, all career management fields, inventory by grade and the AMEDD global requirements. Another way that is more similar to traditional goal programming techniques is to create a weighted objective function that incorporates elements of each career management field's internal inventory – requirements problem.

We turn our attention to the first method. We calculate the total AMEDD requirements per grade and compare these AMEDD requirements to the total number of officers in the inventory per grade. Table 3 summarizes the results from the six individual corps models and displays the inventory – requirement mismatches. The total mismatch between inventory and requirements is 204. If we examine individual grades, we see that shortages in one career management field are negated by excesses in others. For example, AMEDD as a whole has a surplus of 85 O-5 Lieutenant Colonels. This surplus was created by an excess of 163 O-5 Lieutenant Colonels in the Medical Corps and a shortage of 78 O-5 Lieutenant Colonels in the Dental Corps, for a total excess of 85. The Dental Corps has excesses in company grade inventory and shortages in O-5 Lieutenant Colonel and O-6 Colonel inventories. The Medical Corps has shortages in company grade inventory and shortages in the field grade ranks. Thus, many of the mismatches cancel each other out and the overall AMEDD mismatch is 204.

Grade	Requirement	Inventory	Excess	Shortage
Company Grade (O-1, O-2, O-3)	8,111	8,055	-	56
O-4	4,403	4,357	-	46
O-5	2,205	2,290	85	-
O-6	1,231	1,248	17	-
Total Excesses and Shortages, Inventory and Requirement Mismatches	204			

Table 3 Global AMEDD Inventory Requirement Mismatches

The second method of measuring the merit of the global AMEDD policy is the sum of each individual career management field or corps objective function. In addition to the weights already displayed in Equation 10, additional weight parameters are added to represent the relative weight or importance of the six different corps.

$$Global\ AMEDD\ Objective\ Function = \sum_c (global\ weights_c * Objective\ Function_c)$$

Equation 11 Sum of Corps Objective Functions

The weighted objective function, where weights range between the interval [0, 1] and all of the weights must sum to 1, consists of the sum of the total deviations or inventory – requirements mismatches in each corps. Recall that in Table 2, the sum of the total inventory – requirements mismatches is 811. If each career management field is equally weighted, that is each corps objective function contributes 16.67% to the global AMEDD objective function, then the weighted sum of the career management field objective function is 135. These two methods of calculating the global merit of implementing the six independent policies gives us a baseline to allow for comparison of the alternative manpower solutions we will develop.

The next chapter will outline and describe the development of truly global AMEDD model where are all six corps manning policies are simultaneously considered. The next chapter will outline how these six nonlinear goal programming models are transformed into linear, goal programming models. This transformation to a linear model provides many advantages that will be discussed in the next chapter.

4. A Global, Linear AMEDD Manpower Model

The current method of optimizing each of the individual career management fields and implementing the six corps optimal manpower policies to create the global AMEDD policy has two significant disadvantages. First, the models are nonlinear. This nonlinearity increases the computational resources required to solve the problems and makes it very difficult to confirm that a solution to the problem is actually a global solution. The nonlinear problems also fail to consider the interactions that do occur between the corps. Specifically, the models ignore how AMEDD immaterial positions, coded as O5A positions, and transient, training, holding, and student positions, coded as TTHS positions, are distributed. These positions may be assigned to any corps, but each corps model is independent of each other. We can develop an optimization program that optimally assigns these positions. The optimizer will choose to assign the immaterial requirement positions to corps that have shortages or excesses in any grade. By assigning additional requirements, the optimizer essentially has removed the inventory – requirement mismatch. We will also explore whether the six corps optimal policies when combined create a policy that is optimal in terms of the entire AMEDD officer community.

What follows is a description of the construction of one global model that includes all six AMEDD corps or career management fields and the conversion of the nonlinear career management field models to create a linear, global AMEDD manpower optimization model. The conversion from nonlinear to linear is achieved by eliminating the promotion rates as decision variables. The promotion rate decision variables are replaced with new decision variables that represent the numbers of people promoted. The promotion rate lower and upper boundaries are still modeled and can be expressed as limits on the number promoted/total eligible for promotion. An upper limit, say u, on such a ratio, can be expressed as the linear constraint number promoted $\leq u$*(total eligible for promotion). This is equivalent to the original model. We will then describe how we modeled the immaterial positions and modeled the critical interdependencies between the six career management fields. Lastly, we will develop an objective function, relying on goal programming techniques, for this new global AMEDD model. The limitations of this new objective function are discussed later in Chapters 6 and 7.

4.1 Construction of a Global Model

Chapter 3 described the nonlinear programs currently used by AMEDD to optimize their six separate manpower systems. This chapter describes the creation of one global model that encompasses all of the AMEDD corps in one model. This chapter also describes programming enhancements made to improve the model in an effort to improve the model's computation time.

The first step was to remove the constraints that enforce the sparsity of the following matrices of decision variables: $hires_{ayg}$, $promrate_{ayg}$, $promrate\_DC_{ayg}$, $promrate\_MC_{ayg}$, $passover\_rate_{ayg}$, $passover\_rate\_DC_{ayg}$, $passover\_rate\_MC_{ayg}$. We can define these variables to only exist on the desired combinations of (a,y,g) and (y,g). We created a set defined by the feasible combinations of the indices. For example, the set OK_hire is defined by all the feasible combinations of the indices (a,y,g) that are desired. Then we define the decision variable $hires_{a',y',g'}$ to be zero if (a',y',g') is not a member of the set OK_hire. An example of an infeasible triplet would be $hires_{a,y,O\text{-}6}$ because the Army does not hire any new officers and give them the rank of O-6 Colonel. When we apply this method to the AMSC nonlinear model, we reduce the number of constraints from 2,454 to 1,692 and reduce the amount of time required to solve the nonlinear model from 0.359 seconds to 0.14 seconds. We have reduced the number of equations by 30% and the amount of time to solve the model by 61%.

To combine all of the corps into one global model, we will incorporate all of the constraints from the individual models to include lower and upper bounds, conservations of flow, and the calculate of passed over for promotion rates. But we do require some additional constraints. The total number of officers in the inventory must be less than the sum of the corps targets across all corps and all grades.

$$\sum_{c} \sum_{a \in A(c), y, g} (inventory_{a,y,g} + inventorypassedover_{a,y,g}) \leq \sum_{c,g} target_{cg}$$

Equation 12 Global AMEDD Model Upper Bound on Total Inventory

In the original models, we calculated the deviations between inventory and requirements in each corps by Equation 7 and Equation 8. Now, we also want to also calculate the deviation between the inventory and the total AMEDD requirements, as we did for each corps. The following equations will allow us to calculate these deviations. These equations require the introduction of four new decision variables - $global\_pos\_deviation_g$, $global\_neg\_deviation_g$, *global_pos_co_grade_deviation*, and *global_neg_co_grade_deviation*.

The following equations will allow us to calculate the global AMEDD deviations.

$$\sum_{ay} (inventory_{ayg} + \ inventory\ passedover_{ayg}) \leq \sum_{c} target_{cg} \quad for\ all\ g = O-4, \quad O-5, \quad O-6$$

Equation 13 Global Model Field Grade Inventory Deviations

$$\sum_{ayg}(inventory_{ayg} + \ inventory\ passedover_{ayg}) \leq \sum_{c} companygradeofficerstarget_c \ \ for\ all\ g = O-1, O-2, O-3$$

Equation 14 Global Model Company Grade Officer Aggregate Deviations

4.2 Linear Transformation

Transforming the current nonlinear program to a linear program has two distinct advantages. The first is computationally. It took 35 seconds to solve a global, AMEDD nonlinear program. It is difficult to imagine smoothing this nonlinear program to consider a larger system, like the rest of the Army for example. The AMEDD officer manpower system has 15,000 officers while the entire United States Army has close to 500,000 members.

The other advantage of a linear transformation and solving the AMEDD manpower system as a linear program is the guarantee, if there is an optimal solution, we can be sure that it is a global optimal solution. All decision variables in the model are positive real numbers, which is a convex set. Our objective function is a linear mapping of a convex set of decision variables. Convex programming tells us if the decision variables are part of a convex set and our objective function maps this convex set to a real number, then a local minimum of the objective function is also a global minimum **Invalid source specified.**.

The original model owes its nonlinearity to Equation 3 Minimum Number of Transfers and Equation 5 Conservation of Flow of Officers. There are two products terms: the promotion rate multiplied by the number of officers in an inventory state and the transfer rate from one AOC to another multiplied by the number of officers in an inventory state. We will transform each of these cross product terms and replace them with a new linear decision variable that represents respectively, the number of officers promoted and the number of officers transferred. When we do this, we eliminate the promotion and transfer rate decision variables. We consider first the elimination of the transition rate decision variables. The conservation of flow constraints for each state (*a,y,g*) is

$$inventory_{ayg} = hires_{ayg} + c_{ayg} * (inventory_{ay-1g} - \sum_{a'} transrate_{aa'yg} * inventory_{ay-1g} + \sum_{a'} transrate\_a'ayg * inventory_{a'y-1g})) + promrate_{ayg}((* (inventory_{ay-1g-1} - \sum_{a'} transrate_{aa'yg} * inventory_{ay-1g-1} + \sum_{a'} transrate\_a'ayg * inventory_{a'y-1g-1})) \; \forall \, (a, y, g), a \neq a'$$

Equation 15 Nonlinear Conservation of Flow Constraint

Officers transfer from specialty *a* to specialty *a'* at a rate determined in the individual corps models by the decision variable $transrate_{a,a',y,g}$. The percentage of officers that can transfer from specialty *a* to specialty *a'* has to be less than 100%. Since these transfers happen both when officers are ineligible and eligible promotion states, we will keep track of officers that transfer to a promotion eligible state and an ineligible state.

The conservation of flow equation for each inventory state has the nonlinear terms $transrate_{a,a',y,g} * inventory_{a,y-1,g}$ to model transfers of officers that are ineligible for promotion, or not in a state where officers are eligible or up for a promotion. The nonlinear term $transrate_{a,a',y,g} * inventory_{a,y-1,g-1}$ models the transfer of officers that are eligible for promotion. To transform these nonlinear terms to linear ones, we have to make two new decision variables, one to represent the number of officers transferred from state (*a,y-1,g*) to state (*a',y,g*) and the second to represent the number of officers transferred from state ($a',y\text{-}1,g\text{-}1$). The first of these decision variables is $trans\_non\_promo\_yr_{a,a',y,g}$ and the second is $trans\_promo\_yr_{a,a',y,g}$.

The number of officers transferred to state (a',y,g) has to be less than or equal to the number of officers that are in state ($a,y\text{-}1,g$) or ($a,y\text{-}1,g\text{-}1$). We cannot transfer more officers from a feeder specialty to a receiving specialty than were in the feeder specialty state at the outset; officer flow cannot be created. The following two constraints for each inventory state allow us to replace the cross product term in the original models conservation of flow constraints:

$$\Sigma_{a'}\, trans\_non\_promo\_yr_{a,a',y,g} \leq inventory_{a,y-1,g} \;\; \forall a,y,g \text{ where } a' \neq a$$
$$\Sigma_{a'}\, trans\_promo\_yr_{a,a',y,g} \leq inventory_{a,y-1,g-1} \;\; \forall a,y,g \text{ where } a' \neq a$$

Equation 16 Calculating the Number of Officers Transferred Linearly

We turn our attention now to promotion rates. The percentage of officers that AMEDD promotes must meet lower and upper bound promotion constraints. These bounds constrain the promotion rates. Our conservation of flow constraint for each inventory state includes the following component, the cross product between a promotion rate decision variable and an inventory control variable: $prom\_rate_{a,y,g} * inventory_{a,y-1,g-1}$, where $prom\_rate_{a,y,g}$ is the promotion rate to state (a,y,g) and $inventory_{a,y-1,g-1}$ is the number of officers in state ($a,y\text{-}1,g\text{-}1$) that are eligible for promotion to grade g in year y. Note, the eligible population is one year younger and is currently serving in one grade below.

Our linear transformation takes the following form. First we create a new decision variable, $prom_{a,y,g}$, the number of officers promoted to state ($a,y,$g). Based on the principle of conserving the flow of manpower in the system, $prom_{a,y,g}$ must be less than the number of officers that are eligible for promotion, or $inventory_{a,y-1,g-1}$. The promotion rate upper and lower bounds must be considered as well. We cannot promote more than the number of officers in the eligible promotion state multiplied by the promotion rate upper bound. We also cannot promote less than the number of officers in the eligible promotion state multiplied by the promotion rate lower bound. So for each state (*a,y,g*), we create one decision variable, $prom_{a,y,g}$ and two constraints:

$$prom_{a,y,g} \leq promo\_rate\_up_{a,y,g} * (inventory_{a,y-1,g-1} - \sum_{a' \in A} trans\_promo\_yr_{a,a',y,g} + \sum_{a' \in A} trans\_promo\_yr_{a',a,y,g}) \quad \forall a,y,g \text{ where } a' \neq a$$

$$prom_{a,y,g} \geq promo\_rate\_lo_{a,y,g} * (inventory_{a,y-1,g-1} - \sum_{a' \in A} trans\_promo\_yr_{a,a',y,g} + \sum_{a' \in A} trans\_promo\_yr_{a',a,y,g}) \quad \forall a,y,g \text{ where } a' \neq a$$

Equation 17 Calculating the Number of Officers Promoted Linearly

where $promo\_rate\_up_{a,y,g}$ is the promotion rate upper bound and $promo\_rate\_lo_{a,y,g}$ is the promotion rate lower bound. The right side of the constraints updates the number of eligible officers by subtracting those that transfer to all other specialties and adding those that transfer in from all other specialties. In practice these other specialties are limited to the set of feasible AOC transfer pairings.

When the linear terms replace the nonlinear ones, Equation 15, the conservation of officer flow, can now be expressed as such:

$$inventory_{a,y,g} = hires_{a,y,g} + c\_p_{a,y,g} * (inventory_{a,y-1,g} - \sum_{a' \in A} trans\_non\_promo\_yr_{a,a',y-1,g} + \sum_{a' \in A} trans\_non\_promo\_yr_{a',a,y-1,g}) + prom_{a,y,g} \quad \forall a,y,g \text{ where } a' \neq a$$

Equation 18 Linear Conservation of Flow Constraint

The model is now a linear goal programming model that has the structure of a network flow model with side constraints(Jensen, 2003). This means that linear programming techniques can be utilized to solve the model. This transformation has three distinct advantages. After validating the transformation, in the section, these three advantages are discussed.

To ensure this linear transformation is equivalent to the nonlinear models and will lead to an identical solution, as a case study, an examination of the two Dental Corps models is presented here. Identical analysis of the other five models was also conducted. Table 4 compares the results from the nonlinear Dental Corps model and the linear Dental Corps Model. We can see that the results are identical. There is one disadvantage to using this transformation. Current AMEDD policies states the promotion rates for all officers in the Dental Corps, no matter the specialty, are identical for each grade. For example, those dentists in the Public Health Dentist specialty will be promoted at the same rate as all other dentists. This restriction applies to officers in the Medical Corps as well. The new decision variable $prom_{a,y,g}$ includes officer specialty a as an index. Therefore, when we calculate the number of officers promoted, there is the possibility that officers in different specialties will be promoted at different rates. However, if all specialties have identical upper and lower bounds on promotion rates, we are willing to accept this disadvantage to transform the model to a linear program. Interestingly, the Dental Corps model still promotes all officers at the same rate and there is only a slight variation in promotion rates ($\pm$ 1%) in the Medical Corps.

Decision Variables and Objective Function	Non-Linear Model	Linear Model
Hires	87.87	87.87
Promotion Rate to Major	1.00	1.00
Promotion Rate to Lieutenant Colonel	0.93	0.93
Promotion Rate to Colonel	0.85	0.85
Inventory of Captains	385.02	385.02
Inventory of Majors	274.00	274.00
Inventory of Lieutenant Colonels	196.19	196.19
Inventory of Colonels	209.79	209.79
Objective Function - Inventory to Requirements Mismatch	304.05	304.05

Table 4 Comparison of Non-Linear and Linear Model Results - Dental Corps Model

When each individual corps model is converted to an equivalent linear model, we see dramatic decreases in the amount of time it takes the solver to find an optimal solution. Table 5 compares the amount of time it takes to solve the nonlinear model with a solver that does not guarantee that the solution is a globally optimal one with the amount of time it takes the solver to find an optimal solution to the linear program models. Resource usage is the measure of the amount of CPU time it takes the solver to solve the model (Rosenthal, 2014). Also, since we have switched from a nonlinear program where we have to concern ourselves with local optimal solutions to a linear program, we can be certain our linear program solution is a global optimal solution. There is now also no need to use specialty solvers to find a solution to the mathematical program. In fact, analysts at the Army Medical Department Personnel Proponency Directorate have been able to use this linear programming transformation in order to simplify the process of finding the optimal manpower policy. The analysts are able to solve these linear programs in Microsoft Excel with Excel Solver®.

Corps	Non-Linear Model Resource Usage (seconds)	Linear Model Resource Usage (seconds)	Percent Decrease
AMSC	0.14	0.047	66%
DC	1.045	0.047	96%
MC	8.689	0.562	94%
MSC	2.574	0.219	91%
NC	0.951	0.156	84%
VC	0.484	0.032	93%

Table 5 Computer Resource Usage for Non-Linear and Linear Models

4.3 ASSIGNING IMMATERIAL POSITIONS

With the linear transformation complete, we turn our attention to a method of improving the quality of the global manpower model objective function. In order to do this, we identify two types of constraints that can be relaxed. This section examines a portion of the manpower model that was considered as a fixed parameter and describes how the scope of the problem is expanded to provide more flexibility to analysts and to attempt to improve the quality of the linear program solution.

Each corps has been assigned a fixed amount of O5A Immaterial Positions and TTHS Positions. A corps fixed allotment of immaterial positions is based on its overall strength. So the AMEDD policy is to assign these positions based on corps requirements rather than assigning them in a manner that would improve the overall objective, minimizing the deviation between the operating strength and the system manpower requirements, of the manpower system. Here we develop a method where we assign O5A Immaterial and TTHS Positions to improve the manpower system, to minimize the gap between the officer inventory and the officer requirements. It is understood that resulting optimal assignment of these manpower requirements might not be realistic, but this analysis shows that these manpower requirements can be considered as possible force shaping levers. A partial reallocation of the manpower requirements might be realistic and acceptable to decision makers and will result in a superior solution than the one described in Chapter 3.

First we examine why a reallocation of the immaterial positions can improve the manpower system. Recall, the corps target requirement for grade *g* is a function of four things: the budgeted end strength for officers of grade *g* in corps *corps* and the number of immaterial positions assigned to corps *corps* and grade *g*. Further recall there are three types of immaterial positions: O5A positions, TTHS positions, and Corps Immaterial positions. In Equation 7 and Equation 8, we calculated the deviations between inventory and requirements. Now, we are going examine the requirements in an updated manner that will help us model the interaction between the career management fields.

Targets can be decomposed into two types. The first type of target is the flexible target and consists of the O5A positions and the TTHS positions. We call these flexible because of the nature of the positions; these are manpower requirements that can be filled by any AMEDD officer as long as they meet specified grade requirements. Hence, AMEDD can shift these positions from one corps to another. The second type is the fixed target and is a function of the budgeted end strength and the Corps Immaterial Positions. These are fixed because the requirements cannot be satisfied by inventory in another corps.

Now we examine two specific instances from the individual corps models. The Dental Corps has an excess of 152 Captains and the Medical Corps has a shortage of 205 Captains. Table 6 shows how the Captain target is decomposed into the two types. We see that both the Dental and Medical Corps have TTHS positions, one type of flexible target. We also see that the Dental Corps excess inventory could be alleviated if the target or requirement for Dental Corps Captains could grow to 385. Similarly, the

Medical Corps has a shortage of Captains and the shortage would be erased if the target or requirement for Captains in the Medical Corps could be reduced to 1,777.

Corps		DC	MC
Fixed Targets	$\sum_{a \in corps\ c} bes_{a,O-3}$	152	1659
	$Corps\_Immaterial\_Positions_{c,O\text{-}3}$	0	0
Flexible Targets	$O5A\_positions_{c,O\text{-}3}$	0	0
	$TTHS\_positions_{c,O\text{-}3}$	81	323
$target_{c,O\text{-}3}$		233	1982
Captain Inventory		385.0	1776.9
Shortage(-) Excess(+)		+ 152	- 205

Table 6 Captain Inventory in Dental and Medical Corps

If we were to reallocate 152 TTHS Positions from the Medical Corps to the Dental Corps, the model would see a reduction in the deviations between inventory and requirements. The parameter $target_{DC,O\text{-}3}$ would increase to 385 and there would be a perfect match between Dental Corps inventory and its company grade target. In the Medical Corps, $target_{MC,O\text{-}3}$ decreases and the shortage of captains decreases as well from 205 to 53. By taking advantage of the flexible nature of the O5A and TTHS positions, we have improved the manpower system in this specific example.

Corps		DC	MC
Fixed Targets	$\sum_{a \in corps\ c} bes_{a,O-3}$	152	1659
	$Corps\_Immaterial\_Positions_{c,O\text{-}3}$	0	0
Flexible Targets	$O5A\_positions_{c,O\text{-}3}$	0	0
	$TTHS\_positions_{c,O\text{-}3}$	233	171
$target_{c,O\text{-}3}$		385	1830
Captain Inventory		385.0	1776.9
Shortage(-) Excess(+)		0	-53.1

Table 7 Reallocatting O-3 Captain Requirements and O-3 Captain Inventory in Dental and Medical Corps

In a more general manner, we are going to build a model where the optimizer can reallocate these flexible targets in order to minimize the objective function. First, we create two new decision variables $O5A\_positions\_assigned\_dv_{cg}$ and $TTHS\_positions\_assigned\_dv_{cg}$. These variables will represent the assignment of the flexible targets to each (*corps,g*) combination. The total number of positions assigned to each grade must be equal to the total number of positions allocated in the original models. The following constraint enforces this restriction. Additionally, the new decision variables are only defined on the feasible combinations of (*corps,g*). In our example in Table 6, we see the both the Dental and Medical Corps do not have any O5A positions in the grade of Captain. Therefore, $O5A\_positions\_assigned_{cg}$ must be zero for the combination (*DC,O-3*) and (*MC,O-3*).

$$\sum_{c} O5A\_positions\_assigned\_dv_{cg} = \sum_{c} O5A\_positions_{cg} \quad \forall g$$
$$\sum_{c} THS\_positions\_assigned\_dv_{cg} = \sum_{c} THS\_positions_{cg} \quad \forall g$$

Equation 19 Conservation of Flexible Targets

We will separate the inventory targets on the right hand side of Equation 7 and Equation 8 into fixed and flexible targets. By making the flexible targets decision variables, the optimizer can adjust the overall target to minimize the objective function.

4.4 Objective Function

In the individual corps models, the objective function had four components. Each of these components can be considered as a goal component of the goal programming model. The goals are to meet the targeted requirements for the numbers of O-6 Colonels, O-5 Lieutenant Colonels, O-4 Majors, and company grade officers. The deviations from these four targets are summed and provide us with the total deviations between the inventory and target requirements.

In our Global Model, if we simply adopt the same goals on the AMEDD level, we are not incorporating the importance of each corps well-being and merit into the objective function. If our goal is to minimize the deviations from the AMEDD targets, consider a solution where the Dental Corps has an excess of *x* O-3 Captains and the Medical Corps has a shortage of *x* O-3 Captains, where all other corps' O-3 Captain inventory is equal to the O-3 Captain requirements. From a global AMEDD perspective, the manpower system is meeting its O-3 Captain target and there is no mismatch between the O-3 Captain inventory and requirements.

Now consider a solution where only the following has changed. The Dental Corps has an excess of $x + \delta$ O-3 Captains and the Medical Corps has a shortage of $x + \delta$ O-3 Captains. From the global AMEDD perspective, the solutions are equivalent. There is no deviation from the O-3 Captain's inventory because the magnitude of the shortage and the excess are equal and cancel each other out. Obviously, the solutions are not equivalent from the perspective of the individual corps. This brief example demonstrates why we need to include corps objectives into our global model.

Table 8 shows the multiple objectives that will be included the global AMEDD model. The first column consists of the four AMEDD level goals and the second column displays the corps goals. With six corps, there are a total of 24 Individual Corps Goals, giving us a total of 28 goals to be incorporated in the Global AMEDD model objective function. We have already seen an example of how ignoring the Individual Corps Goal would produce subpar results. Ignoring the AMEDD Level Goals would be unwise as well. AMEDD is responsible for managing its entire manpower system to comply with Army level policies, guidelines, and mandates.

AMEDD Level Goals	Individual Corps Goals
AMEDD Company Grade Officer Operating Strength Deviation	Corps Company Grade Officer Operating Strength Deviation
AMEDD Major Operating Strength Deviation	Corps Major Operating Strength Deviation
AMEDD Lieutenant Colonel Operating Strength Deviation	Corps Lieutenant Colonel Operating Strength Deviation
AMEDD Colonel Operating Strength Deviation	Corps Colonel Operating Strength Deviation

Table 8 AMEDD Global Model Objectives

In our constructed objective function, each of these goals is weighted. If the goals are all equally important, they receive a weighting of $\frac{1}{28}$ and the sum of the weights is one. By adjusting weights, we can shift the weights and therefore importance of the goals. Weights still must sum to one. One possible weighting scenario would be to weigh deviations in the Dental and Medical Corps more heavily because their requirements distribution does not follow the typical pyramid stricture of the other corps. Another possible weighting scheme would be to weigh AMEDD level goals heavier than Individual Corps goals if the AMEDD leaders had to adjust their manpower mechanisms to comply with higher level, Army wide manpower guidance.

In this section, we have described the construction of a linear, global multi-objective manpower model that has the ability to reallocate dynamic officer inventory requirements. In the next section, we will explore the solutions to this model and compare them to current individual AMEDD models that are nonlinear and treat officer requirements as fixed parameters that cannot be updated. What follows is an exploration of potential weighting alternatives.

4.5 MODEL SOLUTION, RESULTS, AND DISCUSSION

After solving the six individual corps linear models in section 5.2, we reviewed the ad hoc AMEDD policy, created by implementing the six individual corps optimal manpower policies. With this solution serving as a baseline, we now explore solutions to the global linear model constructed in Chapter 3 with the following specifications. First, we will solve the model with all of the weight on the Individual Corps Goals, with the weight equally distributed among the 24 corps goals. We will consider all of the targets as fixed, which is to say we will not assign any O5A or TTHS positions. The purpose of this scenario is to show the equivalence of our global linear model. The next scenario will be to introduce the O5A and TTHS positions as decision variables. Lastly, we will explore one possible weighting scheme of the objectives to demonstrate how this additional modeling detail can help decision makers.

4.5.1 Global, Linear AMEDD Model – Baseline and Validation

We have already explored one global AMEDD manpower solution. This is the solution obtained by combining the six individual corps models. Our first scenario mimics this method but we obtain it as the solution to one global model. The following tables show that the results are consistent and serve as our first step of model validation.

Sum of Deviations from Individual Corps Targets		
Corps	Original Individual Non Linear Corps Models	Linear, Global AMEDD Model
AMSC	1	1
DC	304	304
MC	507	507
MSC	0	0
NC	0	0
VC	0	0
Sum	812	812

Table 9 Comparing Individual Corps Goals Obtained by Different Models

Grade	Requirement	Inventory Individual Corps Models	Individual Corps Models Deviations	Inventory Global Model	Global Model Deviations
Company Grade (O-1 - O-3)	8,111	8,055	- 56	8,055	- 56
O-4	4,403	4,357	- 46	4,357	- 46
O-5	2,205	2,290	+ 85	2,290	+ 85
O-6	1,231	1,248	+ 17	1,248	+ 17
Total Excesses and Shortages, Inventory and Requirement Mismatches			204	204	

Table 10 Comparing Inventory and Requirement Deviations Obtained by Different Models

Table 9 and Table 10 demonstrate that the two methods are equivalent and that the linear global model formulation is valid. As an added measure of model validity, we constructed a series of reports that capture the flow of officers out of each inventory state. For inventory state (*a,y,g*), we start with the state's start-of-year inventory which is simply the amount of inventory in state (*a,y-1,g*). Then we calculate all of the positive flow – officers hired, promoted, transferred, and that continue or advance into state (*a,y,g*). The negative flow is calculated as well and is defined as the officers that are promoted or transferred out of state (*a,y,g*) as well as the officers that leave the Army. The total flow is determined by summing the positive and negative flow. Total flow is added to the start of year inventory to determine the end-of-year inventory. This value is compared to the sum of the two decision variables that represent end-of-year inventory in the model – $inventory_{ayg} + inventory\_passedover_{ayg}$. The model has captured all flow and ensured the conservation of flow if the difference between the two values for end of year inventory is zero. This reporting procedure allowed us to check any errors in our formulation. If there was an instance where the two end-of-year inventory values did not match, then we were able to determine where flow was not being conserved and to adjust the model. In all, we were able to confirm that over 16,000 inventory nodes were valid and the flow into these nodes did indeed equal the flow out.

In Table 5, we compared the resources required to solve each of the nonlinear and linear individual corps models. A global nonlinear model, a model that includes all six corps and considers flexible targets, takes 35.506 seconds to determine the optimal solution, without a certificate of guaranteeing the solution as a global optimum. Our linear global model can find a global minimum in a drastically improved 0.655 seconds.

4.5.2 Reallocating Dynamic Officer Inventory Requirements

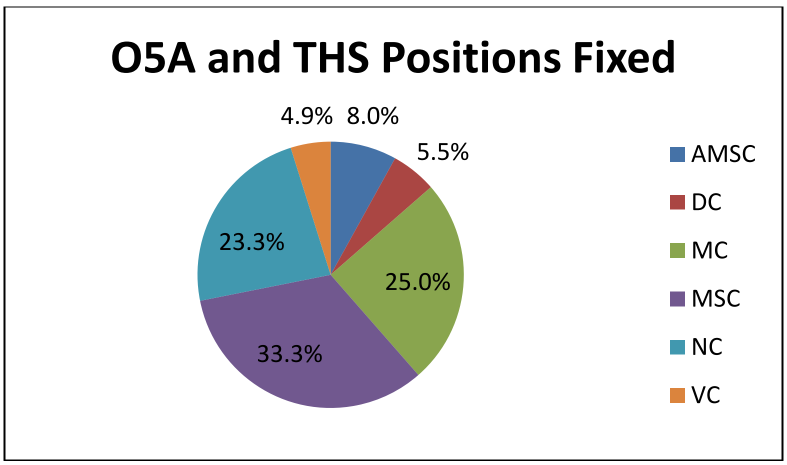
This section explores the assignment of O5A and TTHS positions. We will weigh only the individual corps objectives and they will all have equal weight. The AMEDD level goals are not weighted in the model.

By assigning the O5A and TTHS positions, we can reduce the total number of deviations in the model. In 4.5.1, the sum of the deviations in each corps is 812. By assigning the flexible targets in an optimal manner, there are now only 170 deviations across the six corps. The most dramatic improvement is in the Medical and the Dental Corps.

Sum of Deviations from Individual Corps Targets		
Corps	Model One - Treat All Targets as Fixed	Model Two Assign Flexible Targets Optimally
DC	304	141.4
MC	507	27.8

Table 11 Dental and Medical Corps Objective Functions in Two Models

This model provides dramatic improvements in the overall merit of the AMEDD manpower system. The Dental Corps saw just over a 50% reduction in its deviations and the Medical Corps a 95% reduction. The reallocation of targets changes the complexion of the AMEDD structure and though it provided some dramatic results improvements, the change to the structure is not dramatic. The following chart shows the original and optimal allocation of the flexible targets. We see that the real shift has occurred between the Dental and Medical Corps. The Medical Corps has been relieved of many of its deviations; see Table 8, because the optimizer has shifted 15% of the Medical Corps flexible positions to the Army Medical Specialist and Dental Corps, the two corps whose allocation increases noticeably.



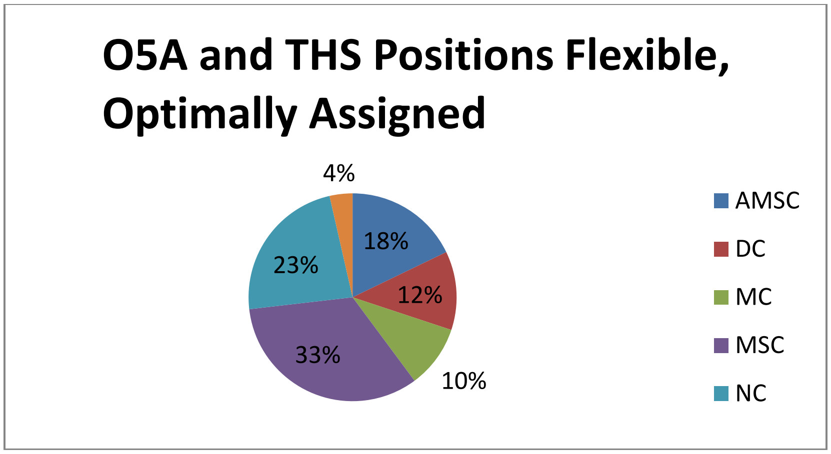


Figure 2 Allocations of O5A and TTHS Positions

4.5.3 A Mixed Strategy

I have discussed the issues with ignoring career management field objectives in the global model. The poor solution that results from the objective function minimizing the deviation between inventory by grade and target by grade does not incorporate corps objectives. We know explore results obtained when we employ an objective that incorporates both AMEDD level goals and each individual corps goals. In the model, every objective function component in Table 8 has a positive weight. All weights are positive and the sum of the weights is 1.

Each objective function component is treated equally. The weight is evenly distributed among the AMEDD objectives and the individual corps objectives. Of the AMEDD objectives, the most weighted component of the objective function is deviations from the Colonel target. These deviations are weighted the most because in practice, if the Army is short one Colonel, then it must find a Lieutenant Colonel to fill the job position. If there is a shortage of Lieutenant Colonels or the practice of moving one up to perform the job with the senior office requirement has created a shortage, a Major must be moved up. Thus, there is a ripple effect and shortages in the senior grades cause ripples and effects in the inventory of lower ranking officers.

The Dental and Medical Corps objectives are more heavily weighted than the other corps. The Dental and Medical Corps, as we have seen, do not have the pyramid like officer distribution structure. It was impossible in the individual corps models to find an inventory structure that perfectly met requirements in these two career management fields. Table 12 lists all of the weights. Note that each column sums to 50%.

AMEDD Level Goals		Individual Corps Objectives – Sum of Grade Deviations	
Goal / Objective	Weight	Goal / Objective	Weight
AMEDD Target Colonel Inventory	20%	Dental Corps	13.8%
AMEDD Target Lieutenant Colonel Inventory	15%	Medical Corps	13.8%
AMEDD Target Major Inventory	10%	Army Medical Specialist Corps	5.6%
AMEDD Target Company Grade Officer Inventory	5%	Medical Services Corp	5.6%
		Nurses Corps	5.6%
		Veterinary Corps	5.6%

Table 12 Objective Function Weights

The optimizer finds a solution with these set of weights that minimizes all deviations between inventory and requirements. There is a tradeoff. At the AMEDD level, there are no shortages in any of the grade requirements, but there are surpluses and excesses at the career management field level. The Army Medical Specialist, the Medical Services, and the Veterinary Corps have excess senior leader inventory to make up for the shortages in the Dental Corps.

	Requirements	Inventory	Deviations
O-6	4403	4403	None
O-5	2205	2205	
O-4	1231	1231	
Company Grade	8111	8111	

Table 13 AMEDD Level Grade Inventory vs. Requirements

	O-6		O-5	
	Excess	Shortage	Excess	Shortage
AMSC	8.36		6.31	
DC		57.08		84.28
MC	35.42		77.98	
MSC	7.31			
NC				
VC	6.00			

Table 14 Corps Level Deviations

There are other weighting schemes that would result in there being no inventory mismatch at the AMEDD level. As the weight shifts towards AMEDD grade targets, the individual corps objectives become less and less important and we begin to see increased corps objective functions, increased sums of the deviations of all ranks in the individual corps. The weighting scheme introduced here is one that produces acceptable results. We have basically the same number of mismatches in the Dental and Medical Corps, a total of 254 deviations between the two of them compared to 168 when the objective function consisted solely of the corps sum of deviations. The benefit, however, is that AMEDD has balanced its grade inventory requirements. If weight is shifted from the AMEDD level objectives, the individual corps objective functions go down.

If the AMEDD level objectives are weighted as little as 36% while the individual corps objectives are weighted 64%, the optimizer still finds a solution with zero inventory mismatch between inventory and AMEDD level grade requirements. When the weight on the AMEDD level objectives is less than 36%, the optimizer finds a solution where there are mismatches of the AMEDD level objectives. This sensitivity analysis was performed by continually solving the model, decreasing the amount of weight placed on the AMEDD level objectives, until the optimal solution included deviations in one or more of the AMEDD inventories and the AMEDD requirements.

5. Linear Goal Programs to Manage Current Inventory of Officers

5.1 Introduction

The purpose of this chapter is to describe a multi-period extension of the models in chapter 5. It uses the existing AMEDD manpower structure as initial inventory, and its decision variables tell how to manage this inventory over time to minimize deviations from targets. As previously discussed, the purpose of the models in chapters 3 and 4 is to determine the optimal number of officers to hire each year and how that cohort of officers should be managed in terms of promotions and transitions to other specialties over the 30 year life-cycle of the cohort. The model does not suggest how to manage the current inventory in order to minimize the deviations between the number of officers currently on hand in the manpower system and AMEDD's manpower requirements. In this chapter, we present a model that provides manpower analysts with the tools to optimize the current officer work force structure.

In Chapter 3, we described in detail the six AMEDD nonlinear manpower programs for each corps. These models tell analysts how to manage a cohort of officers. A major drawback of this model is that it does not provide insight into how to manage the current force. For example, the cohort models tell us how many officers to hire at the start of each year, but they do not take into account the current force structure. The cohort model does not tell us how many officers to promote this year. Rather it tells us how many officers in a cohort should be promoted when that cohort progresses through the life cycle and is ready for promotion.

There is a need for a model that inputs the current inventory of officers in each state (i.e. a combination of area of concentration, years in service, and military grade), and determines the optimal manpower policy over a finite planning horizon that will minimize the gap between the inventory of officers in the system and the AMEDD officer target or requirements. The gap is minimized over the planning horizon and the model outputs the optimal manpower policy in terms of the number of officers to hire, promote, and transfer each year. The purpose of Chapter 5 is to build such a model based on the models discussed in Chapter 4.

The model presented in Chapter 5 has its roots in some traditional manpower optimization models, but there are aspects of the model presented here that are improvements to the previous models. In Chapter 2, we discussed Gass's models (Gass, 1988). His models did not include the AMEDD areas of concentration "possibly due to its designation as a 'specialty branch' based on its unique mission" (McMurry, 2010). Gass's linear programming model of the manpower system is a goal programming model. The model calculates the number of officers to promote each year and then calculates the deviation between the number to promote and the target or goal for the number of officers to promote.

Hall presents a model similar to Gass's model. His model is a linear goal programming model that treats the number of officers to promote as a decision variable much like our model in Chapter 4. However, Hall excludes the 98 AMEDD officer specialties, choosing to ignore specialty branches as Gass did.

5.2 Formulation of a Multi-Period Model

The model presented in Chapters 4 is the foundation for the model presented here in Chapter 5. This chapter will document the creation of a multi-period model and how this linear goal programming model can be implemented.

5.2.1 Sets

This multi period model uses the same sets as the Chapter 4 model, with one important additional set. In addition to keeping track of the number of officers in each inventory node, characterized by the node's state (a,y,g), we now keep track of time.

T = time period with index $t \in T$, $a = 1,2,\ldots,T$

This additional index allows us to differentiate between the numbers of officers in an inventory node from one time period to the next. For example, the decision variable *inventory(**2**,70B,5,O-3)* tells us how many health services administration officers (area of concentration 70B), with five years of service, that have the grade of captain are in the manpower system in period t = 2 and *inventory(**3**,70B,5,O-3)* tells us how many officers of the same specialty, years in service, and grade are in the manpower system in the subsequent time period. In the simplest case the time periods all have length one year. However, it is straightforward to modify the model so that some periods have length longer than one year. For example, one might have the first two or three periods be single years, and then have the remaining periods have increasing lengths of multiple years, so that the sum of all lengths is 30.

5.2.2 Parameters

All of the parameters in the Chapter 4 model are also used in this multi period model presented in Chapter 5. Officer requirements and targets are captured in the budgeted end strength parameter, indexed by area of concentration and officer grade as well as other officer requirements such as the number of officers in training or educational assignments and the number of officers serving in immaterial assignments. We add the index t to these parameters to show that requirements are flexible and can change over time.

As in previous models, we model the probability an officer remains in the manpower system with historical officer continuation rates, indexed by an officer's area of concentration, years of service, and grade. This assumption will be explored in future chapters when we discuss the construction of system dynamics models to model the manpower system.

Without the index of time, the continuation rate is constant for the officer state (a,y,g). We also use weights or parameters in the objective function to give analysts the flexibility to weigh differently deviations in particular grades and particular AMEDD corps. Now with the introduction of the index t, we can also weigh differently deviations from the targets in different time periods. If it is more important to decision makers and analysts to minimize deviations towards the end of the planning horizon T, more weight is placed on the parameter pos_AMEDD_dev_weight_p('T',g) than the parameter pos_AMEDD_dev_weight_p('1',g).

The most important additional parameter included in the multi period model is the October 2011 AMEDD Officer Inventory. The data was provided to the author from the AMEDD Personnel Planning Directorate for the purpose of this research. The data consists of individual record for each officer in the manpower system. This data tells us how many officers were in the AMEDD manpower system as of October 2011, by area of concentration, what year they had entered the manpower system, and current grade.

In October 2011, the AMEDD manpower system had a total of 15,901 requirements and there were only 14,930 officers in the AMEDD system; the AMEDD system was short a total of 971 officers. This inventory data provides some insight into the value of the manpower system when we compare it to the AMEDD officer requirements. As we have in Chapters 3 and 4, we will use the operating strength deviation metric to measure the worth and value of the manpower system. We calculate the number of officers, per grade, the corps is either excess (when the inventory exceeds the corps grade target) or the number of officers the corps is short (when the inventory is less than the corps grade target). The operating strength deviation is then the sum of all excesses and shortages. The operating strength deviation is calculated from an AMEDD perspective, a comparison of the number of AMEDD officers to the AMEDD targets per grade. We also calculate the operating strength deviation for each of the six corps. Further study of the initial conditions of the AMEDD inventory reveals that the bulk of the deviations are due to a lack of Majors and Lieutenant Colonels. Table 15 displays the AMEDD operating strength deviation by grade.

	AMEDD Officer Inventory	Target	Excesses	Shortages
Company Grade	8142	8067	75	-----
O-4	3694	4414	-----	720
O-5	1853	2196	-----	343
O-6	1241	1224	17	-----
Total			92	1063

Table 15 AMEDD Officer Inventory Starting Condition

The total number of deviations, the sum of the number of excesses and shortages, across all grades is 1,155. This number reflects the overall condition of the AMEDD manpower system but it does not reflect the initial condition of each of the six corps in October 2011. Table 16 disaggregates the AMEDD inventory into the six separate AMEDD corps. This table reveals a different perspective of the manpower system.

Table 15 shows that there are only 75 excess company grade officers in the manpower system. Table 16 indicates that though there are only 75 excess company grade officers in the system, each individual corps has a problem meeting its demand for company grade officers. The problem is most evident in the Medical Corps (MC) where there are 510 excess company grade officers. We see a similar phenomenon when we examine each of the other officer grades. There are 17 excess Colonels in the system, but the Dental Corps itself is short 42 of these high ranking officers. Our optimization model will focus on improving the well-being of the manpower system at the AMEDD level and the individual corps level.

	Corps	AMSC	DC	MC	MSC	NC	VC
Company Grade (O-1,O-2,O-3)	Inventory	974	417	1472	2687	2368	224
	Target	1051	233	1982	2407	2173	221
	Excess	-----	184	-----	280	195	3
	Shortage	77	-----	510	-----	-----	----
Majors O-4	Inventory	317	234	1316	1000	699	128
	Target	304	274	1607	1129	908	192
	Excess	13	-----	-----	-----	-----	-----
	Shortage	-----	40	291	129	209	64
Lieutenant Colonels O-5	Inventory	70	95	682	566	365	75
	Target	100	274	683	610	429	100
	Excess	-----	-----	-----	-----	-----	-----
	Shortage	30	179	1	44	64	25
Colonels O-6	Inventory	28	242	555	230	144	42
	Target	27	284	514	229	134	36
	Excess	1	-----	41	1	10	6
	Shortage	-----	42	-----	-----	-----	----
Overall Corps Operating Strength Deviation by grade	Total Deviations	121	445	843	454	478	98

Table 16 October 2011 Operating Strength Deviations

5.2.3 Decision Variables

We have discussed how the decision variables in the models presented in Chapters 3 and 4 can be classified into two categories. The first category is the set of manpower policy decision variables. These are the actual things that manpower system managers and analysts would have to do in order to achieve the minimal operating strength deviation. These inventory control decision variables include the number of officers to hire, the number of officers to promote, and the number of officers to transfer from one specialty to the next. In this multi period model, the index t is added to all of the inventory control decision variables. The inclusion of this index allows the manpower program to identify optimal manpower policies each year, rather than forcing the manpower program to adopt a manpower solution that must be constant over the entire length of the time horizon.

The second type is the set of inventory control decision variables. These count how many officers are in specific inventory nodes. With the addition of the index t, we can count how many officers are in inventory nodes from time period to time period, from year to year. We also use inventory control decision variables to keep calculate both positive and negative deviations from the AMEDD targets. We can now track these deviations longitudinally and infer how well the manpower system is performing over time.

$Hires_{tayg}$ - number of officers hired into state (t,a,y,g) in time period t

$Promrate_{tayg}$ – promotion rate, percentage of officers promoted into state (t,a,y,g) from state $(t\text{-}1,a,y\text{-}1,g\text{-}1)$ in time period t

$passover\_rate_{\,tayg}$ – non select for promotion rate, passed over rate, percentage of officers not selected for promotion into state (t,a,y,g) from state $(t\text{-}1,a,y\text{-}1,g\text{-}1)$ in time period t

promrate_DC $_{tyg}$ - promotion rate, percentage of Dental Corps officers promoted into state (*t,y,g*) in time period *t*; rate is independent of Dental Corps specialty. All Dental Corps officers, regardless of specialty, are promoted at an identical, corps rate.

passover_rate_DC $_{tyg}$ - non select for promotion rate, passed over rate, percentage of Dental Corps officers not promoted into state (*t,a,y,g*) in time period *t*; rate is independent of Dental Corps specialty

promrate_MC $_{tyg}$ - promotion rate, percentage of Medical Corps officers promoted into state (*t,y,g*) in time period *t*; rate is independent of Medical Corps specialty. All Medical Corps officers, regardless of specialty, are promoted at an identical, corps rate.

passover_rate_MC $_{tyg}$ - non select for promotion rate, passed over rate, percentage of Medical Corps officers not promoted into state (*t,a,y,g*) in time period *t*; rate is independent of Medical Corps specialty

transrate$_{taa'yg}$ – percentage of officers that transfer from a donor area of concentration to a receiving area of concentration per year per grade where $a \neq a'$ in time period *t*

inventory$_{tayg}$ - number of officers in state (*t,a,y,g*) in time period *t*

inventory_passedover$_{tayg}$ - number of officers who have not been selected for promotion, but remain in the manpower system in state (*t,a,y,g*) in time period *t*

pos dev$_{tcg}$ - positive deviations, representing excesses or surpluses, of officers when compared to targets or requirements for corps *c* and grade *g* in time period *t*

neg dev $_{tcg}$ - negative deviations, representing shortages, of officers when compared to targets or requirements for corps *c* and grade *g* in time period *t*

pos_co_grade dev $_{tc}$ - positive deviations, representing excesses or surpluses, of the number of company grade officers in corps *c* compared to total number of budgeted end strength for company grade officers in time period *t* *neg_co_grade dev* $_{tc}$ - negative deviations, representing shortages, of the number of company grade officers in corps *c* compared to total number of budgeted end strength for company grade officers in time period *t*

Pos AMEDD dev_{tg} – positive deviations, representing excesses or surpluses, of the number of officers in all of AMEDD in grade *g* and time period *t*

Neg AMEDD dev_{tg} – negative deviations, representing excesses or surpluses, of the number of officers in all of AMEDD in grade *g* and time period *t*

5.2.4 Constraints

As discussed for the other portions of the linear program, the insertion of the index *t* has an effect on the model's constraints. The number of upper and lower bound constraints for the amount of officers in the system increases by a factor of *T* time periods. The constraints that allow the model to calculate the number of officers to hire, transfer and promote also increase by this factor. Deviations between the number of officers in the inventory and manpower system targets are calculated each time period. The following constraints are included in the model. Note the similarity to how the constraint is used in the previous model discussed in Chapter 4. We present the most important constraints – goal programming constraints and conservation of officer flow constraints.

$$\sum_{ayg} inventory_{tayg} + inventory\_passedover_{tayg} \; - pos\ AMEDD\ dev_{tg} + \; neg\ AMEDD\ dev_{tg} = target_g \; \forall t, g = O-4, O-5, O-6$$

Equation 20 Goal Programming Constraint to Calculate Deviation from AMEDD Field Grade Targets

$$\sum_{ayg} inventory_{tayg} + \ inventory\_passedover_{tayg} \quad - \ pos\ AMEDD\ dev_{tg} + \ neg\ AMEDD\ dev_{tg} = AMEDD\ target_{g} \ \forall t, g = O-4, O-5, O-6$$

Equation 21 Goal Programming Constraint to Calculate Deviation from AMEDD Company Grade Targets

$$\sum_{a\prime y} inventory_{tayg} + inventory\_passedover_{ta\prime yg} \quad - \ pos_{tcg} + \ neg_{tcg} = target_{cg} \ where\ a'is\ the\ subset\ of\ all\ AOCs\ in\ corps\ c, c\in\ C\ and\ g\ \text{is}\ O-4, O-5, O-6$$

Equation 22 Calculating Field Grade Inventory Deviations from Requirements

$$\sum_{a'yg'} inventory_{tayg} + inventory \ _{passedover}{}_{ta'yg} \quad - \ poscograde_{tc} + negcograde_{tc} = \ company\ grade\ officer\ targets_{c}\ where\ a'is\ the\ subset\ of\ all\ AOCs\ in\ corps\ c, where\ g'\ \text{is} O-1, O-2, O-3, and\ \forall c\in\ C$$

Equation 23 Calculating Company Grade Officer Aggregate Deviations

$$Inventory_{t,a,y,g} = \ hires_{t,a,y,g} \quad + c\_p_{a,y,g} * (inventory_{t-1,a,y-1,g} - \sum_{a'\in A} trans\_non\_promo\_yr_{t,a,a',y,g} + \sum_{a'\in A} trans\_non\_promo\_yr_{t,a',a,y,g}) + prom_{a,y,g} \ \forall a,y,g\ where\ a' \neq a$$

Equation 24 Linear Conservation of Flow Constraint

5.2.5 Objective Function

The objective function of this multi-period model stems from our discussion of objective functions in Chapter 4. In Chapter 4, we presented an objective function that had two components. The first component was the sum of the manpower system deviations from the global, that is to say total, AMEDD grade requirements. This first component added up the deviations from the total AMEDD targeted number of company grade officers, majors, lieutenant colonels, and colonels. The second component was the sum of the manpower system deviations from the corps grade requirements. As we did at the AMEDD level, with this second component, for each of the six corps, we tallied the deviations from the corps grade requirements.

In this multi period model, our objective function expands to include the tally of deviations, both excesses and shortages, from AMEDD targets and from corps targets over time. For example, we compute the sum of AMEDD excesses and shortages from AMEDD targets for each time period and the sum of the six corps deviations from their respective corps targets over time. Two parameters α_{tg} and $\gamma_{t,corps}$ give analysts the ability to weight the different components of the objective functions. If manpower system managers and decision makers are concerned with minimizing deviations between the total number of officers per grade and the AMEDD grade requirements, then the relative weight of the parameter α_{tg} would be greater than the other types of objective function parameters. Managers and decision makers could even choose to assign a value of 0 to one of the objective function parameter values if they were not interested in minimizing the operating strength deviation for that particular grade or corps at the expense of other grades and corps.

$$\textit{Global Multi Period Objective Function}$$

$$\Sigma_{t,g}\alpha_{tg}\left(pos\ AMEDD\ dev_{tg} + neg\ AMEDD\ dev_{tg}\right) + \Sigma_{t,corps,g}\gamma_{tcorps,g}\left(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}\right)$$

Equation 25 Global Multi-Period Objective Function

5.3 Model Results

Each of the corps can be treated separately and a linear program solved to identify the optimal manpower policy that will minimize operating strength deviation in each of the six corps. Table 17 lists the starting operating strength deviation for each of the six corps and the final operating strength deviation after seven years.

	Operating Strength Deviation		
Corps	t = 1	t = 7	Percent Improvement
AMSC	121	63.8	47%
DC	445	378.3	15%
MC	843	232.6	72%
MSC	454	0	100%
NC	478	40.1	92%
VC	98	20.2	79%

Table 17 Initial and Final Corps Operating Strength Deviations

Analysis of the Army Medical Specialist Corps (AMSC) is presented here followed by a discussion of the global model. The initial operating strength deviation for the AMSC in October 2011 was 121, as shown in Table 17 deviations. Company grade officer shortages accounted for 77 of the 121 deviations.

The AMSC model alone, when the planning horizon for the optimization model consists of seven years or time periods, has 20,000 equations and 26,000 variables. A Dell Latitude laptop with 6 GB RAM and an Intel Core i5 processor required 1.2 seconds to solve the model. The AMSC model in Chapter 4 that determined the optimal manpower policy for a cohort of officers had only 2,900 equations and 3,600 variables and was solved in 0.2 seconds.

The objective function, for the AMSC corps model, is the sum of the operating strength deviation per grade over the seven year time period. The optimizer finds a hiring and promotion policy that results in an operating strength deviation of 63.8 deviations after 7 years. Figure 3 displays the changing AMSC operating strength deviation over time. The minimum operating strength deviation along the seven time periods was 12 deviations after only 3 years. When each operating strength deviation is treated equally, the optimizer does not create a manpower system that at the end of the seven year planning horizon that has the lowest operating strength deviation. We see that minimum operating strength deviation was achieved in the time period t = 3 when operating strength deviation bottomed out at 11.4 deviations. This example demonstrates the need to formulate a model that can minimize the “U-shaped” structure, where the greatest gains in the system happen before we reach the end of the planning horizon.

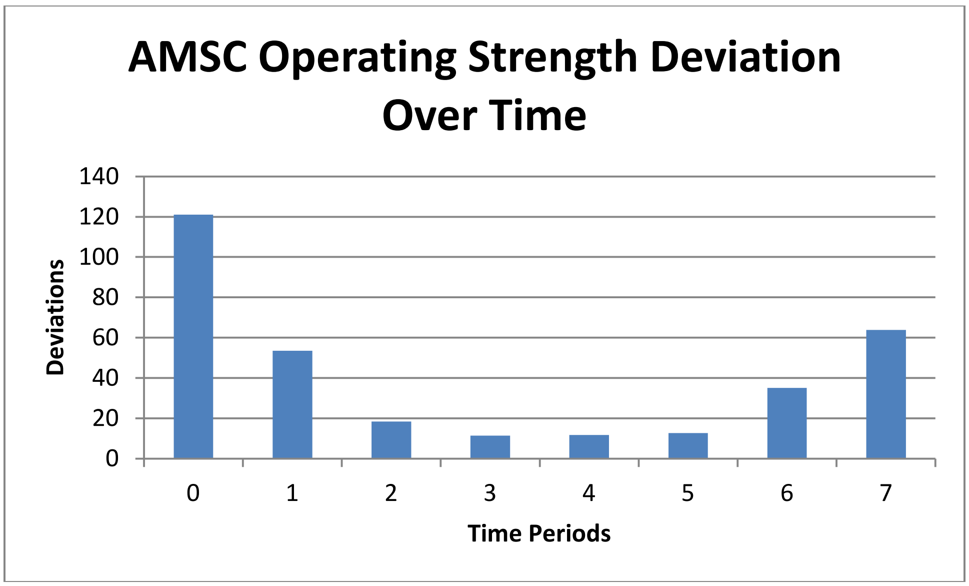


Figure 3 AMSC Operating Strength Deviation t = 0 to t = 7

We present two different techniques here to remedy the problem depicted in Figure 3. The first technique would be to update the objective function and remove all operating strength deviations prior to year seven. The linear program’s objective is now to minimize the operating strength deviation in year 7. Optimizing the operating strength deviation in year 7 results in only 28 deviations at the end of the planning horizon. This may seem like a better ending solution then the results depicted in. However, the maximum operating strength deviation over the 7 year planning horizon is deviation is

296 – worse than the initial, starting operating strength deviation. A plot of the operating strength deviation over time when we are minimizing only the operating system deviation in year 7 shows clearly this solution is not any better than what we obtained in Figure 3.

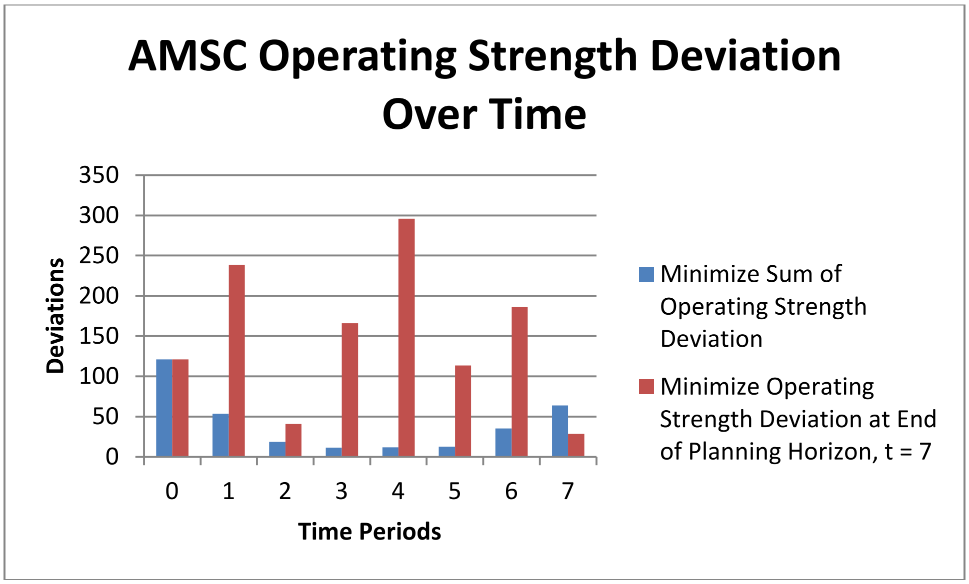


Figure 4 Comparison of Operating Strength Deviation over Time with Different Objective Functions

Our second technique is minimizing a weighted sum of the operating strength deviation. Time period weights, $\gamma_{t,AMSC}$ range between 0 and 1 and the sum of the weights equals 1. Figure 3 provides some inspiration on how we might select these weights. Notice when all time periods are weighted equally, time periods 3 – 5 have the lowest operating strength deviation. One possible weighting scheme would be weight these periods less than the others because these time periods already have a superior operating strength deviation. The later time periods are weighted heavily – one train of thought might prefer a manpower system where the deviations are minimized at the end of the planning horizon. Earlier time periods are important as well. We would want to achieve some immediate improvements in the manpower system. Therefore, time periods 1 and 2 are weighted more than the middle time periods, but less than time periods 6 and 7. Values for $\gamma_{t,AMSC}$ are listed in Table 18 and Figure 5 is Figure 3 a plot of operating strength deviation over time.

γ_1	0.125	γ_5	0.025
γ_2	0.1	γ_6	0.2
γ_3	0.025	γ_7	0.5
γ_4	0.025		

Table 18 Values for $\gamma_{t,AMSC}$

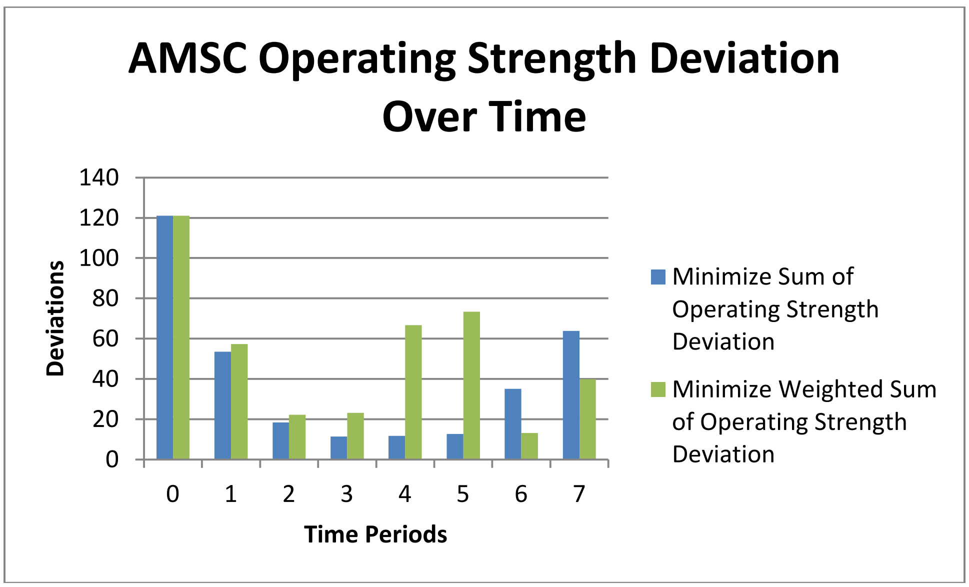


Figure 5 Comparisons of Operating Strength Deviations over Time with Different Objective Functions

Minimizing the weighted sum of the operating strength deviation has a better effect than the other two methods. There is less of a “U Shape” to the plot in Figure 5 and there are no time periods that suffer greatly – at no time is the manpower system worse in terms of operating strength deviation than the initial operating strength deviation of 121. By assessing a set of weights, we can achieve a manpower system that exceeds the current system, but also achieve a system that doesn't mortgage current operating strength deviation for the final, end of planning horizon operating strength deviation. We can develop a solution that does not incur excessive operating strength deviations during the time period between the start and end of the time planning horizon.

In Chapter 6 we introduce a sophisticated method of assigning weights to all components of the objective function. We present a method for soliciting weights for deviation variables in the objective function and a discussion about why the selection of these weights is vital to the goal programming modeling and solution process.

5.4 Global Model

The operating strength deviation in October 2011 of the AMEDD inventory was 1,155 deviations. The majority of these deviations, see Table 15, were in the O-4 and O-5 grades (62% and 30% of all deviations, respectively). At the corps level, the manpower system has a mismatch between the number of officers in inventory and the targeted requirements. The pie chart in Figure 6 Corps Operating Strength Deviation shows us the value of the individual corps operating strength deviation. Table 19 displays the operating strength deviation of each of the six corps and shows what percentage their personnel inventory of each corps deviates from its personnel target. We will call this our initial case and our linear program will identify a set of manpower planning policies to optimally shrink the gap between the numbers of officers on hand and the targeted number of officers.

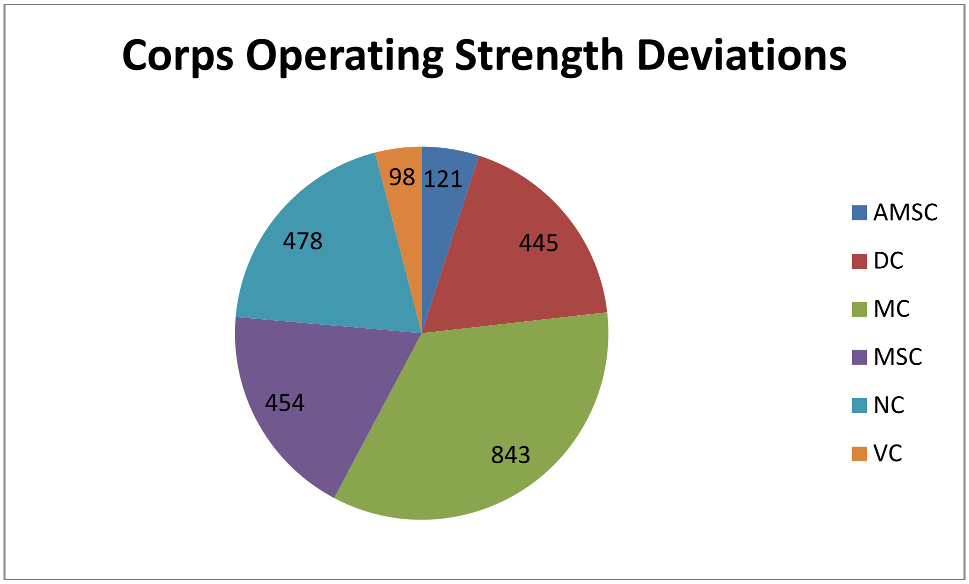


Figure 6 Corps Operating Strength Deviation

	AMSC	DC	MC	MSC	NC	VC
Target	1482	1065	4786	4375	3644	549
Total Excesses and Shortages	121	445	843	454	478	98
Percentage of Deviation of Corps Target	8%	42%	18%	10%	13%	18%

Table 19 Initial Corps Inventory

5.4.1 Global Multi-period Model Linear Program

The global multi-period model linear program is a far larger model than either the global model described in Chapter 4 or any of the individual corps multi-period models. Figure 7 is a plot of the number of equations each model has versus the number of variables in each model. The Global AMEDD Multi-period model is plotted in the far right hand corner of the graph and dominates the other models in terms of both the number of equations and variables. Table 20 Model Performance and Size displays the actual number of variables and equations and displays how long it took to solve each of these models using GAMS, the CPLEX LP Solver.

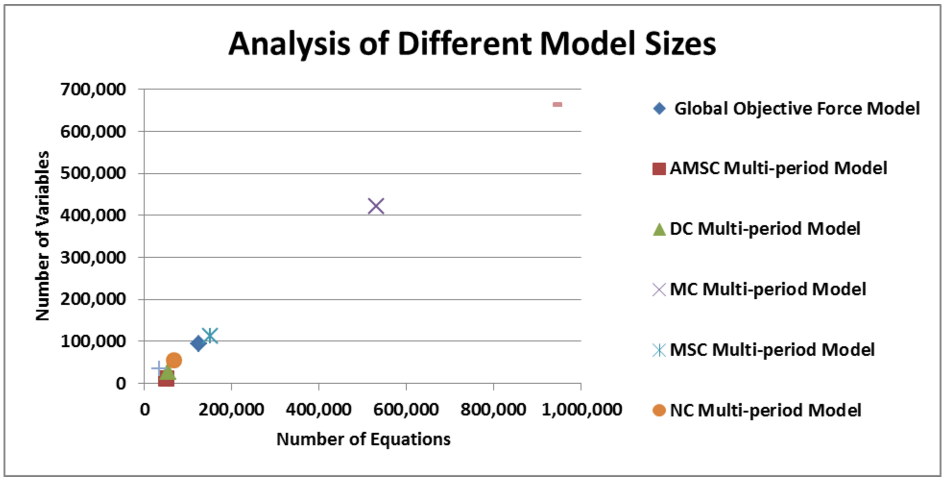


Figure 7 Analysis of Model Sizes

	Time to Solve	Number of Variables	Number of Equations
Global Objective Force Model	0.967 seconds	125,009	94,474
AMSC Multi-period Model	1.3 seconds	49,768	10,818
DC Multi-period Model	0.58 seconds	54,376	27,280
MC Multi-period Model	2.62 seconds	530,743	421,495
MSC Multi-period Model	4.01 seconds	150,204	112,393
NC Multi-period Model	1.51 seconds	67,273	55,887
VC Multi-period Model	0.23 seconds	33,824	34,589
Global AMEDD Multi-period Model	6.93 seconds	938,271	662,739

Table 20 Model Performance and Size

5.4.2 Global Multi-period Model Linear Program Results and Analysis

The objective of the global multi-period linear program is to minimize the grade deviations between the number of officers in each grade and the AMEDD requirements and to minimize the grade deviations between the number of officers in each grade and the AMEDD corps requirements.

$$\text{Global Multi Period Objective Function } \textit{minimize } \Sigma_{t,g}\alpha_{tg}\left(pos\ AMEDD\ dev_{tg} + neg\ AMEDD\ dev_{tg}\right) + \Sigma_{t,corps,g}\gamma_{tcorps,g}\left(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}\right)$$

Equation 26 Global Multi-Period Objective Function

Our objective function then has a total of 392 terms. For now, α and γ both equal 1 and every term in the objective function is treated with equal importance. We will readdress the weighting of objectives in Chapter 6.

	AMEDD		Corps - AMSC, DC, MC, MSC, NC, VC	
t = 1 to 7	Positive deviations	Negative deviations	Positive deviations	Negative deviations
g = Company Grade Officers, O-4, O-5, O-6	Total of 7 time periods Number of AMEDD level objective function terms = 7 time periods X 4 grades X 2 deviations (positive and negative) = 56 terms		Total of 7 time periods Number of corps level objective function terms = 6 corps X 7 time periods X 4 grades X 2 deviations (positive and negative) = 336 terms	
56 terms + 336 terms = 392 total terms				

Table 21 Characteristics of Objective Function

Corps	Initial t = 0	Final t = 7	Percent Improvement
AMSC	121	45.5	62%
DC	445	407.9	8%
MC	843	327.8	61%
MSC	454	0	100%
NC	478	51.7	89%
VC	98	19.7	80%

Table 22 Corps Operating Strength Deviation

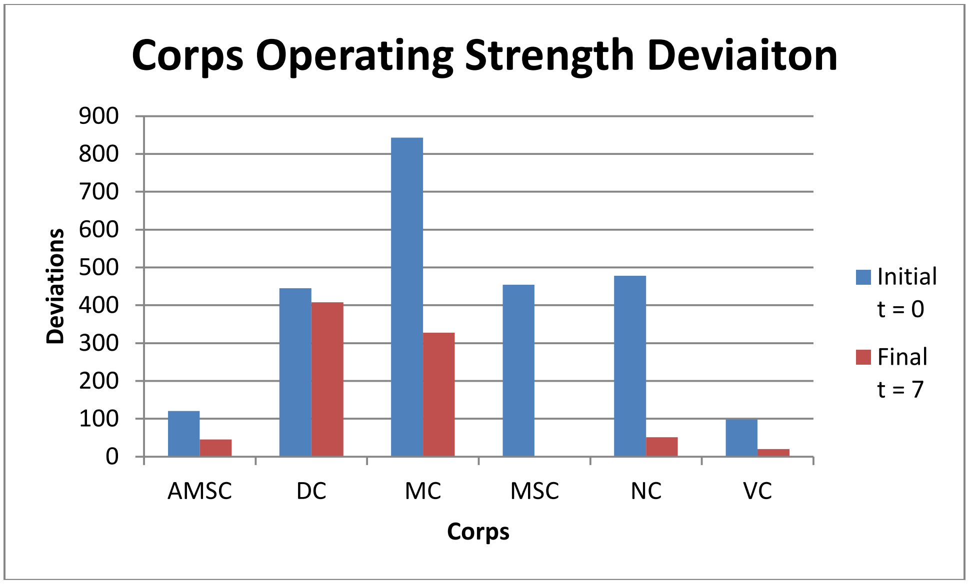


Figure 8 Corps Operating Strength Deviation

The model's optimal manpower policy finds on average a 67% improvement in corps operating strength deviation for the six corps. The model is able to remove the mismatch between personnel in the inventory and personnel requirements in the Medical Service Corps as seen by its operating strength deviation of 0. The gains in the Dental Corps are not as dramatic as the other corps. But we recall from Chapter 3, the Dental Corps has a unique, personnel requirement structure that demands more senior officers in comparison to the other grades. Therefore it must carry a large inventory of junior officers to ensure a large number of colonels is developed in the system.

At the AMEDD level, the improvements are as dramatic. The initial operating strength deviation for the entire AMEDD manpower system was 1,155 deviations. The system was short 720 O-4 Majors and 343 O-5 Lieutenant Colonels. Over the course of the seven year planning horizon, the optimal manpower policy reduces this initial operating strength deviation to **175** deviations, an 85% improvement. At the O-4 Majors level, the optimal manpower policy removes the shortage of 720 O-4 Majors and is able to match the personnel inventory to the requirements. The optimal manpower policy is also able to reduce the shortage of O-5 Lieutenant Colonels from 343 officers to 8. These gains in O-4 Majors and O-5 Lieutenant Colonels are made at the cost of the well-being of the officers in the O-6 Colonel grade. The optimal manpower policy creates a manpower system with a shortage of 167 of these senior officers.

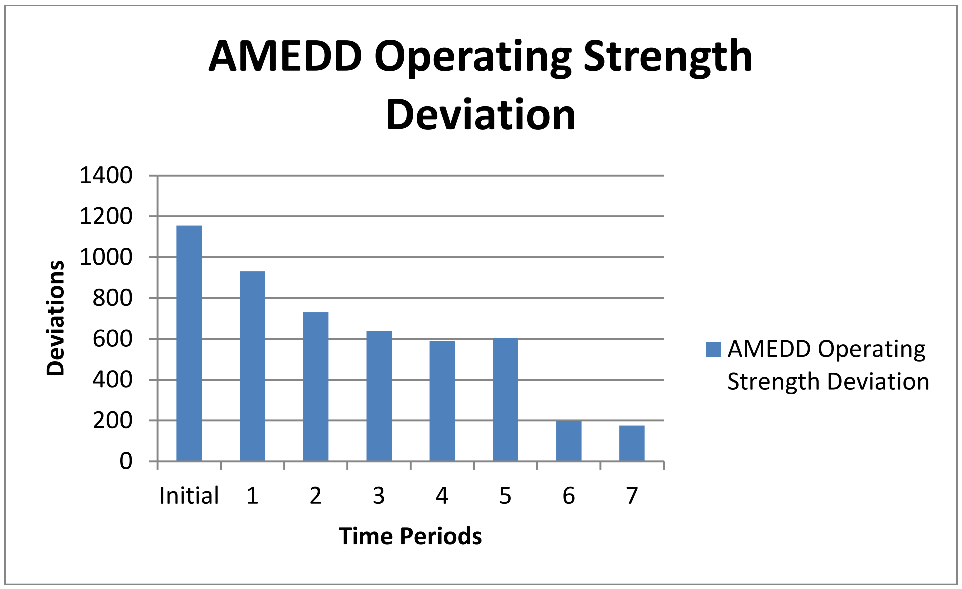


Figure 9 AMEDD Operating Strength Deviation

	AMEDD Officer Inventory	Target	Excesses	Shortages
Company Grade	8,067	8,067	0	0
O-4	4,414	4,414	0	0
O-5	2,188	2,196	0	8.3
O-6	1,058	1,224	0	166.3
Total			0	174.6

Table 23 AMEDD Operating Strength Deviation t = 7

5.4.3 Comparison of Global AMEDD Multi-Period Model Solutions

As we did in Chapter 4, we will examine how the solution presented in Section 5.4.2 changes when we wish to minimize only the AMEDD objectives or only the six corps objectives. This analysis is presented to demonstrate the importance of developing a technique to determine how to weight the 392 terms in the objective function. The determination of weights will have a dramatic effect on the global AMEDD and corps manpower systems. We will compare three cases. Case One is the base case described in Section 5.4.2 when all components of the objective function are equal. Case Two is when we will only minimize the sum of the AMEDD Operating strength deviation and Case Three is when we will only minimize the sum of the six corps operating strength deviations.

In Case Two, we can improve the Global AMEDD operating strength deviation from 174.6 deviations to 77.4 deviations. First we examine the performance of the Global AMEDD inventory. The operating strength deviation is reduced to 77.5 deviations, a reduction of 55%. The inventory system also has a perfect match between the number of company grade officers, O-4 Majors, and O-5 Lieutenant Colonels.

	AMEDD Officer Inventory	Target	Excesses	Shortages
Company Grade	8,067	8,067	0	0
O-4	4,414	4,414	0	0
O-5	2,196	2,196	0	0
O-6	1,146.6	1,224	0	77.4
Total			0	77.4

Table 24 Case Two Global AMEDD Operating Strength Deviation

This reduction in AMEDD operating strength deviation comes at the expense of the corps performance. On average, the six corps see an increase in operating strength deviation of 157 deviations. The Medical Service Corps goes from having a perfectly balanced system with zero operating strength deviation to having an operating strength deviation of 220.

In Case Three, the Global AMEDD operating strength deviation now pays the price and grows to 267 deviations as their improvements in the operating strength deviations of the individual corps. Since we are minimizing the sum of the corps operating strength deviations, we do see one corps, AMSC, that does not have an improved final operating strength deviation in the t = 7 time period. Despite this once case, we see dramatic improvement in performance in the corps manpower system more similar to what we observed in Case Two.

	Case One Minimize Sum of Both Global AMEDD and Six Corps Operating Strength Deviations	Case Two Minimize Global AMEDD Operating Strength Deviation	Case Three Minimize Six Corps Operating Strength Deviations
AMEDD	175	77.4	268
AMSC	45.5	178.2	64.0
DC	407.9	586.4	378.4
MC	327.9	448.1	232.6
MSC	0	222.0	0.0
NC	51.7	293.9	40.1
VC	19.7	69.5	20.2

Table 25 Comparison of Operating Strength Deviation across Cases

We will examine the deviations across grades in Case Three. Each of our four grades has a shortage, the largest being in the O-6 Colonel grade, where we see almost twice as many shortages as witnessed in Case Two.

	AMEDD Officer Inventory	Target	Excesses	Shortages
Company Grade	8061.3	8067	0	5.7
O-4	4357.2	4414	0	56.8
O-5	2141.0	2196	0	55.0
O-6	1074.5	1224	0	150.5
Total			0	268.0

Table 26 Case Three Global AMEDD Operating Strength Deviation

5.5 Smoothing Critical Decision Variables – Hiring and Promotion Policies

We turn our attention to two of the critical decision variables and the desire to minimize the variation in their values over the time horizon. Our manpower planning models provide us with the optimal manpower policy to achieve the minimal operating strength deviation. The optimal policy consists of the number of officers to hire each year, the number of officers to promote, and the number of officers transferred from one specialty to another. One aspect of these manpower policies that would be important to practitioners would be a certain level of consistency and limited variability. The Army would prefer an optimal hiring policy that brings in new hires of recruited specialties each year, rather than a policy that recruited a subset of specialties in only certain years. Manpower practitioners would also prefer that their annual hiring targets were consistent and stable from year to year. Since the targeted recruited force can be a direct output of our optimization model (recruiters would be assigned to recruit the number of officers per specialty that the optimal policy dictated), we can incorporate this desire to have stable, consistent policies.

We will extend this desire to the number of officers promoted each year. For many of the same reasons it is important to have a stable hiring pattern, it is also important to have a stable promotion pattern. Additionally, an unstable promotion pattern could have an adverse effect on officer retention. If promotion rates are to grade *g* are dependent on time that would have a strong influence on the individual officer's decision to stay in the army one year to the next.

5.5.1 Current Assessment

We will examine these critical decision variables in the Army Medical Specialist Corps model. The change was made to all of the AMEDD corps. The solution presented in Figure 5 serves as a baseline to discuss why it is important to introduce into the objective function a portion that will increase the amount of stability and consistency in the objective function.

The solution in Figure 5 results in a manpower system with an operating strength deviation of 40, a 67% improvement over the initial value of the starting operating strength deviation of 121. Figure 10 reveals another portion of this solution that must be addressed.

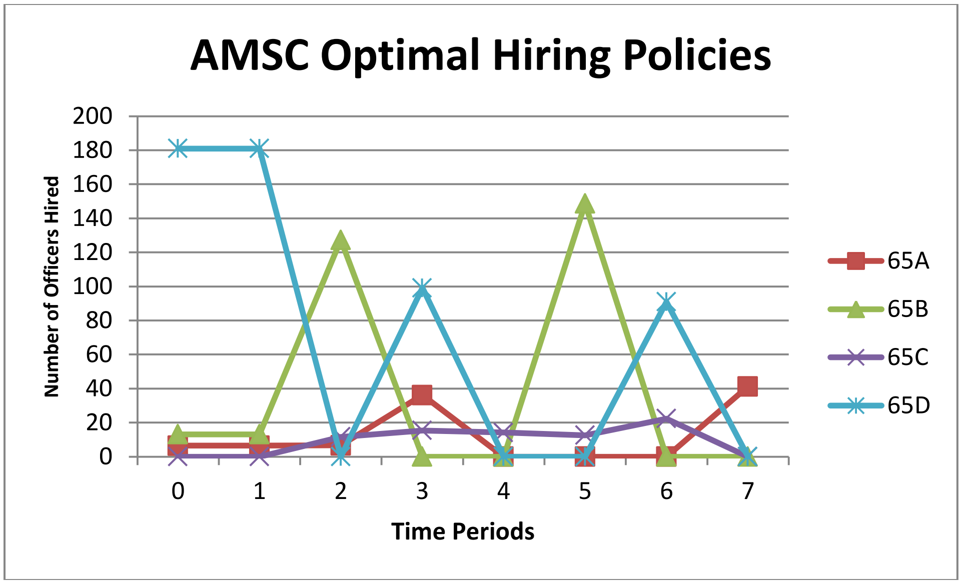


Figure 10 Optimal Hiring Policies for AMSC

Figure 10 shows the optimal number of officers to hire into each of the four specialties that comprise the Army Medical Specialist Corps. We can see that the hiring policy for the 65D specialty has the greatest amount of turbulence. The early hiring policy is to hire 180 officers for the first two time periods. For subsequent years, the optimal hiring policy is to alternate between hiring 0 and almost 100 officers. Two other specialties, 65A and 65B have the same shape to their hiring policy series. The model requires officers to be hired only every other year.

This alternating problem creates a major problem in the future for the cohort of officers. Officers are selected for promotion when they reach certain years in service requirements. For example, if during time *t*, the manpower system hired 100 second lieutenants (O-1), in *t+4*, they would be promoted to the rank of captain (O-3). But if the manpower system did not hire any second lieutenants (O-1) in year *t+1*, then there would not be any officers eligible for promotion to captain in year *t+5*.

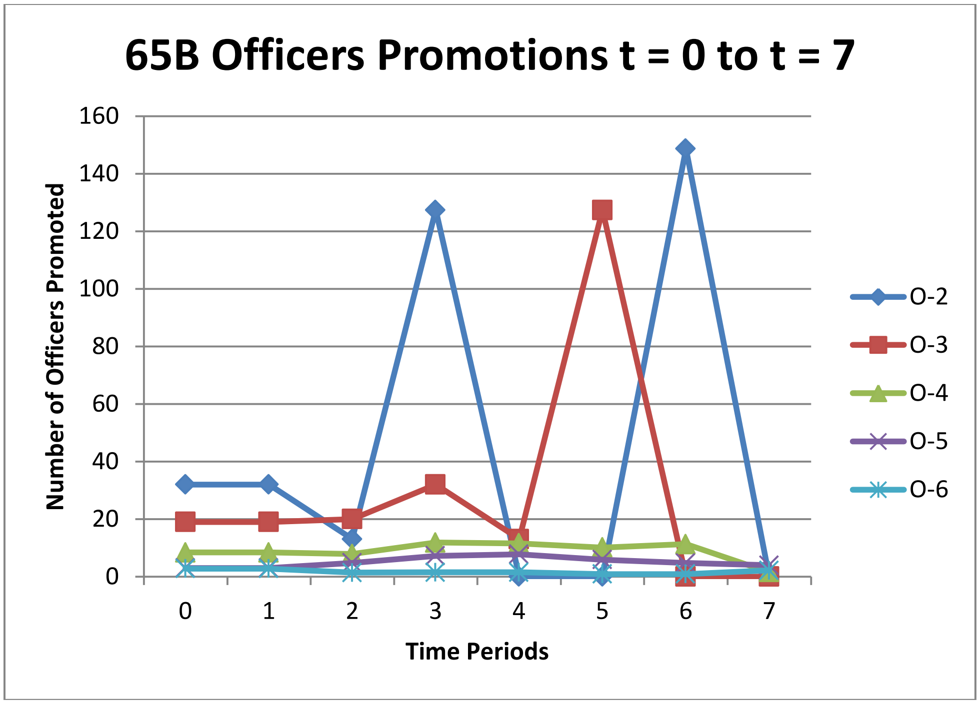


Figure 11 Officer Promotion Policies to Different Grades Overtime

Figure 11 shows the effect of such a promotion policy. Recall from Figure 4, the 65B specialty hired 127 officers it t =2. All of those officers were selected for promotion to captain year t = 6. However, since no new 65B officers were hired in years t=4 or 5, no officers were promoted to captain in year t = 7. If we extended the model, this would have cascading effects in years to come. Our model already has lower and upper bounds for the percentage of officers promoted from an eligible to pool to the next grade, but we see from this figure that it may be possible to improve the stability of the number of officers promoted each year.

5.5.2 Modeling to Account for These Variations

We introduce new variables that monitor the deviation between the number of officers hired one year to the next and the number of officers promoted one year to the next. Additional constraints are added to the multi period model to calculate the deviation between the number of officers hired in time period t and time period $t + 1$ as well as the difference between the number of officers promoted between consecutive time periods.

$$hires\ dv_{t,a,y,g} - pos\ dev\ hires_{t,a,y,g} + neg\ dev\ hires_{t,a,y,g} = hires\ dv_{t+1,a,y,g}\ \forall\ t,a,y,g$$

$$prom\ dv_{t,a,y,g} - pos\ dev\ prom_{t,a,y,g} + neg\ dev\ prom_{t,a,y,g} = prom\ dv_{t+1,a,y,g}\ \forall\ t,a,y,g$$

Equation 27 Calculating Deviations in Number of Officers Hired and Promoted

Hall includes a smoothing constant, he calls it a scaling factor, in his manpower model objective function that we all also incorporate here (Hall, 2010). Recall, that our decision variables are the actual manpower policies that need to be implemented in order achieve the optimal manpower state. The model directs how many officers to hire and how many officers to promote. In an effort to stabilize the system and minimize large fluctuations in the manpower policies, we add a component to the objective function that minimizes these fluctuations and smoothes the hiring and promotion policies. We also add a component that minimizes the deviations between the numbers of officers promoted each year.

5.5.3 Hiring Smoothing Results

We first consider modifying the objective to smooth the hiring and promotion policies individually so we can study the effect on the overall manpower system. We begin by looking at the hiring policy. With the goal of minimizing the changes to the manpower system's hiring policy included now in the objective and appropriate decision variables and constraints added as well, we can examine the new optimal policy and its negative consequences.

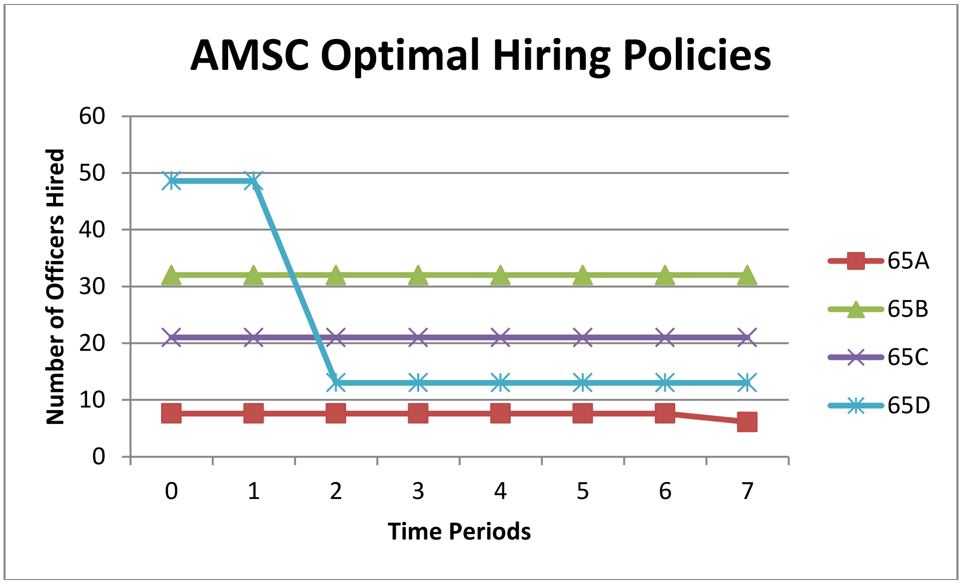


Figure 12 AMSC Hiring Policies Overtime - Smoothing Term Included in Objective Function

Figure 12 shows that for three of our specialties, the number of officers hired per year appears to remain constant. In fact, the maximum deviation between the numbers of officers hired in successive years is only 1.48 for the three specialties 65A, 65B, and 65C. The hiring policy for the 65D specialty is initially just below 50 for the first two time periods, but then stabilizes at 13 new hires each year for the remainder of the model. While Figure 12 demonstrates the model smoothes the hiring policy very well and eliminates any variability in the hiring policies, Figure 13, examines the effect of adding this objective to the objective function. We would expect with this additional objective to smooth hiring that the operating strength deviation of AMSC corps would increase, so seeking a smoother, more constant hiring policy would come at some cost.

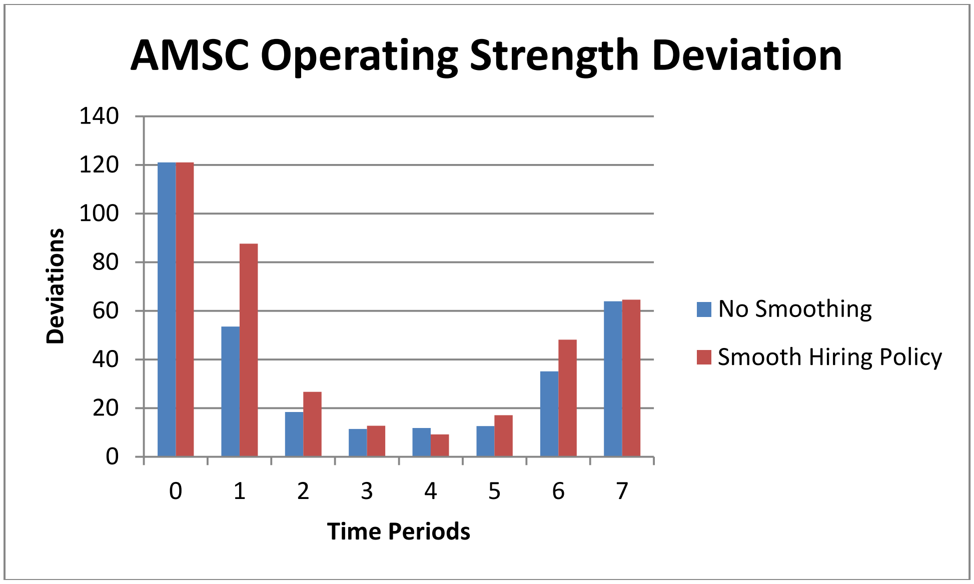


Figure 13 AMSC Operating Strength Deviation with/without Smoothing Hiring Policies

The resulting operating strength deviation associated with smoothing the hiring policy is comparable to the operating strength deviation when no such hiring policy is enforced. At worst, the operating strength deviation with the hiring smoothing policy enforced is 34 deviations greater in time period 1 compared to the optimal policy with no smoothing enforced. But as time goes on, the optimal policy with smoothing begins to greatly improve. In at least one time period, $t = 4$, the operating strength deviation with smoothing outperforms the operating strength deviation without smoothing. In the end, the operating strength deviation at $t = 7$ with smoothing is 65.6 deviations compared to 63.9 deviations without and the average annual operating strength deviation with smoothing is 48.4 deviations compared to 41.0 deviations without. AMEDD can adopt this smoothed hiring policy which would improve system consistency and stability without a considerable cost to the overall corps operating strength deviation. We now explore the effect of adding a similar policy of smoothing officer promotions. We will then explore the effects of adding both policies.

Additional analysis supports the claim that the hiring policy becomes more stable. To measure the stability of each of the two hiring policies, we calculated the absolute deviation between the number of officers hired in year *t* and the average number of officers hired in the seven year time period. The mean absolute deviation for the seven year time period is calculated. The larger the mean absolute deviation, the less stable the hiring policy is. This technique is similar to the practice of calculating the mean absolute deviation to measure the value of a forecasting method (Jacobs & Chase, 2014).

Appendix B shows the number of officers hired each year for each of the four specialties in the Army Medical Specialist Corps. Case One refers to the AMSC solution not considering any hiring smoothing factors and Case Two includes the objective to minimize the deviations between the numbers of officers hired each year. The inclusion of the objective to scale officer hires did not degrade the overall operating strength deviation and, as indicated by the comparison of the mean absolute deviations for the each of the four areas of concentration in the two cases, was very successful at smoothing the number of officers hired per year. The Case Two hiring policy for two of the areas of concentration is to hire a constant number of officers per year. This stability would increase the ability for military recruiters to forecast requirements and to plan to meet their hiring targets. This constant stream of officers coming into the system would also increase the ability of military manpower managers to assign new officers to jobs available if they knew the number of officers coming into the system each year was constant.

5.5.4 Promotion Smoothing Results

The purpose of the second smoothing factor is to minimize the fluctuations in the officer promotion policy as demonstrated in Figure 11. We pay specific attention to area of concentration 65B as an indicator how well the policy does at smoothing promotion policies. We will explore the effect of smoothing the number of officers promoted on all areas of concentration as well as examine how the addition of this objective affects other important manpower criterion like the operating strength deviation.

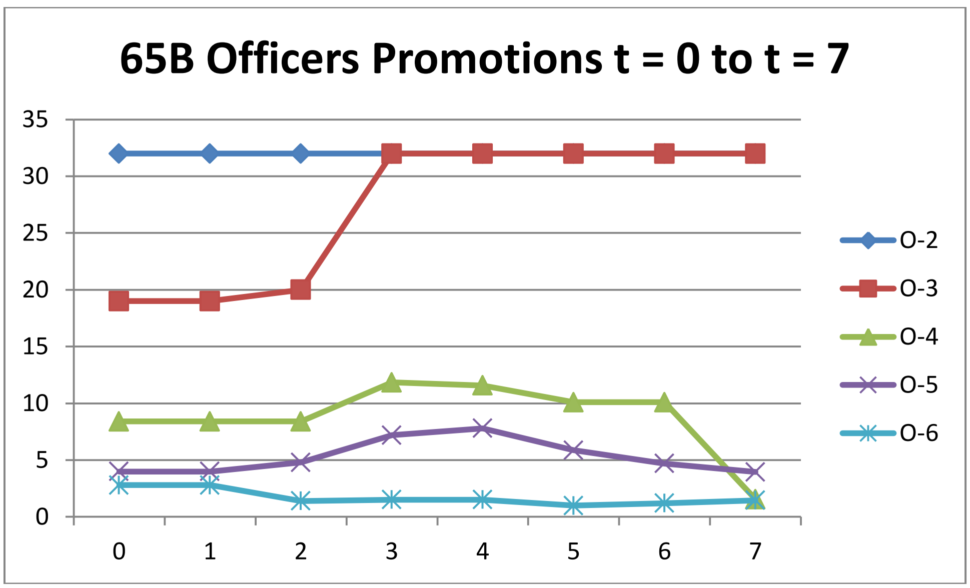


Figure 14 65B Promotions Overtime - Smoothing Term Included in Objective Function

Figure 14 shows the how the number of officers promoted in the 65B specialty varies over time. The optimal policy is not as smooth as the scaled hiring policy but this policy is a considerable improvement compared to the optimal promotion policy when promotion smoothing is not enforced displayed in Figure 11. The large deviations in the number of officers promoted are not present with the addition of the objective to minimize the deviation of the number of officers hired one year to the next. As we did when we implemented smoothing the number of officers hired, we will examine how the addition of this objective affects the operating strength deviation of the manpower system.

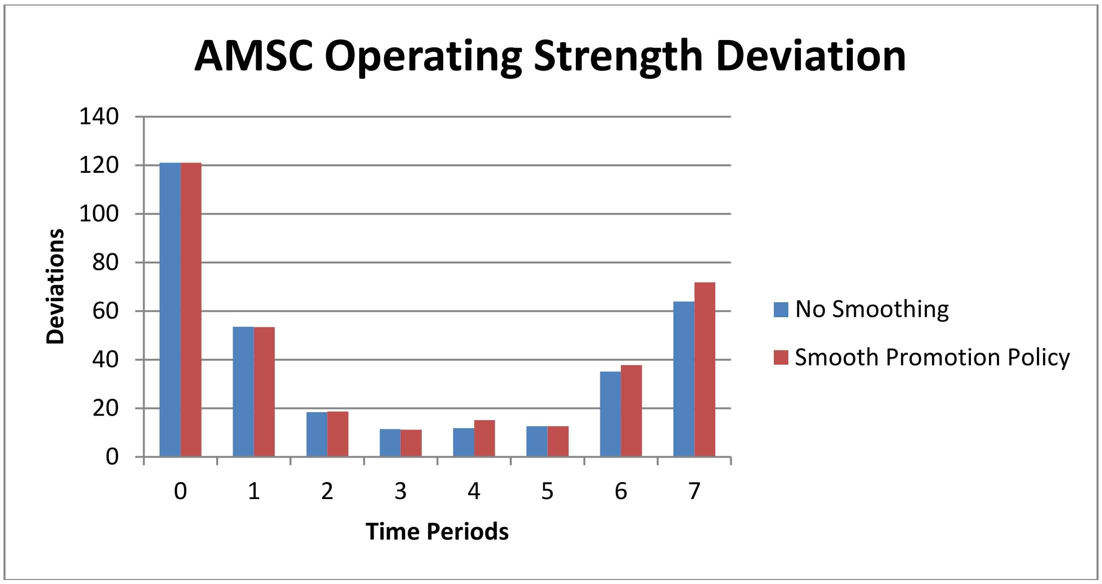


Figure 15 AMSC Operating Strength Deviation with and without Smoothing Promotion Policies

As we saw with the addition of the objective to scale the number of offices hired, there is not a dramatic inflation in the manpower system operating strength deviation with the inclusion of the objective to minimize the deviation between the numbers of officers promoted year to year. At the end of the planning horizon, the t = 7, the operating strength deviation when we consider the objective to scale the number of officers promoted is only 12 deviations larger than the operating strength deviation when we do not consider this additional objective (*71.8 to 83*.9). The adoption of the policy to scale officer promotions would cost the Army Medical Specialist Corps 12 deviations, but there are many advantages to smoothing the number of officers to be promoted. For one thing, officers are more likely to remain in the Army if they believe they have a chance to be promoted. Officers are better able to predict their chance of being promoted if the at large number of officers promoted is steady and stable. Steady promotions, as is the case with steady hiring practices, is to the advantage of the military manpower manager who now has a steady stream of officers, essentially resources, to assign to positions, essentially personnel requirements.

	O-2		O-3		O-4		O-5		O-6	
	Case One	Case Two	Case One	Case Two	Case One	Case Two	Case One	Case Two	Case One	Case Two
65A	NA	NA	20.25	2.13	1.73	1.56	0.94	0.94	0.36	0.37
65B	34.40	0	11.12	5.10	2.40	2.35	1.39	1.36	0.51	0.36
65C	6.10	0	4.66	4.90	1.97	1.95	1.16	1.14	0.70	0.61
65D	NA	NA	57.30	6.37	11.47	12.16	2.07	1.98	1.11	1.09

Table 27 Calculating Mean Absolute Deviation of Officers Promoted Annually to Measure Policy Stability

Table 27 supports our interpretation of Figure 12. As we did when we examined the stability of the hiring policies, we calculate the mean absolute deviation for the number of officers promoted in each specialty to each grade. In 18 of the eligible pairs to compare, the mean absolute deviation of the number of officers promoted when the smoothing objective is included in the objective function is less than the man absolute deviation of officers promoted when the smoothing objective is not included. The magnitude of the difference is not as great as it was when we calculated the effect of the hiring policies because promotion rates are constrained tightly by lower and upper bounds.

We conclude that adding each of these smoothing policies to the objective function does not have a significant adverse effect on the corps operating strength deviation. Lastly, we add both of the smoothing policies. Similar to the individual addition of the two smoothing policies, the addition of both policies does not inflate the objective function. The operating strength deviation at the end of the seven year model is 66 deviations compared to 63 deviations in the model that does not consider smoothing.

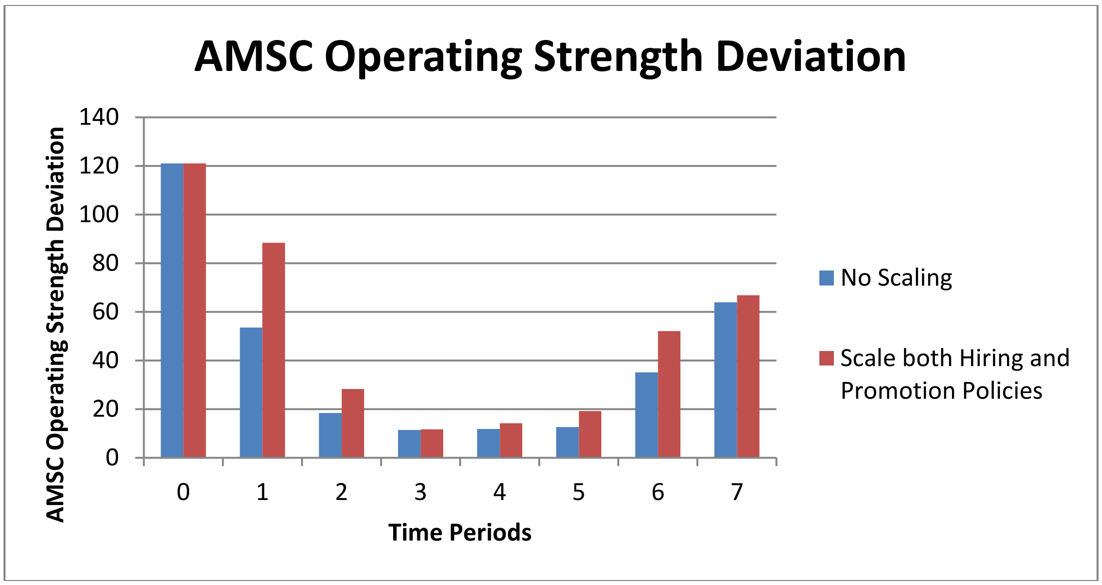


Figure 16 Operating Strength Deviation with and without Smoothing Hiring and Promotion Policies

5.5 Goal Programming Modeling Summary

In this chapter, we developed and described a manpower linear program that will manage the current inventory of officers in the manpower system. This linear program, modeled after the advancements we made in Chapter 4, can provide us with the optimal manpower policy to manage the current inventory force. But the expansion of this model to include multiple time periods comes with an increase in the number of terms in our objective function. We explored some very multiple objective decision analysis techniques in this chapter when we assigned weights in a seemingly random manner.

In the next chapter, we present two techniques that will help manpower decision makers make decisions about our manpower systems. The first technique will convert the value of man power system deviations to a value score. The second technique demonstrates a possible weighing of the 231 objective function components, but more importantly, a method that could be duplicated to weigh the multiple objectives in a similar manpower system.

6. Value Modeling

The purpose of this chapter is to apply a value modeling methodology to the problem of finding the optimal AMEDD manpower system. As we have seen in Chapters 3-5, the AMEDD manpower system is a complex system with many competing objectives. Our linear programs minimize the operating strength deviation of company grade officers, majors, lieutenant colonels, and colonels of the entire AMEDD manpower system, the operating strength deviation of these specific grades in the six AMEDD corps, and scales the number of officers hired and promoted each year. Given a seven year planning horizon, four officer grades, and six corps, the linear program objective function has 231 terms. In this chapter, we adopt a value modeling methodology; specifically swing weighting, to construct a hierarchy of these 231 objective function terms. This value modeling methodology assigns a weight to each of the 231 terms and ensures the most important objective function terms have the greatest amount of influence on the overall manpower system.

In much of the systems design and systems engineering literature, the development of a value hierarchy and value function is done even before models are constructed and experiments executed to measure how well different candidate solutions perform with respect to the value hierarchy. In this problem instance, the alternate manpower policies that are outputs of the optimization models described in Chapters 4 and 5, are the different candidate solutions. The value functions will convert the number of deviations in each candidate solution to a value score. The value scores will then be maximized. In essence, we will develop a manpower policy, a set of hiring, promotion, and transferring decisions to be made that will maximize the value of the AMEDD manpower system, rather than the objective as outlined in Chapters 4 and 5 of minimizing the deviations in the manpower system. A system of weights is developed that will allow the objectives deemed to be the most important to the contribution of the fundamental AMEDD objective to contribute more than lesser important objectives to the achievement of the fundamental objective.

6.1 INTRODUCTION

The sheer magnitude of the number of terms in the objective function makes it clear that it is an arduous, nontrivial task to assign weights to each of the objective function terms in the multiple time period linear program model of the AMEDD manpower system. Parnell and Trainor (2013) cite many reasons to adopt a swing weight matrix methodology when confronted with a multiple objective decision analysis problem.

The first reason is the complexity in system design. They write "systems are designed to meet the future needs of stakeholders". The swing weigh matrix method is designed to incorporate the input from multiple stakeholders. Each attribute that contributes to the overall value of the system is included. The AMEDD manpower system stakeholders consists of, but is not limited to, the Army leaders and personnel managers, leaders and personnel managers of the AMEDD system, and leaders and personnel managers in the individual six AMEDD corps. The methodology we present is adaptable and usable by stakeholders of complex manpower systems.

Parnell and Trainor also recognize that the more stakeholders a system has, the more likely it is that the system will have multiple objectives. "As a result of the increased stakeholders and increased complexity, the number of conflicting objectives that systems engineers must identity and measure to assess the potential future performance increases." (Parnell and Trainor) The swing weight methodology provides analysts a technique to assign weights to all objectives in a consistent, reliable manner.

Using the weights developed for each of the manpower system's 231 objective function terms, manpower analysts can understand the system tradeoffs associated with adopting one manpower policy compared to another. For example, the value score of an aggressive promotion policy can be compared to the policy that promotes officers at a slower rate. The weights and the value scores of alternatives make it possible to compare multiple policies and the tradeoffs in system performance associated with implementing one policy over another. The comparison comes in calculating the value score for the manpower system created by alternative policies?

Multi-objective decision analysis is aided by use of swing weight matrices. Managing the AMEDD manpower system, and other large manpower systems, involves multiple objectives. An example of two competing objectives is should the manpower policy optimize the overall operating strength deviation of the AMEDD officer corps at the expense of the operating strength deviations for some of the six corps.

The swing weighting methodology allows analysts to use an additive value model, the most common, well researched and used in practice. The additive model is clear, concise, but provides analysts and decision makes with the ability to consider multiple objectives, the inputs of multiple stakeholders, and the ability to model complex systems.

The additive model is shown in Equation 28, where v(x) is to be maximized:

$$v(x) = \sum_{i=1}^{n} w_i v_i(x_i)$$

Equation 28 Additive Value Model

where

v(x) is the manpower policy's value

i = 1 to n is the number of manpower policy objective function terms

x_i is the value of the ith attribute, on which the ith value measure depends

$v_i(x_i)$ is the value of the ith value measure

w_i is the importance weight of the i^{th} value measure

where $\sum_i^n w_i = 1$ all objective function weights must sum to one.

Besides the specific swing weight matrix, Parnell advocates the use of a value system modeling technique rooted in the development of a value hierarchy. The value hierarchy is an extension of a functional hierarchy or decomposition, standard in the systems engineering literature and practice that depicts all of the functions a system has to be able to perform. The value hierarchy is a collection of measures of effectiveness to measure how well alternative systems meet system objectives and perform the functions depicted in the functional hierarchy.

6.2 AMEDD Manpower System Value Hierarchy

We present the AMEDD manpower system value hierarchy. The value hierarchy has a single, fundamental objective. This objective is the primary reason we are searching for different manpower policies to optimize the manpower system. The fundamental objective of the AMEDD manpower system is to provide the US Army a medical department of officers that is capable of meeting all Army directed and internal

AMEDD manpower requirements. AMEDD must provide the Army an officer corps that has enough officers to meet Army manpower requirements. AMEDD also generates manpower requirements and mans those requirements in order to best support the Army at large.

This highest level objective is directly supported by four lower level objectives, see Figure 17. These four objectives either minimize the deviation between the on hand inventory of officers and officer requirements in subsets of the AMEDD officer population or they scale, minimizing the variability, in the system hiring and promotion policies. Since the on hand inventory model determines the optimal manpower policy over a seven year planning horizon, each of the four objectives minimizes the sum of the operating strength deviation over the entire planning horizon or minimizes deviations from year to year in the hiring and promotion policies.

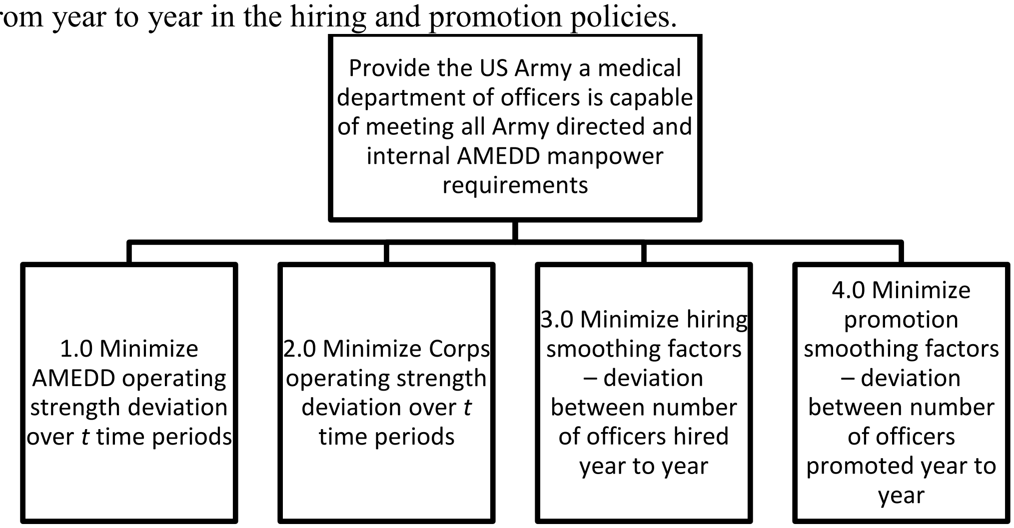


Figure 17 AMEDD Manpower System Value Hierarchy

6.2.1 AMEDD Operating Strength Deviation

The optimal AMED manpower system minimizes the sum of the AMEDD manpower system's operating strength deviation over the entire planning horizon. As discussed in Chapter 5 and shown in the following equation, our model takes into account the operating strength deviation of each grade level and sums the deviations over the planning horizon.

$$\Sigma_{t,g}\alpha_{tg}(pos\ AMEDD\ dev_{tg}\ +\ neg\ AMEDD\ dev_{tg})$$
$$where\ t = 1\ to\ 7,\ g = Company\ Grade, O-4,\ O-5,\ O-6\ officers$$

Equation 29 Objective 1.0 Minimize AMEDD operating strength deviation over *t* time periods

Our value hierarchy and swing weight method allows us to develop relevant and consistent values for the weights, α_{tg}, that model the decision makers preferences. It is likely that all α_{tg} are not equal, since it is more important to minimize the operating strength deviations of senior leaders compared to junior leaders. Additionally, it may be more important to minimize the operating strength deviation in earlier time periods, rather than later time periods where additional factors external to the manpower system, like changing Army requirements, are not as certain as they are in earlier time periods. Figure 18 displays the sub-hierarchy of minimizing AMEDD operating strength deviation. This chart depicts how Objective 1 Minimize AMEDD Operating Strength Deviation over 7 Time Periods from Figure 17 is measured.

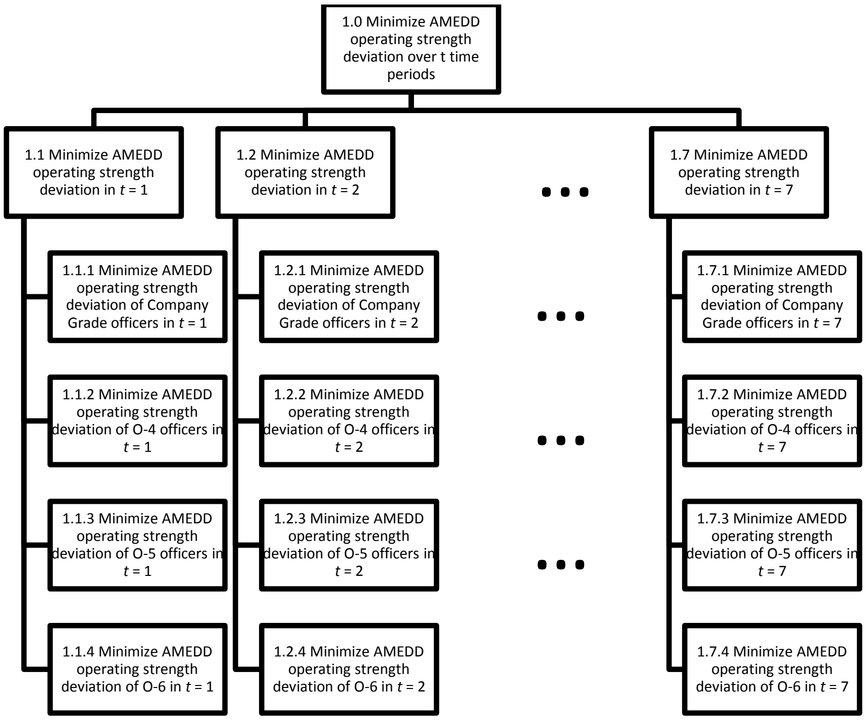


Figure 18 Minimize AMEDD Operating Strength Deviation

6.2.1.1 AMEDD Operating Strength Deviation in Time Period t

Objective 1.1 minimizes the operating strength deviation of the AMEDD officer corps in $t = 1$. There are six other objectives of the same nature that minimize the operating strength deviation across the seven year planning horizon of our model. For each of these objectives, the deviation from the required number of officers in four grades is calculated and we sum those deviations to calculate the operating strength deviation for time period t.

6.2.1.2 Minimize AMEDD Operating Strength Deviation of Grade g

Objective 1.1.1 seeks to minimize the operating strength deviation of company grade officers in time period $t = 1$. Objective 1.7.4 seeks to minimize the operating strength deviation of O-6 officers in time period $t = 7$. There are a total of 7 time periods and 4 grades, and a total of 28 objectives in this portion of the value hierarchy.

6.2.2 Cumulative Corps Operating Strength Deviation

Objective 2.0 is to minimize the operating strength deviation in each of the six AMEDD corps. Each of the six corps is essential to AMEDD providing necessary services to the Army and being able to complete its mission. But based on the number of requirements that each corps has, the number of officers they are required to have to provide these services and complete its mission, all corps are not equal. Minimizing corps that have more requirements will have a greater influence on minimizing the overall AMEDD operating strength deviation than smaller corps. For example, minimizing the operating strength deviation in the Medical Corps that has 4,098 requirements will have a greater effect on achieving the overall objective of the AMEDD manpower system than minimizing the operating strength deviation of the Veterinary Corps that has only 426 officer requirements.

The corps operating strength deviation is calculated by summing the deviations between the number of officers on hand in each grade and the required number of officers in each grade for each of the six corps. Equation 30 is used to calculate this objective for each of the 6 corps. Our swing weight methodology allows us to develop relevant and consistent weights for the parameter $\gamma_{t,corps,g}$ that reflect the relative influence of the six corps on the overall objective.

$$\Sigma_{t,g}\gamma_{t,corps,g}\left(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}\right)\ \forall corps = AMSC, DC, MC, MSC, NC, VC$$

Equation 30 Objective 2.0 Minimize Corps Operating Strength Deviation

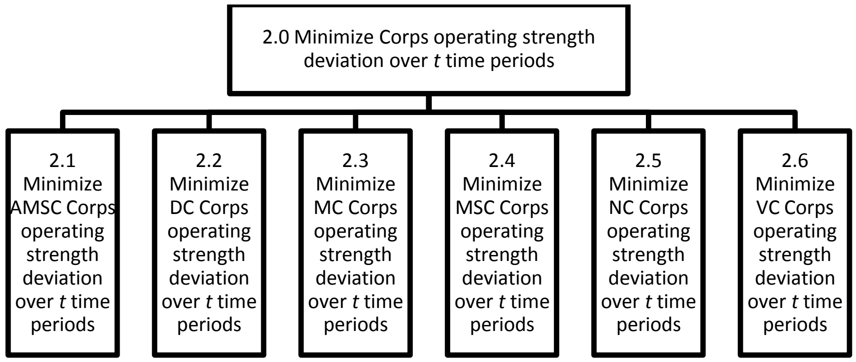


Figure 19 Minimize Corps Operating Strength Deviation

6.2.2.1 Cumulative AMSC Corps Operating Strength Deviation across Planning Horizon

Objectives 2.1 thru 2.7 minimize the operating strength deviation of the each of the six corps over the duration of the planning horizon. For example, Objective 2.1, shown in Figure 20, minimizes the operating strength deviation of the Army Medical Specialist Corps. There are five other objectives of the same nature that minimize the operating strength deviation across the seven year planning horizon of our model for their respective. For each of these objectives, the deviation from the required number of officers in four grades is calculated and we sum those deviations to calculate the operating strength deviation for time period t.

Objective 2.1 is achieved by minimizing its 28 sub objectives, depicted in Figure 20. Objective 2.1.1 seeks to minimize the operating strength deviation of all Army Medical Specialist Corps officers in time period $t = 1$. Objective 2.1.1 is further defined by minimizing the operating strength deviation of company grade officers in AMSC in $t = 1$ time period. And the operating strength deviation of all other ranks in AMSC in $t = 1$. Objective 2.1.7.4 seeks to minimize the operating strength deviation of AMSC O-6 officers in time period $t = 7$. There are a total of 7 time periods and 4 grades or ranks, hence, a total of 28 objectives that contribute to the achievement of Objective 2.1. Figure

20 only displays the AMSC portion of Objective 2.0. There are identical objective for the five other AMED corps, resulting in an additional 140 objectives, for a total of 168 lower level objectives that help achieve the higher level Objective 2.0 Minimize Corps operating strength deviation over seven time periods

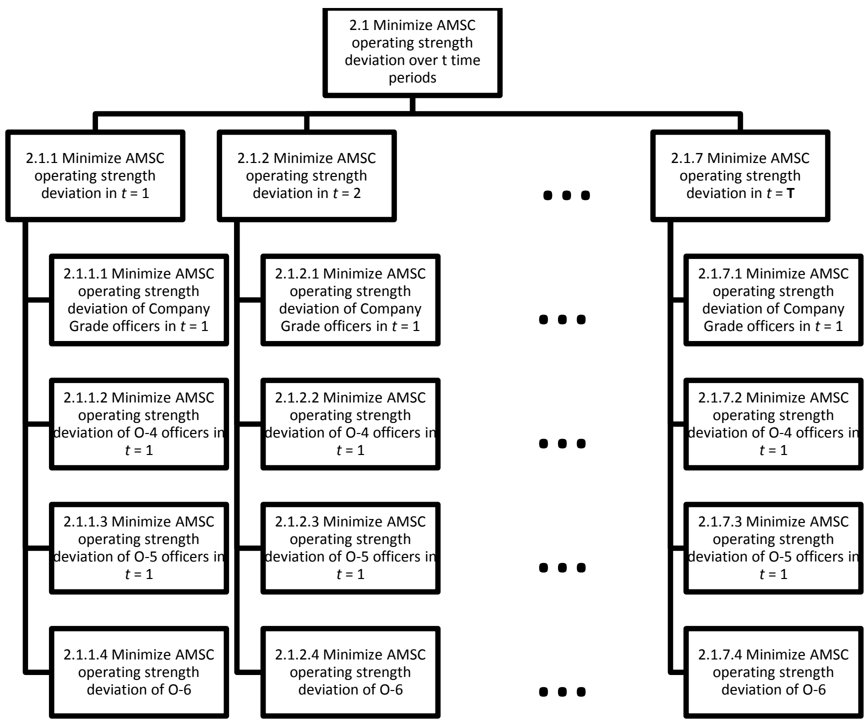


Figure 20 Minimize AMSC Corps Operating Strength Deviation

6.2.3 Hiring Smoothing

New officers enter into the AMEDD manpower system by being hired. A hiring policy that minimizes variability helps the AMEDD manpower system achieve the fundamental objective of providing the US Army a medical department of officers that meets all Army directed and internal AMEDD manpower requirements. A flow of officers into the manpower system that has limited variability year to year improves the ability for AMEDD manpower managers to meet officer requirements. It is more difficult to forecast the number of officers that will be available in the manpower system if the number of officers entering the system varies widely from year to year.

If there is large variability in the number of officers that enter into the manpower system year to year, that variability is carried over into future inventory states in the manpower system. For example, if a small cohort of group of officers enters the system in time period *t*, then there will be a small number of officers eligible for promotion to grade *g* in year $t + \delta$. This variability creates a shortage of officers that remains in the system and the system is more sensitive. Officers who leave the system from normal attrition have a greater negative impact on the state of the manpower system.

Objective 3.0 minimizes the hiring smoothing factor - the difference between the number of officers hired between *t* and $t + 1$. Figure 21 shows that the achievement of Objective 3.0 is achieved by minimizing the hiring smoothing factor over the seven year planning horizon. Objective 3.1 minimizes the hiring smoothing factor between $t = 0$ and $t = 1$. In total, there are seven total sub objectives that minimize the smoothing factor from year to year. The deviation between the numbers of officers hired year to year is calculated as described in Chapter 5. Objective 3.0, minimizing the hiring smoothing factor is calculated in Equation 31. $\beta_{t,}$ is the weight assigned to the sum of hiring deviations across all areas of concentration a, all years *y*, and all grades *g* in time period *t*.

$$\Sigma_{t,a,y,g}\beta_t\left(hires\ pos\ dev_{t,a,y,g} + \ hires\ neg\ dev_{t,a,y,g}\right)$$

Equation 31 Calculation of Objective 3.0

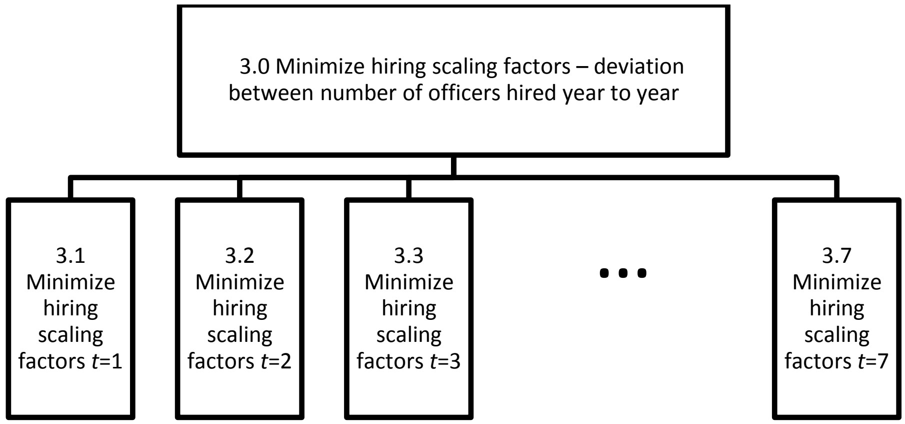


Figure 21 Minimize Hiring Smoothing Factors

Objective 3.1, minimizing the hiring smoothing factor in $t = 1$, is calculated in Equation 28, where β_1 is the weigh assigned to the hiring smoothing factor in $t = 1$ and represents how important Objective 3.1 is on the overall AMEDD objective.

$$\sum_{a,y,g} \beta_1 \left(hires\ pos\ dev_{1,a,y,g} + \ hires\ neg\ dev_{1,a,y,g} \right)$$

Equation 32 Calculation of Objective 3.1

6.2.4 Promotion Smoothing

As it is important to minimize the change in the number of officers hired time period to time period, it is important to minimize the variability in the number of officers promoted to grade g between time period t and $t + 1$. A promotion policy that minimizes variability helps the AMEDD manpower system achieve the fundamental objective of providing the US Army a medical department of officers that is capable of meeting all Army directed and internal AMEDD manpower requirements. A flow of officers from grade g to grade $g + 1$ that has limited variability year to year improves the ability for AMEDD manpower managers to meet officer requirements. It is more difficult to forecast the number of officers that are available in the manpower system if the number of officers promoted from year to year varies greatly.

If there is large variability in the number of officers that enter into the manpower system year to year, that variability is carried over into future inventory states in the manpower system. For example, if a small cohort of group of officers enters the system in time period t, then there will be a small number of officers eligible for promotion to grade g in year $t + \delta$. This variability creates a shortage of officers that remains in the system and the system is more sensitive to normal attrition. Officers who leave the system from normal attrition have a greater negative impact on the state of the manpower system, because the number of officers in a state t,a,y,g is not as stable because of the variation.

Objective 4.0 minimizes the promotion smoothing factor - the difference between the number of officers promoted between t and $t + 1$. Figure 22 shows that the achievement of Objective 4.0 is achieved by minimizing the promotion smoothing factor over the seven year planning horizon. Objective 4.1 minimizes the promotion smoothing factor between $t = 0$ and $t = 1$. In total, there are seven total sub objectives at this level that minimize the smoothing factor from year to year. Within each of these objectives, we minimize the smoothing factor for company grade, O-4, O-5, and O-6 officers. This objective is differentiated at the grade level unlike Objective 3.0. The reason is because there are promotions going on at all ranks in each time period t. If we do not differentiate between them, then a possible solution would have a large deviation of the promotion smoothing factor for one grade that was cancelled about by a deviation, equal in magnitude, but opposite in direction (either shortage or excess) in the same time period. This detail is shown in Figure 22 which shows a sampling of the 28 sub objectives 4.1.1 to 4.7.4 that enable the AMEDD system to achieve Objective 4.0.

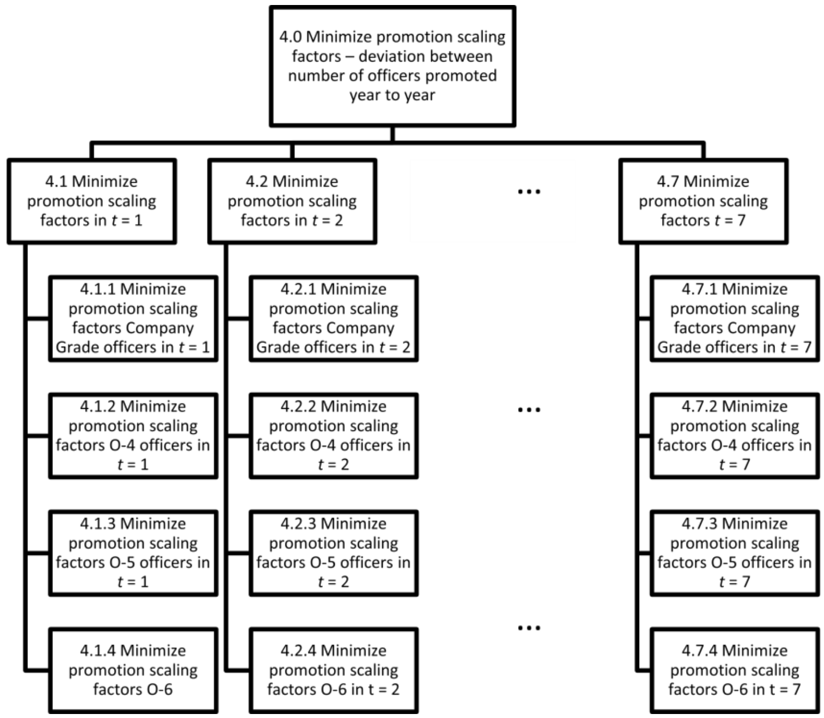


Figure 22 Minimize Promotion Smoothing Factors

The deviation between the numbers of officers promoted year to year is calculated as described in Chapter 5. Objective 4.0, minimizing the promotion smoothing factor is calculated in Equation 33. $\kappa_{t,g}$ is the weight assigned to the sum of promotion deviations across all areas of concentration a, all years y, and all grades g in time period t. We update the weight κ_{tg} for varying indices of t and g but assume it is equal for all a. By making it constant for all areas of concentration, we are saying that deviations in promotion in all specialties are as equally as harmful to the achievement of the overall objective. This assumption allows us also to not have to calculate different values for κ_{tg} for each of the 98 areas of concentration.

$$\Sigma_{a,y,g}\kappa_{tg}\left(prom\ pos\ dev_{t,a,y,g} + \ prom\ neg\ dev_{t,a,y,g}\right)\ \forall t = 1\ to\ 7$$

Equation 33 Calculating Objective 4.0

6.3 Developing Value Functions

The four highest level objectives, Objectives 1.0 to 4.0, have a total of 231 sub objectives. Each of these 231 sub objectives at the lowest level of the AMEDD manpower value hierarchy can be measured. The optimization model in Chapter 5 tallies each of the objectives. Since each of the objectives has the same units, the deviation of the number of officers from a target, the 231 values for each lowest level objective can be summed to assess the total value of the manpower system. However, this practice would not lend itself to comparison to other manpower systems of different size, of different structure, and would not provide decision makers with a relative measure of well the AMEDD manpower system is performing.

In this section, we will convert the raw data, the actual number of deviations for the 231 objectives, into a value score between 0 and 100; 0 being the worst possible value, 100 being the best possible value. In order to convert the number of deviations in each objective to a value score, we develop value functions.

A value function is a mapping of the number of deviations in a particular measurement that converts the raw data into a value score. All of the objectives seek to minimize the number of deviations to achieve the fundamental objective. All of the metrics in the model are "less is better" metrics. The smaller the value of the metric, the better off the AMEDD manpower system is.

Each of the 231 objectives has a value function. For the AMEDD manpower system, we used linear value functions, decreasing in the number of deviations. As the number of deviations for a particular measure increased, the value score for that metric decreased. A manpower system with more deviations in a particular metric does not provide as much value to the achievement of the fundamental objective as a system with fewer deviations with respect to the same metric.

Linear value functions take the form Value Score = $mx + b$, where x is the number of deviations in a particular objective and m and b are constants. For all of our value functions, b = 100. Zero deviations in any particular measurement will provide the maximum amount of value to the manpower system. We set the value for *m* so that the maximum numbers of deviations for a particular metric across different candidate manpower systems results in a value score of 0. Since the value functions will be decreasing in the number of deviations, the slopes of all of the value functions will be negative. There are more complex value functions that might actually capture and model a decision maker's preference more accurately. The simple linear value function has a constant slope. It might be more appropriate to use a nonlinear function at times in order to model how the return to scale is not equal. There might be a greater penalty to go from 10 to 20 deviations than the penalty going from 90 to 100 deviations. However, the use of linear value functions has two primary benefits. First, it serves as a baseline, a starting point. Second, it allows us, as we will see later, to incorporate the linear value function into the linear programs. The linear programs previously discussed minimized the number of deviations. Using these linear value functions, we will construct a linear program that maximizes the overall value of the manpower system.

In the following examples, we demonstrate how we developed value functions for each lowest level objective. The first example explores the development of a value function for the sub objectives 2.1.1.1 thru 2.1.1.4. These are the sub objectives associated with minimizing the operating strength deviation of AMSC officers of all four grades in time period 1.

As previously mentioned, zero deviations in any metric results in a value score of 100 points. Therefore, the parameter *b* is set to 100 for all value functions. The setting of the level of the parameter *m* requires additional steps. A linear program optimizing the operating strength deviation of the AMSC corps, with each time period and each grade having equal weight and equal contribution the objective function was solved. For company grade officers, the maximum number of deviations in the manpower system between the numbers of officers on hand and the required number of officers on hand, occurred at the start of the seven year planning horizon and was 77 deviations. The maximum number of deviations for the other three grades is displayed in Table 28. This table tells us the magnitude of the maximum number of AMSC officer deviations for each grade across the seven year planning horizon and when that deviation occurred. This maximum number of deviations provides a benchmark for how poorly the manpower system can perform.

Grade	Maximum # of Deviations in Seven Year Planning Horizon	When the Maximum # of Deviations Occurred
Company Grade Officers	77	$t = 0$
O-4 Majors	57	$t = 7$
O-5 Lieutenant Colonel	30	$t = 0$
O-6 Colonels	6	$t = 7$

Table 28 Number of AMSC Officer Deviations

The minimum value of the value function is 0. To ensure we do not have functions that violate this rule, we scale the slope of the value function appropriately. The slope of the line has to be such that it intersects with a 100 when there are no deviations in the system and it intersects with 0 when the system has the maximum number of deviations in the system. To properly program the maximum number of deviations in the system, we observed the maximum deviation for each grade in each corps in the system. To guard against there being a future scenario where the maximum number of deviations exceeds this worst case condition shown in Table 28, we add a safety stock to the worst case scenario. We set this safety stock to a value greater than zero to ensure when we are solving the global AMEDD manpower system problem we do not have an incident where the maximum number of deviations exceeds the Table 28 worst case parameters.

Table 29 shows the calculations for *m* and displays the value functions used to convert deviations into a value score between 0 and 100. For example, if a manpower policy resulted in 0 deviations in the company grade officers ranks, than that policy would receive a value score of $\frac{-100}{(77+\delta)}(0)$ + 100 or 100 points. If the manpower policy resulted in $77 + \delta$ company grade officer deviations, then that manpower policy would have a value score of $\frac{-100}{(77+\delta_g)}(77 + \delta)$ + 100 or 0 value points.

Grade	Maximum Number of Deviations + Safety Stock (δ)	m	Value Function, where x is the number of grade deviations
Company Grade Officers	$77 + \delta_g$	$\frac{-100}{(77 + \delta_g)}$	$\frac{-100}{(77+ \delta_g)}$x + 100
O-4 Majors	$57 + \delta_g$	$\frac{-100}{(57 + \delta_g)}$	$\frac{-100}{(57+ \delta_g)}$ x + 100
O-5 Lieutenant Colonel	$30 + \delta_g$	$\frac{-100}{(30 + \delta_g)}$	$\frac{-100}{(30+ \delta_g)}$ x + 100
O-6 Colonels	$6 + \delta_g$	$\frac{-100}{(6 + \delta_g)}$	$\frac{-100}{(6+ \delta_g)}$ x + 100

Table 29 Calculation of *m* for Objective 2.1.1 Value Functions

Figure 23 graphs four value functions for officer deviations in the Army Medical Specialist Corps. As mentioned, all of the linear functions are decreasing in the number of officer deviations. The slope of the O-6 Value Function is the steepest. This captures the value that deviations in this specialty, at the most senior levels are more detrimental to the AMEDD manpower system than equal deviations in the company grade ranks. Another way to say it is that increases in the number of deviations of O-6 officers has a larger negative effect on the overall value of the AMEDD system than increases in the number of deviations in the other three officer ranks. Put another way, $m_{O-6} < m_{O-5} < m_{O-4} < m_{Company\ Grade}$. This relationship is shown in Figure 23.

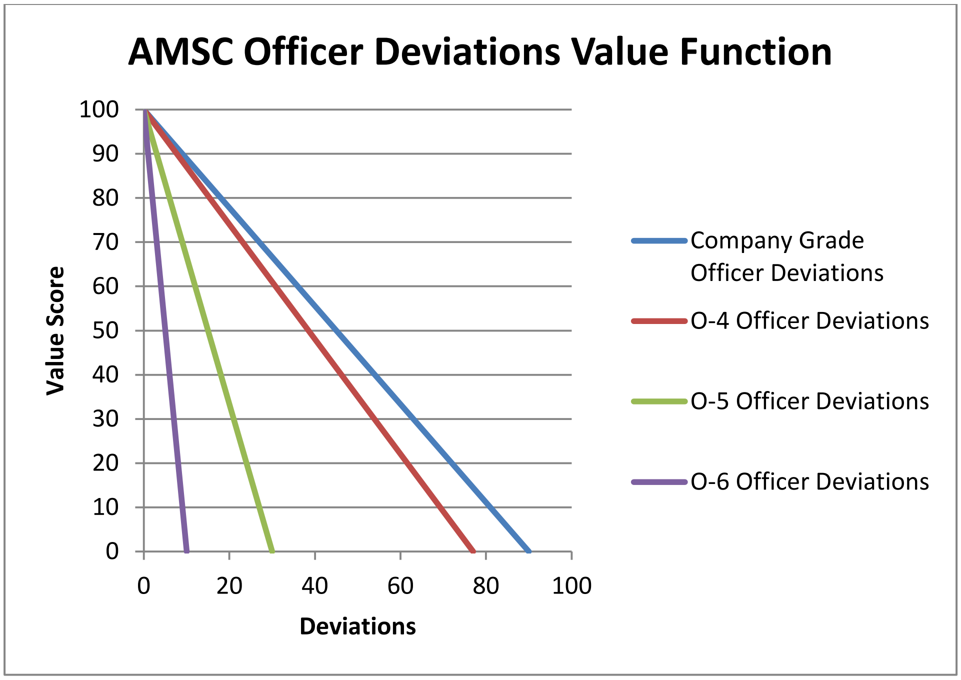


Figure 23 AMSC Grade Deviations Value Function

A similar process, for each of the five other corps, was repeated to calculate value functions for officer deviations in all AMEDD corps. The relationship in Figure 23 does not hold for all officer deviations in each of the six corps. The smaller the number of maximum number of deviations in a particular grade are, the larger the value of *m*. For example, in the Dental and Veterinary Corps, the two smallest corps in terms of officer requirements, *m* is not decreasing in rank. The number of deviations in the Dental and Veterinary Corps at the company grade level and O-4 is considerably less than the number of deviations in the other ranks or grades. This results in the slope of the value function being steepest in the Dental Corps for O-4 Majors and in the Veterinary Corps for Company Grade Officers. The same value functions are used to convert the number of deviations in each corps and each officer grade to a value function score in the seven time periods.

	Slopes for Each of the Six Corps					
	AMSC	DC	MC	MSC	NC	VC
Company Grade Officers	-1.1	-0.5	-0.2	-0.4	-0.5	-33.3
O-4 Majors	-1.3	-2.5	-0.3	-0.8	-0.5	-1.4
O-5 Lieutenant Colonel	-3.3	-0.5	-0.7	-1.8	-1.6	-4.0
O-6 Colonels	-10.0	-0.5	-1.6	-10.0	-4.1	-16.7

Table 30 Slope of Value Functions for Grade *g* Deviations in Corps *c*

Similar processes provided value functions for the deviations of officers in the total AMEDD officer system. As calculated for the corps deviations, the maximum number of deviations in the AMEDD operating strength deviation is identified and used as a worst case scenario, with a safety stock, to determine how many deviations would be transformed into a value score of 0.

This same process was used to build value functions for the two smoothing factors we developed to minimize the variability in the number of officers hired year to year and the number of officers promoted from year to year. The global on hand inventory model described in Chapter 5 was solved without controlling for smoothing the hiring and promotion factor. This solution revealed the maximum number of deviations in the hiring and promotion smoothing factor. These maximum values were then used as the basis to calculate *m*, the value function slopes for the value functions to convert the number of deviations in hires and promotions from year to year to a value score.

In total, we constructed a total of 33 value functions. The first four value functions convert the number of officer deviations in each grade in AMEDD as whole. One function is used for each rank, but that function is used for that particular grade for each time period. The next 24 convert the number of deviations in each grade in each of the six corps operating strength deviation, again for each of the seven time periods. One value function converts the hiring smoothing factor each year to a value score and the last four value functions convert the number of deviations in the promotion smoothing factor per grade to a value score.

6.4 Assigning Weights to AMEDD Manpower System Objectives

We present an application of the swing weight methodology here in Chapter 6. Swing weighting assigns weights to different system objectives and sub objectives. Some alternate techniques ask decision makers to answer the very difficult question "How much do you prefer one objective to another?" Our objective function consists of 231 terms; it would be difficult to answer this question relative to each term in a consistent manner.

The swing weight methodology assesses weights for the different objectives based on importance as well as the amount of variation in the scale of the values assigned to the value measures that enable the achievement of associated objectives. In this section, we will demonstrate how we used the swing weight methodology to assess the weights for the 28 value measures that support the achievement of Objective 1.0. Identical techniques were used to determine weights for the 168 value measures that support the achievement of Objective 2.0, the seven value measures that support the achievement of Objective 3.0, and the 28 value measures that support the achievement of Objective 4.0.

Given the linear program described in Chapter 5 that minimizes the operating strength deviation of the AMEDD officer manpower system over seven time periods, the operating strength deviation of the six individual corps, the hiring smoothing factor, and the promotion smoothing factor, with all of the objective function terms equally weighted, to determine how much each objective function contributes and should contribute to the final objective function value, we solve two instances or two scenarios with varying weights. In the first scenario, we place all of the weight in the objective function on the AMEDD objective with no weight on Objectives 2 – 4. The purpose of this scenario is it reveals the best possible case for minimizing the AMEDD operating strength deviation. For example, when solved, Scenario One produces a manpower system that has only 77 deviations. This is the best we can possible do in terms of minimizing the AMEDD operating strength deviation.

The second scenario reveals the AMEDD operating strength deviation when there is no weight placed on Objective 1.0. All of the weight is placed on Objectives 2.0 – 4.0. This solution reveals the worst possible case for the AMEDD operating strength deviation. The solution to this scenario produces an AMEDD operating strength deviation of 266 deviations. We can see how the value of the AMEDD operating strength deviation objective function varies based on the assignment of weights in the objective function. Table 31 displays the performance of the operating strength deviation for the two scenarios. The range column tells us how much variability there is between the results of the two scenarios and helps us to assign weights to the lowest level objectives, minimizing the AMEDD operating strength deviation in year *t* and grade *g*. Table 31 reveals that the number of deviations of O-6 officers has the greatest amount of variation. The number of deviations can swing from a low of 77 deviations to a high of 169 deviations. This large range suggests that the number of deviations of O-6 officers has a great amount of variation and this will be considered when assigning a weight to how important the objective of minimizing O-6 deviations in the AMEDD system is. This suggests that improvements and gains to the manpower system can be made by reducing the number of deviations of O-6 officers. This potential area for improvement to the overall system can be exploited by increasing the amount of weight assigned to the objective of minimizing O-6 officer deviations. On the other hand, there is very little variability in the number of company grade officers. This suggests that there is less to gain in improving the overall system by reducing the number of company grade officer deviations. There just is not the same potential space for improvement as there is in the O-6 officer grade.

	AMEDD Operating Strength Deviation		
Grade	$\alpha_{AMEDD} = 0$	$\alpha_{AMEDD} = 1$	Range
Company Grade	5.7	0.0	5.7
O-4	56.8	0.0	56.8
O-5	35.3	0.0	35.3
O-6	169.2	77.4	91.8
Total	266.9	77.4	

Table 31 AMEDD Operating Strength Deviation Performance with varying α_{AMEDD}

The variation of the measures must be considered as well as the importance of the measure. Just because there is large variation in the measure does not mean we should weigh that objective more heavily than other terms. We must consider how important each measure is. To do so, we examined the distribution of officer requirements in Figure 24. Company grade officers make up 51% of the overall requirements. This suggests that minimizing the deviations in this grade is of greater importance than minimizing the deviations of the officers in the grade of O-6 that only make up 8% of the AMEDD requirements.

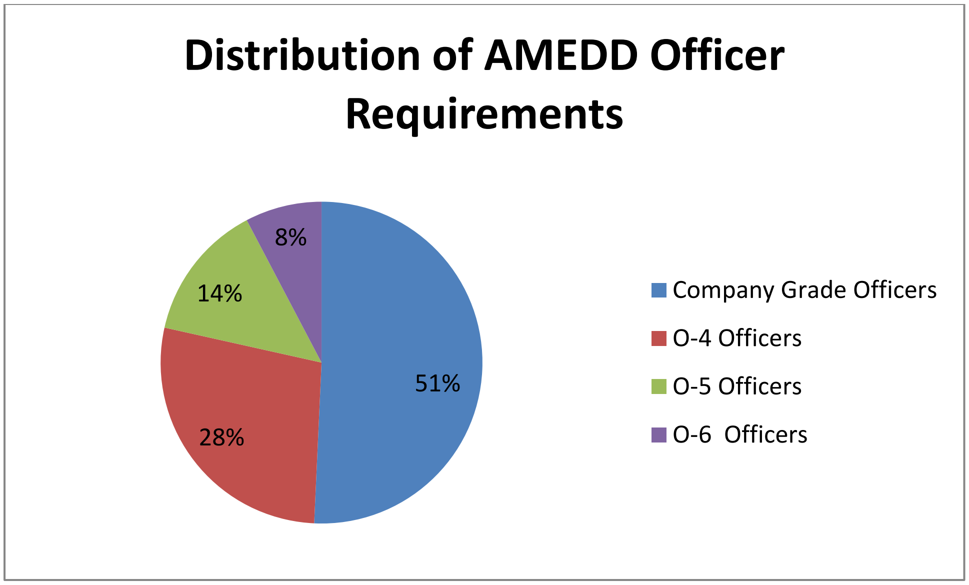


Figure 24 Distribution of AMEDD Officer Requirements

6.4.1 Swing Weight Matrix – AMEDD Operating Strength Deviation and Grade

Parnell's swing weight matrix technique will assist us in assigning the actual weights to the sub objectives of minimizing the number of deviations per grade. Table 31 displays the amount of variation in each rank's operating strength deviation. Figure 24 captures how much each rank contributes to the AMEDD requirements and the importance of each grade operating strength deviation to contributing to the accomplishment of Objective 1.0, minimizing AMEDD operating strength deviation. Parnell describes the very basic premise for how to use Table 32 to determine weights for the multiple objectives. If the operating strength deviation of grade *g* is more important than the operating strength deviation of grade *g'*, than grade *g* will be weighted higher than grade *g'*. If the operating strength deviation of grade *g* has more variability in it than the operating strength deviation of grade *g'*, than grade *g*'s operating strength deviation should be weighted more than the operating strength deviation of grade *g'*. A very important measure with a high variation in its range will be assessed a higher weight than a very important measure with low variation in its range.

		Level of Importance of the Value Measure		
		Very Important	Important	Less Important
Variation in Measure Range	High		O-4	O-6
	Medium			O-5
	Low	Company Grade		

Table 32 Swing Weight Matrix for Grade Deviations in AMEDD Operating Strength Deviation

There is the least amount of variability in the number of company grade officer deviations between the two solutions found by varying the weight or importance of AMEDD operating strength deviation. Regardless of the weighting, the linear program solution produces a manpower system with minimal operating strength deviation in the company grade rank. Hence, the company grade officer deviations are assessed as having low variability and are placed in the lowest row in Table 32. On the other hand, Figure 24 suggests that the company grade officers make up the largest portion of AMEDD officer system and the number of company grade officer deviations is very important to the overall AMEDD operating strength deviation. O-6 officer deviations are assessed as having the greatest amount of variability but being the least important to the overall AMEDD operating strength deviation because O-6 officers only make up 8% of the entire AMEDD officer population.

In order to translate the relationships in Table 32 to a set of weights, some basic relationships must hold. The weights assigned to a particular measure should decrease as we move diagonally from the upper left hand corner of the matrix to the lower right hand corner of the matrix. The weight, here we use a value between 0 – 100, assigned to measure *A* must be greater than all of the other weights assigned to the other measures. B_1 must be greater than all of the measures except for A and B_2.

		Level of Importance of the Value Measure		
		Very Important	Important	Less Important
Variation in Measure Range	High	A	B_2	C_3
	Medium	B_1	C_2	D_2
	Low	C_1	D_1	E

Table 33 Swing Weight Relationships and Consistency

The following rules must apply to the weights assigned to all of the components in Tables 34 and 35.

$$A > \text{all other cells}$$
$$B_1 > C_1, C_2, D_1, D_2, E$$
$$B_2 > C_2, C_3, D_1, D_2, E$$
$$C_1 > D_1, E$$
$$C_2 > D_1, D_2, E$$
$$C_3 > D_2, E$$
$$D_1 > E$$
$$D_2 > E$$

Equation 34 Strict Relationships for Assignment of Swing Weights

<table>
<tr><td colspan="2"></td><td colspan="3">Level of Importance of the Value Measure</td></tr>
<tr><td colspan="2"></td><td>Very Important</td><td>Important</td><td>Less Important</td></tr>
<tr><td rowspan="3">Variation in Measure Range</td><td>High</td><td></td><td>O-4
60</td><td>O-6
25</td></tr>
<tr><td>Medium</td><td></td><td></td><td>O-5
15</td></tr>
<tr><td>Low</td><td>Company Grade
90</td><td></td><td></td></tr>
</table>

Table 34 Swing Weight Matrix for Grade Deviations in AMEDD Operating Strength Deviation

Table 33 captures the relationship between the variation and importance of our measures but also now has a weight in each cell to represent how important each measure is to minimizing the AMEDD operating strength deviation. Minimizing the operating strength deviation of company grade officers is assigned the highest weight because 51% of the officers in the system are company grade offices. The operating strength deviation of O-4 officers gets the second highest weighting. There is a large amount of variability in the number of O-4 officer deviations when we vary the weighting of our two scenarios and O-4 officers make up 28% of the AMEDD officer population. The operating strength deviation of O-5 officers is assigned the least amount of weight based on its medium variability and the smaller percentage of officers in the AMEDD officer population.

The weights in Table 33 are normalized to a weight between 0 and 1, by dividing each entry by the sum of all the entries in Table 33. Table 35 shows the calculation of α_g, the weight associated with AMEDD operating strength deviations in grade g. These weights will be used for all of the grade deviations in Objective 1.0. For example, the amount of weight assigned to company grade officer deviations in t = 1 is equal to the amount of weight assigned to company grade officer deviations in t = 7. This assumption is made because we considered the time series of operating strength deviation when assigning weights to the grade operating strength deviations. In the next section, we will describe how we determined weights associated with the seven different time periods.

Grade	Weight	$\alpha_g = \frac{Weight_g}{\sum_g Weight_g}$
Co_Grade	90	47%
O-4	60	32%
O-5	15	8%
O-6	25	13%
Total, Sum of Weights	190	100%

Table 35 Normalization of Swing Weights for *g* Grade

6.4.2 SWING WEIGHT MATRIX – AMEDD OPERATING STRENGTH DEVIATION AND TIME PERIODS

The swing weight methodology also helps to determine how weights should be assigned to the seven different time periods. As we did to assess the weights for different grades, we solved the global linear program described in Chapter 5 to find the resulting manpower system for two scenarios. In the first scenario, all of the weight in the multi-objective objective function is placed on minimizing the AMEDD operating strength deviation, at the expense of ignoring the weighting of the other objective function components. In the second scenario, none of weight is placed on minimizing the AMEDD operating strength deviation, and it is equally distributed among the three other objectives.

t Time periods	$\alpha = 0$	$\alpha = 1$	Range
1	959.7	907.8	51.8
2	831.4	685.5	146.0
3	854.3	567.3	287.0
4	809.7	425.4	384.3
5	812.6	357.9	454.7
6	253.0	92.0	161.0
7	266.9	77.4	189.6

Table 36 AMEDD Operating Strength Deviation from t = 1 to 7

Table 36 shows that the most variability in the AMEDD operating strength deviation occurs when the range between the operating strength deviations for the two scenarios is greatest. The greatest amount of variability is in periods $t = 4$ and 5. The importance of each of the measures is assessed in a more subjective manner. The principles or guiding objectives are that the AMEDD manpower system wants to improve sooner than later and the system is willing to trade off immediate improvements to short planning horizon time periods, like $t = 1$ and 2, for improvements in the middle time periods, $t = 3,4,5$. Improvements in these time periods are early enough in the planning horizon to be able to provide more immediate benefit to the system rather than delaying all benefits and improvements till the end of the planning horizon. But considering the midterm time periods as more important than the earlier measures, prevents the model from optimizing the system in the near term at the expense of the future well-being of the system.

		Level of Importance of the Value Measure		
		Very Important	Important	Less Important
Variation in Measure Range	High	3,4 100	5 75	
	Medium		6 50	7 40
	Low		2 25	1 10

Table 37 Swing Weight Matrix for AMEDD Operating Strength Deviation Across Planning Horizon

Time Periods	Weight	$\alpha_t = \frac{Weight_t}{\sum_t Weight_t}$
1	10	3%
2	25	6%
3	100	25%
4	100	25%
5	75	19%
6	50	13%
7	40	10%
Total, Sum of Weights	400	100%

Table 38 Normalization of Swing Weights for t Time Periods

As we did for assigning weights to the grade deviations, all relationships in Equation 34 are maintained to ensure consistency of the weighting scheme. Time periods $t = 3$ and $t = 4$ are assessed the greatest amount of weight. These two time periods have the third and second highest range in varying operating strength deviation across the two scenarios. These two time periods are also most important to improving the AMEDD operating strength deviation. Making improvements in these two time periods set a strong foundation for the overall well-being of the manpower system to be successful for the duration of the seven year planning model. The least amount of weight is assessed to the time period $t = 1$. There is low variability in the difference between the two scenarios and the linear program can only do so much in one time period to improve the manpower system. Real improvements come after a few years when the linear program has had an opportunity to optimize multiple time periods to improve the system.

6.4.3 Assigning Weights among Four Highest Objectives

As we assess weights among the sub objectives that support the accomplishment of the four objectives outlined in Figure 17 AMEDD Manpower System Value Hierarchy, we need to assess the weights among these four objectives. The two scenarios we have described that we used to calculate weights associated with the time periods and grade sub objectives that support Objective 1.0 are not be used in this case. We need to consider the four highest level objectives. A linear program is solved with each of the four objectives being equally weighted and Table 28 captures how each of the four objectives behaves over time.

Time	AMEDD Operating Strength Deviations	Corps Operating Strength Deviations	Hiring Deviations	Promotion Deviations
1	1,090.1	1,389.2	517.4	260.3
2	895.5	1,227.1	71.8	1,014.9
3	866.1	1,202.5	114.9	808.0
4	825.5	1,201.3	68.1	583.3
5	887.7	1,304.7	1.1	459.5
6	400.0	1,176.8	-	913.1
7	378.7	1,210.5	-	589.1
Average	763.4	1,244.6	110.5	661.2
Range	711.4	212.4	517.4	754.6

Table 39 Measures of Four Highest AMEDD Manpower System Objectives

The AMEDD operating strength deviation and the number of promotion deviations are the two measures with the greatest amount of variability. The two most important measures to the overall worth and value of the AMEDD manpower system are the AMEDD operating strength deviation and the corps operating strength deviations. These relationships are captured in the swing weight matrix for our four highest objectives.

		Level of Importance of the Value Measure		
		Very Important	Important	Less Important
Variation in Measure Range	High	AMEDD Operating Strength Deviation 100		Promotion Deviations 50
	Medium		Hiring Deviations 50	
	Low	Corps Operating Strength Deviation 95		

Table 40 Swing Weight Matrix Objectives 1.0 – 4.0

Objectives 1.0 to 4.0	Weight	$w_i = \frac{Weight_i}{\Sigma_i^4 Weight_i}$
AMEDD Operating Strength Deviations	100	34%
Corps Operating Strength Deviations	95	32%
Hiring Deviations	50	17%
Promotion Deviations	50	17%
Total, Sum of Weights	295	100%

Table 41 Normalization of Swing Weights for Objectives 1.0 to 4.0

Objectives 1.0 and 2.0 are assessed as having the greatest weights. AMEDD operating strength deviation has the largest amount of variability and has the greatest effect on achieving the fundamental objectives. The corps operating strength deviation, despite its low variability, is assessed as the second most important objective. This assessment is based on the importance to maintain healthy, valuable corps, corps that has minimal operating strength deviations in order to achieve the fundamental objective of Provide the US Army a medical department of officers is capable of meeting all Army directed and internal AMEDD manpower requirements.

6.4.4 Objective 1.0 and Sub Objective Weights

We introduced the parameter α_{tg}in Chapter 5 as the amount of weight placed on the AMEDD operating strength deviations per grade per time period. We are now able to assess those values for all time periods and grades.

$$\alpha_{tg} = Weight_1 * \alpha_t * \alpha_g$$

Equation 35 Calculating Sub Objective Weights

where *Weight*$_{1.0}$ = 0.34 from Table 41, α_t is obtained from Table 38, $\alpha_g$is obtained from Table 35.

		α_g			
$Weight_{1.0}$	0.34	Co_Grade	O-4	O-5	O-6
Time period *t*	α_t	47%	32%	8%	13%
1	3%	0.4%	0.3%	0.1%	0.1%
2	6%	1.0%	0.7%	0.2%	0.3%
3	25%	4.0%	2.7%	0.7%	1.1%
4	25%	4.0%	2.7%	0.7%	1.1%
5	19%	3.0%	2.0%	0.5%	0.8%
6	13%	2.0%	1.3%	0.3%	0.6%
7	10%	1.6%	1.1%	0.3%	0.4%

Table 42 Calculation of Weights Supporting Objective 1.0

Table 42 shows the weights for all 28 sub objectives that support the achievement of Objective 1.0. The maximum value for α_{tg} is $\alpha_{3,Company\ Grade}$ and $\alpha_{4,Company\ Grade}$

and they are both equal to 4%. This means that minimizing company grade deviations in time periods 3 and 4 contribute the most to the achievement of not only Objective 1.0, but more than any other combination of grade and time period deviations to the achievement of our fundamental objective.

Weights for the 168 sub objectives that support the achievement of Objective 2.0 were assessed also using the swing weight methodology. The global linear program was solved to optimize the corps operating strength deviation for each individual corps. The importance and variation of grade and time periods were assessed as before. Grade and time period variation was analyzed by studying how much variation there was in the measure, specifically the range between the highest deviations in a grade or time period and the lowest number of deviations in a grade or time period. The importance of the measure was measured by calculating what percentage of total deviations could be attributed to a particular grade *g* or time period *t*. Appendix A displays the 168 weights for the sub objectives that support the accomplishment of Objective 2.0, as well as weights for the remaining parts of the value hierarchy.

The weights for the seven individual sub objectives of Objective 3.0 are listed in Table 43 and Table 44 lists the weights for the 28 individual sub objectives for Objective 4.0. Weights for sub objectives supporting Objective 3.0 are calculated by the product of $\text{Weight}_{3.0}$ and β_t. Weights for sub objectives supporting Objective 4.0 are calculated by the product of Weight_4, κ_t, and κ_g.

Weight$_{3.0}$	17%	
Time period *t*	β_t	Weight$_3$ * β_t
1	7%	1%
2	7%	1%
3	11%	2%
4	19%	3%
5	19%	3%
6	19%	3%
7	19%	3%

Table 43 Calculation of Weights Supporting Objective 3.0

Weight$_4$	17%	κ_g			
		Co_Grade	O-4	O-5	O-6
Time period *t*	κ_t	42%	29%	21%	8%
1	16%	1.15%	0.81%	0.58%	0.23%
2	3%	0.18%	0.12%	0.09%	0.04%
3	13%	0.89%	0.62%	0.44%	0.18%
4	11%	0.80%	0.56%	0.40%	0.16%
5	13%	0.89%	0.62%	0.44%	0.18%
6	25%	1.77%	1.24%	0.89%	0.35%
7	20%	1.42%	0.99%	0.71%	0.28%

Table 44 Calculation of Weights Supporting Objective 4.0

In the following chapter, we will apply the value scoring methodology and swing weighting technique described here to the linear program developed in Chapter 5. The linear program described in the next chapter will also use the weights assesses in this chapter so that the maximization of those sub objectives that is more important to the overall accomplishment of the overall AMEDD manpower system objective can be pursued more vigorously than other lesser important objectives. The linear program will find the optimal man power policy that maximizes the man power system's value score, rather than the practice of minimizing the operating strength deviation as we explored with earlier models.

7. Maximizing the Value Score of the AMEDD Manpower System

In this chapter, we will apply the value scoring methodology and swing weighting technique described in the previous chapter to the linear program developed in Chapter 6. That linear program was programmed and formulated to minimize the overall AMEDD operating strength deviation for all grades, the operating strength deviation for all grades for each of the six individual AMEDD corps, and to minimize both the smoothing factors for officer hires and promotions. The value scoring methodology allows us to convert the number of deviations in each of these objectives to a value score that ranges from 0 to 100. Zero deviations in any term will relate to a value score of 100. Therefore, the linear program described in this chapter will be programmed to maximize the value score of the AMEDD manpower system. The linear program described in here will also use the weights assessed in Chapter 7 so that the maximization of those sub objectives that is more important to the overall accomplishment of the overall AMEDD manpower system objective can be pursued more vigorously than other lesser important objectives.

7.1 Objective Function

The objective function for the linear program described in this chapter is to maximize the value score of the AMEDD manpower system. As in the linear program described in Chapter 5, a set of constraints is used to calculate the following inventory deviations, the deviations between the required number of officers and the actual number of officers in the manpower system and the deviation between the number of officers hired and promoted each year.

$pos\ AMEDD\ dev_{tg}$	$neg\ AMEDD\ dev_{tg}$
$pos\ dev_{t,corps,g}$	$neg\ dev_{t,corps,g}$
$pos\ dev\ hires_{t,a,y,g}$	$neg\ dev\ hires_{t,a,y,g}$
$pos\ dev\ prom_{t,a,y,g}$	$neg\ dev\ prom_{t,a,y,g}$

Table 45 Inventory Deviations

In Chapter 5, our objective was to minimize the sum of these deviations. Here we apply the value scoring methodology from Chapter 6. We calculate the number of deviations as described in Chapter 5 using the inventory control constraints. We also calculate the number of deviations between the total number of officers hired year to year and the number of officers promoted in each grade, year to year.

The new objective function takes into account the work described in Chapter 6. First, the objective function will serve as the value score transformation functions. The objective function is still a function of the deviations in Table 45, but we use the value function parameters to transform the deviations to value scores. Second, we add the 231 objective function weights developed in Chapter 6 to the new linear program. The objective function of the linear program described in Chapter 5 has four components. We will describe each component here and how it is transformed from a minimization of total deviations to a maximization of value score for each component. We also include the weights associated with each of the four components and its sub components.

7.2 AMEDD Operating Strength Deviation

Objective 1.0 is to minimize AMEDD operating strength deviation over the seven year planning horizon. This objective has 28 sub objectives, one for each of the seven time periods and one for each of the four officer grades. α_{tg} represents the weights associated with these 28 sub objectives. The slope of the linear value function is determined as described in Chapter 6. The intercept term for the value function is 100 - if there are zero deviations for a particular grade during a time period, than it provides the maximum amount of value to the overall objective function.

Grade *g*	Slope, ε_g
Company Grade	-0.78
O-4	-0.14
O-5	-0.29
O-6	-0.59

Table 46 Slope of Value Function for AMEDD Deviations in Grade *g*

The following equation is used to calculate the value score associated with deviations between the total number officers in grade *g* in time period *t* in the manpower system and the total number of officers required. ε_g is the slope of the value score function and represents how much the value score changes when the number of deviations in the manpower system increases by one unit.

$$Value\ Score\ AMEDD\ Deviations_{tg} = \epsilon_g\left(pos\ AMEDD\ dev_{tg} + neg\ AMEDD\ dev_{tg}\right) + 100\ \forall t, g$$

Equation 36 Convert AMEDD Operating Strength Deviation to Value Score

Equation 36 is used to calculate the value score for the 28 sub objectives associated with Objective 1.0. It is used in the objective function for the linear program that maximizes the value score of the AMEDD manpower system along with the weights, α_{tg}, for the 28 sub objectives in Objective 1.0. The Objective 1.0 terms in the objective function, with assigned weights are –

$$Maximize \sum_{tg} \alpha_{tg} (\epsilon_g (pos\ AMEDD\ dev_{tg} + neg\ AMEDD\ dev_{tg}) + 100)$$

Equation 37 Maximize AMEDD Manpower System Objectives - AMEDD Deviations

In this equation, we sum the decision variables that are indexed by *t* and *g* over all time periods and grades and the result is a scalar term, as in all of the subsequent objective function terms described in this section

.

7.3 Corps Operating Strength Deviation

Objective 2.0 is to minimize each individual corps operating strength deviation over the seven year planning horizon. This objective has a total of 168 sub objectives – there are six corps, seven time periods, and four officer grades (6 * 7 * 4 = 168). In chapter 6, we developed the slopes for the value functions associated with converting grade deviations in each corps between the numbers of officers on hand and the required number of officers. Equation 38 calculates the value score for the number of deviations in a corps per grade *g* in time period *t*. $\phi_{corps,g}$ is the slope of the value score function and represents how much the value score changes when the number of deviations in the manpower system is increased by one unit. The slope remains constant for the couplet *corps,g* across the entire time horizon.

$$Value\ Score\ Corps\ Deviations_{t,corps,g} = \phi_{corps,g} (pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}) + 100\ \forall t, corps, g$$

Equation 38 Convert Corps Operating Strength Deviation to Value Score

Equation 38 is also a component of the Objective 2.0 terms in the linear program's objective unction to maximize the overall value score of the AMEDD manpower system. Specifically, the Objective 2.0 terms are –

$$Maximize\ \Sigma_{t,corps,g}\gamma_{t,corps,g}(\phi_{corps,g}(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}) + 100)$$

Equation 39 Maximize AMEDD Manpower System Objectives - Corps Deviations

7.4 HIRING SMOOTHING FACTOR

Objective 3.0 is to minimize the deviations between the total number of officers hired in one time period t and the number of officers hired in time period t + 1. This objective has seven sub objectives, one for each time period *t*. β_t represents the weight associated with these seven sub objectives. The slope of the linear value function converting the number of hiring deviations is described in Chapter 6. The intercept term for the value function is 100 – if there are zero deviations between the numbers of officers hired between two time periods than the manpower system is afforded the maximum value score of 100. η is the slope of the value function that converts the number of hiring deviations into a value score.

$$Value\ Score\ Hiring\ Scaling\ Factor_t = \sum_{ayg} \eta(pos\ dev\ hires_{t,a,y,g} + neg\ dev\ hires_{t,a,y,g}) + 100 \quad \forall\ t$$

Equation 40 Convert Hiring Smoothing Factor to Value Score

Equation 40 is used to calculate the value score for the seven sub objectives associated with Objective 3.0. It is also used in the objective function for the linear program that maximizes the value score of the AMEDD manpower system along with weights β_t. The Objective 3.0 terms in the objective function, with assigned weights that maximize the overall value score of the AMEDD manpower objective function are described in Equation 41.

$$Maximize \sum_{t,a,y,g} \beta_t(\eta(pos\ dev\ hires_{t,a,y,g} + neg\ dev\ hires_{t,a,y,g}) + 100)$$

Equation 41 Maximize AMEDD Manpower System Objectives – Hiring Smoothing Factor

7.5 PROMOTION SMOOTHING FACTOR

Objective 4.0 is to minimize the deviations between the total number of officers promoted in one time period *t* and the number of officers hired in time period *t* + 1. This objective has 28 sub objectives, one for each time period *t* and one for each grade *g*. $\kappa_{t,g}$ represents the weight associated with these 28 sub objectives. The slope of the linear value function converting the number of promotion deviations is described in Chapter 6. The intercept term for the value function is 100 – if there are zero deviations between the numbers of officers promoted between two time periods than the manpower system is afforded the maximum value score of 100. μ is the slope of the value function that converts the number of promotion deviations into a value score.

$$Value\ Score\ Promotion\ Scaling\ Factor_{tg} = \sum_{ay} \mu_{tg}\big(pos\ dev\ prom_{t,a,y,g} + neg\ dev\ prom_{t,a,y,g}\big) + 100\ \forall t,g$$

Equation 42 Convert Promotion Smoothing Factor to Value Score

Equation 42 is used to calculate the value score for the 28 sub objectives associated with Objective 4.0. It is also used in the objective function for the linear program that maximizes the value score of the AMEDD manpower system along with weights κ_{tg}. The Objective 4.0 terms in the objective function, with assigned weights that maximize the overall value score of the AMEDD manpower objective function are described in.

$$Maximize \sum_{t,a,y,g} \kappa_{t,g}(\mu_g(pos\ dev\ prom_{t,a,y,g} + neg\ dev\ prom_{t,a,y,g}) + 100)$$

Equation 43 Maximize AMEDD Manpower System Objectives – Promotion Smoothing Factor

7.6 MAXIMIZING THE AMEDD MANPOWER SYSTEM OBJECTIVE FUNCTION

If we combine the terms in Equations 32, 34, 36, 38, we obtain the objective function for the AMEDD manpower value function linear program. This aggregate equation converts deviations and smoothing factors from our four objectives into value scores between 0 – 100 and multiplies the value score for each sub objective by the weights assessed in Chapter 6. Our linear program will seek to maximize this function subject to the same constraints described in Chapter 5. Because of the nature of the weights, the final value score for the entire AMEDD manpower system will also be a number between 0 and 100.

$$\sum_{tg} \alpha_{tg}(\epsilon_g(pos\ AMEDD\ dev_{tg} + neg\ AMEDD\ dev_{tg}) + 100) +$$
$$\sum_{t,corps,g} \gamma_{t,corps,g}\left(\phi_{corps,g}(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}) + 100\right) +$$
$$\sum_{t,a,y,g} \beta_t(\eta(pos\ dev\ hires_{t,a,y,g} + neg\ dev\ hires_{t,a,y,g}) + 100) +$$
$$\sum_{t,a,y,g} \kappa_{t,g}(\mu_g(pos\ dev\ prom_{t,a,y,g} + neg\ dev\ prom_{t,a,y,g}) + 100) +$$

Equation 44 AMEDD Manpower System Value Function

7.6.1 Solving the Value Score Linear Program

Maximizing Equation 44 builds a manpower system that provides the manpower system with the greatest value and best attains the fundamental AMEDD objective of providing the US Army a medical department of officers capable of meeting all Army directed and internal AMEDD manpower requirements. The set of hiring policies, promotion policies, and the number of officers to transfer from one area of concentration results in this optimal manpower system. The optimal value for score for the AMEDD manpower system using the weights developed and described in Chapter 6 has a value score of 71.6. Figure 25 shows the contribution of each of the four objectives to the overall value score of the AMEDD manpower system. The hiring smoothing factor provides the most unweighted value, which is its value score is 93.3 before accounting for the relative importance of the hiring smoothing factor. The sum of all of the corps deviations, Objective 2.0, has the lowest unweighted value score. When the weights of each objective are considered, Objectives 1.0 and 2.0, the two highest weighted objectives make the greatest contribution to the overall AMEDD value score.

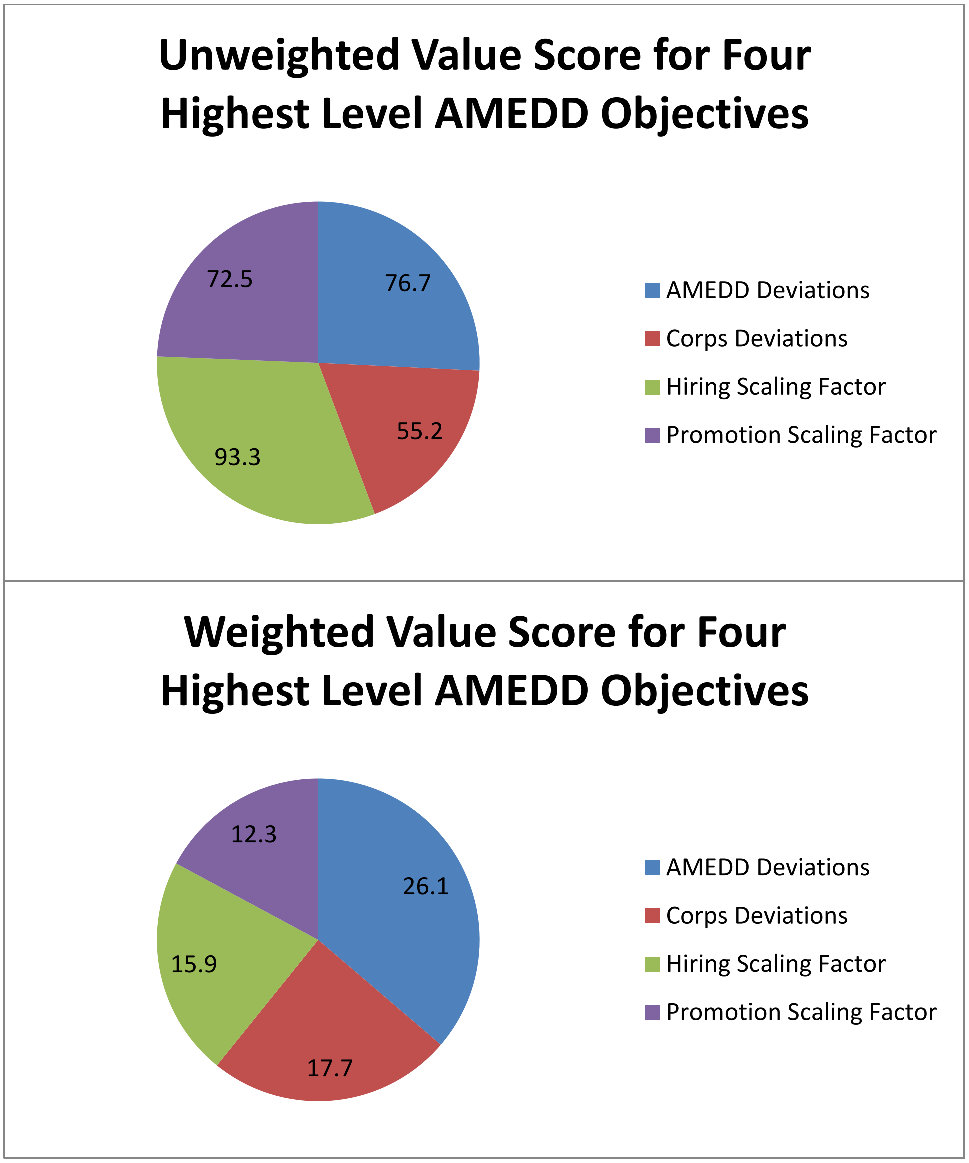


Figure 25 Contribution of Objectives 1.0 to 4.0 to AMEDD Value Score

7.7 Analysis of Four Scenarios

In order to further analyze the solution developed by finding the optimal manpower value score, we consider the optimal manpower system under four different conditions. The first scenario is the one described in the beginning of this section. We maximize Equation 44, the weighted sum of the manpower system value functions. The second scenario is also based on Equation 44 – we maximize the sum of the manpower value score function, but we treat all 231 sub objectives equally and do not use the weights developed in Chapter 6 to give some sub objectives that chance to contribute more to the overall objective function. Scenario 3 ignores Objectives 2.0 thru 4.0 – we only wish to maximize the sum of the AMEDD operating strength deviations. Lastly, Scenario 4, similar to Scenario 3, only considers maximizing the sum of the corps operating strength deviations. Scenario 3 can be considered as the optimal AMEDD level solution, but it sacrifices the performance of the corps manpower systems. Scenario 4 sacrifices the AMEDD level objective and ignores it while it only seeks to maximize Objective 2.0. By studying these four scenarios, we are able to gain a better understanding of the true value, or of the lack of value, of some of the solutions that may appear to be optimal at first glance and we can see how well these optimal solutions developed from different models perform relative to the value scoring hierarchy developed in Chapter 6.

The objective function of the linear program was modified to in accordance with the description of the four scenarios. As expected, Scenarios 1 and 2 perform the best in terms of overall AMEDD value score. Scenario One is able to achieve a higher value score than Scenario 2 because some sub objectives are that are more important to the overall value of the system are weighted more heavily. Scenarios 3 and 4 perform poorly in terms of the overall AMEDD value score. These two objective functions for these two scenarios only optimize one individual higher level objective and the scenarios perform poorly with regards to the unweighted objectives.

Scenario 3 performs the best in terms of minimizing the AMEDD deviations. Scenario 3 has over 100 less deviations in the AMEDD operating strength compared to Scenario 1. However, because we calculated the value score for both scenarios, we know that those 100 less deviations in Scenario 3 come at a very significant cost, a cost of 56 value score points. Although the objective used in Scenario 3 might be attractive to some manpower analysts or decision makers, our technique of calculating the value score for each scenario now describes how costly the Scenario 3 solution can be to the overall AMEDD system.

Scenario 4 is very similar to Scenario 3. It may appear to be an attractive solution because it minimizes some of the individual corps operating strength deviation scores, but it does not perform better than Scenario 1 with regards to the Army Medical Specialist Corps and the Medical Services Corps, two of the larger AMEDD corps. Scenario 4 improves the operating strength deviation of four of the six corps relative to Scenario 1, but like Scenario 3, there is a very significant cost in value score. The difference between the two value scores for Scenarios 1 and 4 is 42.8.

	Scenarios			
	1	2	3	4
Value Score	71.6	65.2	15.3	28.8
AMEDD Operating Strength	184.9	287.9	77.4	266.9
AMSC Operating Strength	50.1	58.2	85.5	64.0
DC Operating Strength	410.9	388.8	595.7	378.4
MC Operating Strength	433.1	360.8	506.7	232.6
MSC Operating Strength	38.9	6.9	270.9	40.1
NC Operating Strength	171.9	152.3	326.6	0.0
VC Operating Strength	25.7	30.1	69.1	20.9

Scenarios
1 - Sum of Weighted Value Score
2 - Sum of Equally Weighted Value Score
3 - Maximize Objective 1.0
4 - Maximize Objective 2.0

Table 47 Value Scores and Other Descriptive Statistics from Scenario Analysis

Table 47 shows the total AMEDD value score for each of the four scenarios as well as the actual operating strength deviation for the entire AMEDD system and for each of the six corps. The two most important columns are Scenarios 1 and 2. Since we have weighted Objective 1.0 higher than Objective 2.0, we would expect the number of AMEDD Deviations to be lower in Scenario 1 than in Scenario 2 when we are weighing all objectives equally. Table 48 shows that Scenario One dominates Scenario Two in only three of the metrics included in the table. Specifically, Scenario 1 is better than Scenario 2 in terms of Value Score, AMEDD Operating Strength Deviation, Army Medical Specialist Corps Operating Strength Deviation, and Veterinary Corps Operating Strength Deviation. Scenario 2 is better in terms of the four other corps in terms of 146 deviations. Our value scoring methodology can now help us to understand the true cost of these 146 deviations. It equates to a loss of overall value of 6.4 value points or 0.44 value score points per deviation.

Metrics	Δ between Scenarios 1 and 2
Value Score	-6.4
AMEDD Operating Strength	-103.0
AMSC Operating Strength	-8.1
DC Operating Strength	22.1
MC Operating Strength	72.3
MSC Operating Strength	32.0
NC Operating Strength	19.6
VC Operating Strength	-4.4

Table 48 Further Comparison of Scenarios 1 and 2

7.8 CONCLUSION

The value scoring methodology has allowed us to construct a manpower system that optimizes the overall AMEDD system not just one portion of it. It has also allowed us to develop weights in a consistent, analytical manner that allows decision makers and analysts to discriminate between the many objective function components, something we would not have been able to do if we tried to compare the terms subjectively. This methodology also allows us to compare the worth and well-being of each of the corps to each other. Instead of just comparing the operating strength deviation of each corps to each other, we know have a tool we can use to compare the corps more precisely. The value score provides a more holistic view of all the objectives the corps must satisfy. This same tool can be used to compare the AMEDD manpower system to other Army manpower systems. One likely scenario to consider is an Army level manpower manager who has to allocate resources to maintain an acceptable level of operating strength in many different specialties. A value score methodology like described here could be used to improve the analysis and comparison of different career fields that perform very different missions.

The next chapter presents another modeling approach to the AMEDD manpower model. The AMEDD manpower system is modeled in a system dynamics simulation model. This sets a foundation for developing a simulation that updates officer continuation rates based on internal and external environment feedback. System dynamics ability to model the flow of material and the effect feedback loops on the flow makes it an excellent platform to model manpower systems like this one.

8. System Dynamics Model of the AMEDD Officer Manpower System

8.1 Introduction

The purpose of this chapter is to describe the formulation and design of a system dynamics model of the AMEDD officer manpower system. This model will combine the two models we have previously discussed and it has two phases. In phase one; the system dynamics model will build the objective force, the distribution of officers across their 30 years of service that minimizes the AMEDD operating strength deviation. In phase 2, the model will then simulate the objective force's performance and how the manpower system's operating strength deviation behaves over time. The system dynamics model will simulate changes and updates to the officer continuation parameters. The changes will be based on external and internal factors and will create a system of feedback where the worth or value of the manpower system will actually influence how well the manpower system performs in future time periods. This chapter begins with a description of the purpose of this model and why system dynamics simulation was chosen to model the manpower system. This chapter will also include why this model can be an improvement to the optimization models discussed in the previous chapters. Lastly, this chapter will discuss the results obtained from the AMEDD manpower system dynamics model.

8.2 System Dynamics Model Purpose

The linear program developed in Chapter 4 modeled the optimal way to distribute officers across the thirty years of service they can remain in the system to best meet the manpower system requirements. The linear program in Chapter 4 tells manpower analysts the optimal distribution of officers across the manpower system. For example, say the optimal number of officers in grade *g*, in the optimal solution of the Chapter 4 model is $inventory_g$. It is essential that the quantity of officers, $inventory_g$, is optimally distributed over the years of service that officers spend in the manpower system in grade *g*. If the distribution of officers, $inventory_g$ is too skewed towards higher years of service, than a larger percentage of officers than required will be eligible for promotion to grade *g+1*, possibly leaving a shortage of officers in the current grade *g*. It is important to consider this optimal distribution, but it does not lend itself to understanding how to manage the actual inventory of officers in the manpower system.

The linear program developed in Chapter 5 manages this actual inventory of officers in the manpower system. The optimization model determines the optimal manpower decisions to minimize the operating strength deviation, and can be modeled as we developed in Chapters 6 and 7, to include multiple manpower system objectives, not just minimizing the AMEDD operating strength deviation. But this model is dependent on the static continuation rates, the predictors of the percentage of officers that will remain in the system from one year to the next.

A more realistic model of the AMEDD, and any other manpower, system would model how the optimal distribution of officers in the system performs in terms of AMEDD manpower objectives and individual corps objectives. A better model of the AMEDD manpower system would include a method to update continuation rates. Continuation rates are influenced not only by external factors, but by internal factors as well.

The system dynamics model developed here models the performance of the AMEDD objective force. Phase one of our system dynamics model will last thirty years. During phase one, the model will populate each inventory stock in the manpower system with the optimal number of officers that minimizes the AMEDD operating strength deviation. The second phase of the model will include feedback loops that will update officer continuation rates. The system dynamics model will explain how well the set of optimal manpower decisions performs in an environment where continuation rates are a function of the manpower system and the environment itself. The model provides insights not available from our previously discussed optimization models. The system dynamics model will provide manpower analysts a better understanding of the effect that shortages and excesses in the manpower system have on the behavior of officers and their decision to remain in the service from one year to the next. The system dynamics model also provides a technique to use multiple, updated estimates of continuation rate, something that optimization models do not do.

In our optimization models, we modeled the flow of officers in the AMEDD manpower system and the flow of the officers from one inventory state to a successive inventory state using conservation of flow constraints in the linear program. This conservation of flow constraint ensures that all officers progressed or flowed through the manpower system each year or they exited the system due to personnel attrition.

The optimization models' many parameters included the number of officers required to be in the manpower system by grade and area of concentration. The most important parameter with respect to the flow of officers from one year to the next, from inventory state (a,y,g) to the subsequent inventory state $(a,y+1,g)$, is the continuation rate. The continuation rate is the historical average of the percentage of officers in inventory state (a,y,g) who remain in the inventory system to the subsequent inventory state $(a,y+1,g)$.

8.3 Model Formulation and Design

This section will discuss the formulation and design of the AMEDD manpower system in a system dynamics modeling software system, Vensim. The objective function in the simulation is, as with the optimization models in Chapter 5, to build an AMEDD manpower system with a minimal operating strength deviation. The Vensim model has limited optimization capabilities and these will not be used in this model. Therefore, the optimal decision variables from the optimization models must be incorporated into the simulation model. Specifically, the optimal decision variables from the optimization models in Chapter 5, are inputs to the Vensim model. These inputs define the amount of flow between the model's inventory stocks.

The system dynamics model will consist of two phases. Phase one has a time horizon of thirty years. This will allow the optimal work force structure to be built, to grow, and to flow into all inventory stocks. Phase two of the model will last 15 years. There is the opportunity to increase the length of the planning horizon without significant computational cost.

8.3.1 Stocks

In our optimization models, each officer was assigned to a state (*a,y,*g). Officers could be fully defined and described by their state. In the system dynamics model, there exists an inventory bin, or in system dynamics parlance, a stock, for each inventory state. Each inventory state (*a,y,g*) is represented in the system dynamics model as a stock. These inventory stocks will change over time, each time period. The number of officers in each inventory stock depends on the number of officers in previous time periods and the flow of officers into that inventory stock and out of that inventory stock. These stocks increase and decrease based on the number of officers in the stock as well as the other variables that influence the rate of flow in and out of the stock.

The Vensim modeling guide defines mathematically the level of a stock as the solution to the following equation. The flows will determine how much the inventory level changes from time period to time period. The simulation model treats time as continuous, which explains the use of the integral to calculate the stock level, compared to the optimization model where time was discrete.

$$Inventory\ Level\ Stock\ (a, y, g)_t = \int_0^t flows\ (a, y, g)_t dt$$

Equation 45 Inventory Level

Our model contains a total of 16,020 stocks. There is one stock for each of the inventory states; the pairing for each of the 89 areas of concentration, thirty years of service officers can remain in the manpower system, and the six officer grades.

8.3.2 Flow of Officers

Officers flow or enter into each inventory stock by the same four methods described in the optimization models. For those stocks that are eligible, new officers are hired and enter into those eligible stocks. New hires come into the system and only enter O-1, O-2 and O-3 company grade officer inventory stocks. The optimization model that constructed the AMEDD objective force in Chapter 4 sets the level of new hires. We are hiring the optimal of officers that will, as they progress through the inventory system from time period to time period, construct the AMEDD optimal officer distribution.

The second component of officer flow is officer promotions. Officers that are eligible for promotion can advance from one inventory stock (*a,y',g*) to the inventory stock (*a,y'+1,g+1*). The requirement on *y'* is that the officer must have enough years in service to be eligible for the next promotion. As we did for the hiring component of officer flow, the optimal promotion rates from the Chapter 4 optimization model are inputted into the system dynamics model as serve as the promotion rates to build the AMEDD optimal officer distribution.

The third component of officer flow is the flow of officers from one area of concentration, or military specialty, to another. Many of the areas of concentration, usually specialized fields, do not hire new officers, but receive officers from other areas of concentration. For example, dentists who enter the AMEDD manpower system are all assigned as general dentists and transfer to more specific specialties during their career. Again, the AMEDD optimal officer distribution provides us with the optimal transfer rates to ensure that each area of concentration in the AMEDD manpower system receives its optimal flow of officers.

The fourth and the last component of officer flow is the flow of officers from one year to the next year in the manpower system. Each year officers flow or continue in the system from one inventory stock (*a,y,g*) to the next successive inventory stock, (*a,y+1,g*). The continuation rate models the percentage of officers that flow from inventory stock (*a,y,g*) to the next successive inventory stock, (*a,y+1,g*). The continuation rate is a model parameter in both the optimization and system dynamics models.

We now expand Equation 45 and add additional detail to the term officer flow based on our description of the four components of officer flow.

$$\begin{aligned} &Inventory\ Level\ Stock\ (a,y,g)_{\ t} \\ &\qquad = \int_0^t (hires_t(a,y,g) + promo_t(a,y,g) + \ trans_t(a,y,g) \\ &\qquad + \ cont\_rate(Inventory\ Level\ Stock_{t-1}(a,y-1,g))\ dt \end{aligned}$$

Equation 46 Expanded View of Officer Flow

The four components of officer flow are explicit in the description of Equation 46. The number of officers hired is a constant. The manpower system each year is able to take in the optimal number of officers into the system. In Equation 46, we simplify the expression for the number of officers promoted and the number of officers transferred. The number of officers promoted to inventory stock (*a,y,g*) is a function of the number of officers that were in the inventory stock (*a,y'-1,g-1*) where *y'* is a year officers are eligible for promotion and the optimal promotion rate. The optimal promotion rates for all grades were one of the outputs from the Chapter 4 optimization models. Recall, we were able to make linear the optimization model by transforming the promotion constraints from nonlinear constraints, where we had the product of two decision variables, the number of officers in an eligible promotion state and the optimal promotion rate. The linear model determines the optimal number of officers to be promoted, considering the promotion rate's upper and lower bounds.

We calculated the number of officers transferred from one area of concentration to another in a very similar manner. Equation 46 contains the component of officer transfers. The number of officers transferred to inventory stock (*a,y,g*) is a function of the number of officers that were in the inventory stock (*a',y-1,g*) where *a'* is an area of concentration that transfers officers to area of concentration *a*. The optimal transfer rates were obtained as the optimal promotion rates were from the Chapter 4 optimization models.

The fourth component of officer flow is the number of officers that continue in the system from one year to the next. The number of officers in a stock that remain in the manpower system is the product of the continuation rate for officers in that stock moving to stock (*a,y+1,g*) . The fraction of officers that do not remain in the system, the number of officers in a stock multiplied by the complement of the continuation rate, do not flow from inventory stock (*a,y,g*) to stock (*a,y+1,g*). Equation 46 represents how the system dynamics model conserves the flow of officers in the manpower system, similarly to how the conservation of flow constraints models maintained the flow of officers in the optimization models.

8.3.3 Model Parameters

The system dynamic model parameters include two types of officer continuation rates and as discussed when defining the flow of officers, the values for inventory levers. The continuation rates are the most interesting parameter in the model. The optimization model solutions are based on the assumption that the behavior of officers and the propensity to remain in the manpower system is going to remain as constant. In the system dynamics model, we can relax this assumption. We can model the manpower system in such a way that the continuation rate parameters will be updated. The model also includes the continuation rate for officers that are passed over for promotion.

The continuation rates are so interesting because, from a manpower policy perspective, this is the only place manpower system decision makers can look to in order to make improvements to the optimal distribution of AMEDD officers. Once the optimal policy has been implemented, the system cannot achieve a better value score. Other than changing the manpower system requirements themselves which is not likely a feasible manpower option, the continuation rates is an area that manpower decision makers can look to in order to minimize the operating strength deviation or as we did in Chapter 7, maximize the value score of the AMEDD manpower system. The system dynamics model provides the opportunity to make changes and updates to the continuation rate parameters and the modeling simulation provides us with an understanding of the effect these changes to continuation rates have on the overall value of the manpower system.

The system dynamics model also incorporates all of the manpower system requirements as parameters in the model. The manpower system requirements are indexed by area of concentration and grade. The simulation tallies the manpower power grade requirements for each of the six corps and for the entire AMEDD system. Besides the manpower requirements per specialty per grade, the system dynamics model includes the additional manpower system requirement parameters. For example, the model includes data about how many officer positions each corps has that are AMEDD immaterial, corps immaterial, and training, holding, and student positions. The sum of these requirements provides us with the target number of officers for each grade. The model will compare the number of officers in the inventory per grade to the target per grade to evaluate the worth or value of the manpower system.

8.3.4 Model Construction

One of the significant advantages the system dynamics simulation has over the optimization software is that Vensim allows you to create a visual representation of the manpower system. Using the Vensim graphical interface, we can draw and program the simulation at the same time. Each officer grade is represented by a stock. Another advantage of the Vensim modeling language is the ability to use subscripts and indexes as we did in the optimization model. Vensim will use the indexes areas of concentration, years of service, and grade. This allows us to use a stock for grade *g* and to define that stock to represent all officers in grade *g* regardless of area of concentration or years of service.

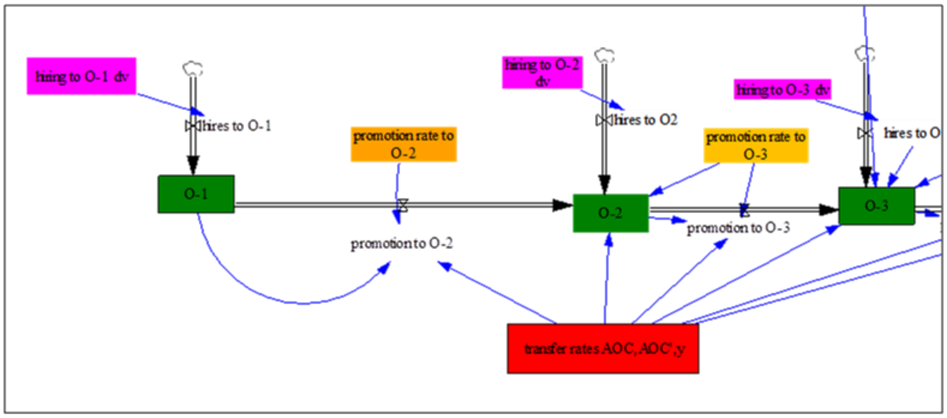


Figure 26 Snapshot of AMEDD Manpower Subsystem in Vensim

We see in Figure 26 a representation of a portion of the manpower system. The officer inventory stocks for grades O-1, O-2, and O-3 represent all officers in these grades, in all specialties and for all years of service. The Vensim equation editor permits the programming of multiple equations to define the flow of officers into different stocks within the same grade. Specifically, there are 105 equations in the O-3 inventory stock and 30 in the O-2 inventory stock. Recall, many of the areas of concentration do not start their area of concentration manpower sub system till the grade of O-3 captain.

Two of the four components of flow, officer hires and promotions are represented by arrows between officer stocks. The value for the level of the flow comes from a parameter representing the optimal level of flow. For example, in Figure 26, we see that the hiring to O-1 decision variable influences the level of the flow variable, hires to O-1. The hiring to O-1 variable has the suffix “dv” to remind us that the values for this variable in the system dynamics simulation are drawn from the optimization model decision variable values. The hires to O-1 flow variable sets the level of the flow equal to the values from the hiring to O-1 decision variable. The same relationship happens for the promotion flow variables shown in

The other two components of flow – the transfer of officers from one specialty to another and the continuation rate of officers are modeled with equations inside each of the inventory stocks using the previously mentioned subscript and index feature. This allows the model to have all of the necessary equations but the ease of being able to compartmentalize them inside the stocks these equations which are so frequent and prevalent in the model makes the graphical depiction of the model far simpler than if we had to show the flow for all transfers and all continuation values.

Another modeling advantage that Vensim provides users is the ability to create multiple views of the simulation. Figure 26 shows a subset of the manpower system. One view in the model contains the graphical representation of officer flow. A second view shows how the actual inventory of officers in the system is tallied. The model determines the value of the manpower system by comparing inventory to system manpower requirements and calculating the operating strength deviation of the system. A third view has all of the continuation rate parameters and is where we model the feedback loops where the system will influence the continuation rate parameters and the tools required to conduct our sensitivity analysis.

Even when the system dynamics model in Vensim is programmed using the graphical interface, Vensim begins to turn modelers' graphical inputs into integral equations that must be solved in order to determine the number officers in each inventory stock. Equation 47 is one example of the 14,154 level equations that need to be solved.

"O-3"[AMSC,year5]= INTEG (Continuation Rate O-3 Prime[AMSC,year5]"O-3"[AMSC,year4]*
-"O-3"[AMSC,year5],0) ~~|

Equation 47 Calculate the Stock of Inventory (AMSC, 5, O-3)

As depicted in Figure 26, the inventory levels are the actual officer grades. The optimization models kept track of the different officer grades with the index *g*. Here, we create an inventory stock for each grade. The term *AMSC* in *"O-3"[AMSC, year5]* refers to a subset of the 88 areas of concentration. The subset *AMSC* contains the six areas of concentration in the Army Medical Specialist Corps. The *year 5* refers to those O-3 captains that are in the Army Medical Specialist Corps that have been in the AMEDD manpower system for 5 years. In this example, there is only one component of officer flow. Officers flow into the inventory stock *O-3[AMSC,year5]* from the stock *O-3[AMSC,year4]*. To calculate the level of the flow, we multiply the continuation rate of officers from the previous inventory stock *O-3[AMSC,year4]* by the number of officers in that inventory stock. The system dynamics model uses the continuation rate parameter and the inventory stock level for *O-3[AMSC,year4]* to solve Equation 47

Before we begin to model updates to the continuation rate parameters, we demonstrate the system dynamic model constructed is identical to the optimization model in Chapter 4. By presenting these intermediate results, we demonstrate that the system dynamics model is a valid representation of the AMEDD manpower system. Using the optimal decision variables as input parameters to the system dynamics model, when we run the model for thirty years, for phase one, the AMEDD manpower system has the same operating strength deviation as the optimization model in Chapter 4. Each of the six corps has the same corps operating strength deviation as the corps operating strength deviation in the system dynamics simulation. The overall AMEDD operating strength deviation for the two models is equivalent as well. This equivalency check strengthens our assumption that the system dynamic model is an accurate, valid, representation of the AMEDD manpower system.

	Optimization Model	System Dynamics Model
AMSC Operating Strength Deviation	5.2	5.2
DC Operating Strength Deviation	304.0	304.1
MC Operating Strength Deviation	497.4	497.4
MSC Operating Strength Deviation	0.0	0.0
NC Operating Strength Deviation	0.0	0.0
VC Operating Strength Deviation	0.0	0.0
AMEDD Operating Strength Deviation	198.6	198.6

Table 49 Comparison of Optimization and System Dynamic Model Outputs

We know that no model is perfect, but Table 49 tells us that the system dynamics model in Vensim is as "good as" the optimization model at representing the manpower system. The system dynamic model accurately models the flow of officers from entry into the manpower system till the officers make it to the terminating inventory stock of having served in the system for 30 years. This completes the first phase of the simulation. Each inventory stock has the optimal number of officers in it in order to minimize the AMEDD operating strength deviation. We now can develop how we will model changes to the continuation rate parameters and how the changes will affect the manpower system, and how those changes to the manpower system will continue to affect the system continuation rates.

8.4 Modeling Updates to the Parameters of Interest

This section covers a two pronged approach to sensitivity analysis and feedback loops. These two prongs take advantage of the special aspects of system dynamic models and allow us to conduct what-if analysis and to understand how the system changes, when important parameters are varying. First, a description of how critical optimization model decision variables, which are treated as parameters in the system dynamics model and the system's continuation rates are varied to study the effect on the overall value of the manpower system. Second, the model is expanded to include feedback loops – how changes in the performance of the system at time t affect the performance of the system at $t+1$.

8.4.1 Sensitivity Analysis of Critical Parameters

The following parameters were identified as being the most critical. Two of them were decision variables from the optimization model – the number of officers to hire, the percentage of officers to promote. The other two are system parameters – the continuation rate of the officers from one year to the next and the number of officers required by grade for each specialty. The simulation is programmed to vary each of these four parameters plus or minus 10% of its original variable. For example, if the optimization model outputs said the optimal number of officers to hire into the AMSC65 specialty in the grade of O-1 Second Lieutenant was 40, then the simulation tested how the AMEDD operating strength deviation was affected by varying the number of hires from 36 to 44 officers.

How the sensitivity analysis was conducted for each of the four parameters is identical. For example, a new auxiliary variable called "Hiring Sensitivity Analysis" was included in the model. This is the value that was changed from 90% all the way to 110%. The "Hiring Sensitivity Analysis" variable does not directly affect the number of hires each year into the manpower system. There is a delay of 31 time periods or years. The purpose of this delay is that it allows all the inventory stock levels in the system to build to their optimal levels before the simulation begins to feel some perturbations. Once the delay time period is expired, then each hiring variable in the three company grade officer ranks for 46 areas of concentration is either augmented or depleted by the factor set by the "Hiring Sensitivity Analysis".

The three other parameters were modeled in a similar fashion and we will explore model results in after a discussion of how the Vensim system dynamics software could conduct the sensitivity analysis. The Sensitivity Simulation Set Up module in Vensim is a powerful sensitivity analysis tool that makes it possible to study the effects of varying many parameters on many different objective functions very quickly. As shown in Figure 27, the simulation will complete, in this case, a total of 21 iterations, varying "Hiring Sensitivity Analysis" from 0.9 to 1.1.

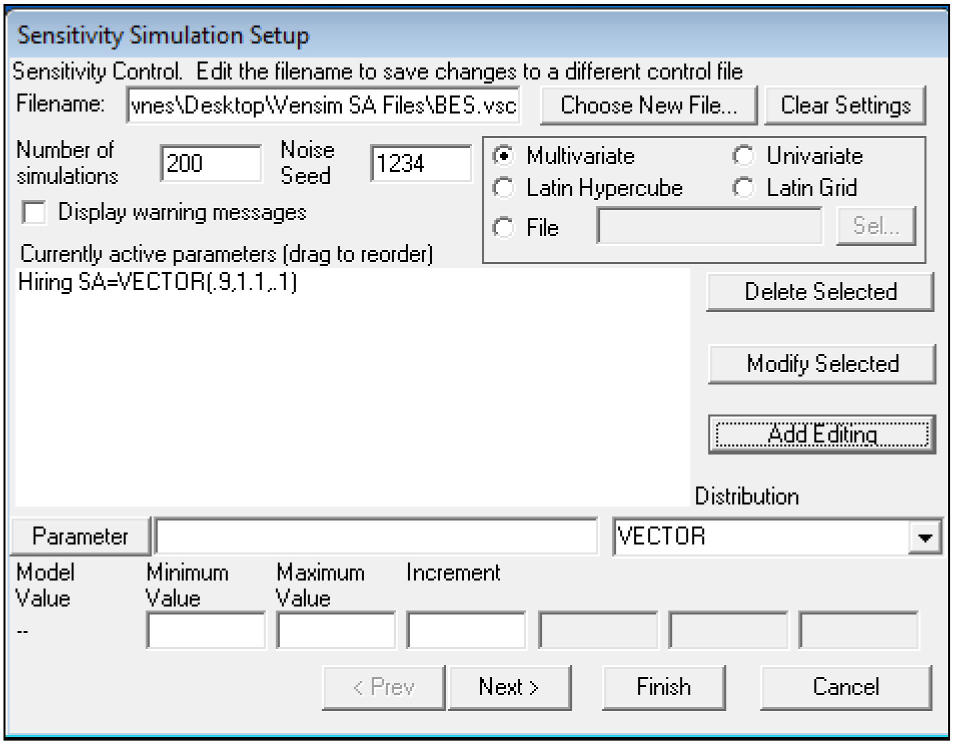


Figure 27 Sensitivity Simulation Setup Application

The Sensitivity Simulation Setup tool will collect data on requested system variables. In Figure 28, we see the second screen of inputs that are required to execute the sensitivity analysis. We will collect information about the AMEDD operating strength deviation as well as the operating strength deviation for six of the each corps. This ensures that Vensim will capture how the changes, in this case to the hiring variables, influence the variables that provide an indication of how well the manpower system is performing. The variables are examined independently. The simulation is run for varying levels of hiring policies, then varying levels of promotion policies, then the other aforementioned parameters.

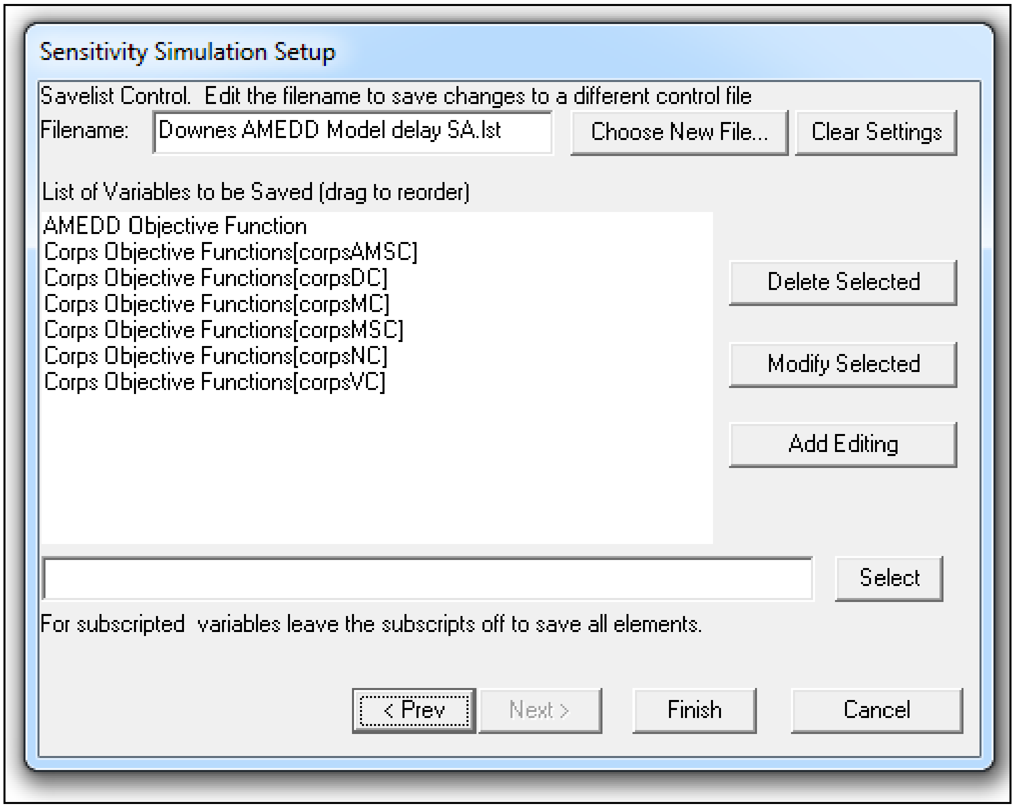


Figure 28 Sensitivity Simulation Setup

8.4.2 Sensitivity Analysis of Critical Parameters Results

The first parameter examined was variable hiring policies. Table 50 lists the upper bounds the hiring variables took on. All variables have zero as a lower bound. By varying the "Hiring Sensitivity Analysis" parameter between [0,2], we are searching over a very large parameter space. But since some of the optimal hiring variables are relatively small because the specialty does not have large personnel requirements, we examine a wide range of different hiring policies to understand better the relationship between the number of officers hired and the overall system objectives.

AOC	Grade	Optimal Hiring Value	Upper Bound
AMSC65A	O-2	7	15

AOC	Grade	Optimal Hiring Value	Upper Bound
MC61R	O-3	15	30

AOC	Grade	Optimal Hiring Value	Upper Bound
AMSC65B	O-1	26	52
AMSC65C	O-1	12	25
AMSC65D	O-2	48	96
AMSC65D	O-3	54	108
DC63A	O-3	88	176
MC60J	O-3	19	37
MC60K	O-3	6	12
MC60L	O-3	6	11
MC60N	O-3	14	29
MC60P	O-3	36	71
MC60S	O-3	6	11
MC60T	O-3	7	14
MC60V	O-3	6	13
MC60W	O-3	21	42
MC61F	O-3	56	111
MC61H	O-3	56	112
MC61J	O-3	20	40
MC61M	O-3	19	38
MC61P	O-3	4	9
MC61Q	O-3	1	1

AOC	Grade	Optimal Hiring Value	Upper Bound
MC61Z	O-3	2	4
MC62A	O-3	30	60
MC62B	O-3	32	65
MSC67E	O-3	13	25
MSC67F	O-3	13	26
MSC67G	O-3	1	3
MSC67J	O-1	52	104
MSC70B	O-1	131	262
MSC71A	O-3	3	7
MSC71B	O-3	4	9
MSC71E	O-3	7	14
MSC71F	O-3		14
MSC72A	O-1	11	22
MSC72B	O-1	3	6
MSC72C	O-2	3	6
MSC72D	O-1	17	34
MSC73A	O-2	21	42
MSC73B	O-3	12	23
NC66H	O-1	202	404
VC64A	O-3	38	75

Table 50 Range of Hiring Officer Values for Sensitivity Analysis

Figure 29 tells us that moving even slightly away from the optimal hiring variables can have a drastic, adverse effect on the AMEDD operating strength deviation. The AMEDD operating strength deviation is minimized when we implement 101% of the hiring policy that is when we increase the number of officers we hire for each specialty 1%. It is very interesting that the simulation, keeping all other parameters to include promotion rates and transfer rates, identified an optimal value of the AMEDD Operating Strength Deviation less than the value discovered by the optimization programs. This suggests that some other constraints that the optimization model includes but is not included in the system dynamics model is likely violated, perhaps a promotion or percentage of officers that needs to be transferred, is violated.

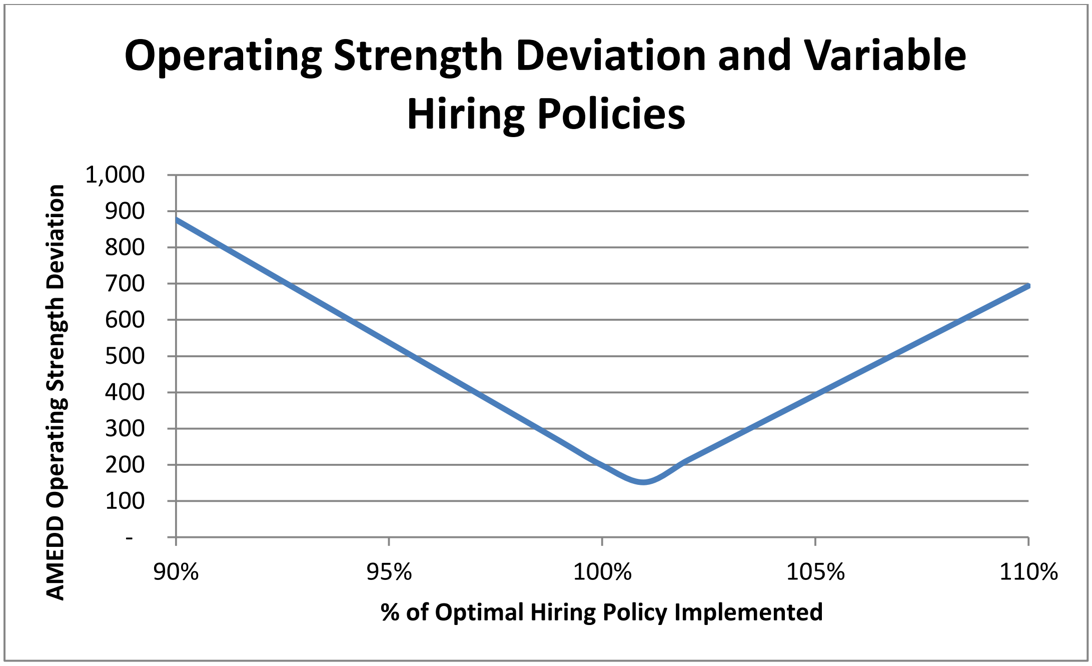


Figure 29 AMEDD Operating Strength Deviation and Variable Hiring Policies

Figure 30 shows the behavior of the corps operating strength deviation over the entire “Hiring Sensitivity Analysis” parameter space. Four of the AMEDD corps have minimal operating strength deviation when the “Hiring Sensitivity Analysis” parameter is 1. The Dental Corps has to reduce the “Hiring Sensitivity Analysis” parameter to 0.6 to achieve its minimal operating strength deviation. The Medical Corps has to increase the “Hiring Sensitivity Analysis” parameter to 1.1 to achieve its minimal operating strength deviation. Recall the uneven requirement structure of the Dental Corps and this provides us an explanation why the number of officers hired would have to be reduced so greatly to achieve an optimal operating strength deviation.

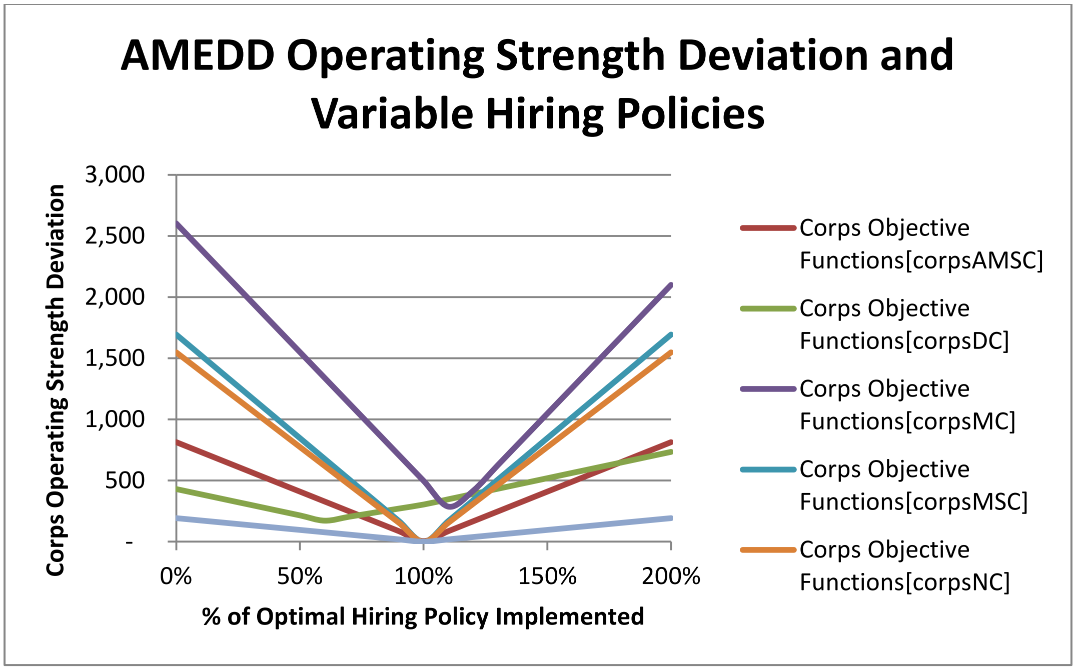


Figure 30 Corps Operating Strength Deviations and Variable Hiring Policies

The next parameter we varied was the promotion rates of officers. As we did with the hiring variables, we created an auxiliary variable named "Promotion Sensitivity Analysis". This variable represents the percentage change the simulation will make for 274 optimal promotion rates for officers that are inputted into the model from the optimization programs. Table 51 shows the range assigned to the optimal promotion rates for this sensitivity analysis. We study the effect of a $\pm$ 10% change in the optimal promotion rates.

	O-2	O-3	O-4	O-5	O-6
AMSC65A	NA	[0.9, 1.1]	[0.63, 0.77]	[0.54, 0.66]	[0.36, 0.44]
AMSC65B	[0.9, 1.1]	[0.9, 1.1]	[0.63, 0.77]	[0.54, 0.66]	[0.36, 0.44]
AMSC65C	[0.9, 1.1]	[0.9, 1.1]	[0.63, 0.77]	[0.54, 0.66]	[0.36, 0.44]
AMSC65D	NA	[0.9, 1.1]	[0.81, 0.99]	[0.61, 0.75]	[0.36, 0.44]

Table 51 Range of Promotion Rates for AMSC Corps Officers

Varying the promotion rates even this small amount has drastic effects on the AMEDD and corps operating strength deviations. Figure 31 shows that even a ± 5 % change in the optimal promotion rate can cause severely adverse effects. When the "Promotion Sensitivity Analysis" parameter = 0.95, the AMEDD operating strength deviation is 3 times as great as the optimal AMEDD Operating Strength Deviation. The effect is not as dramatic when the "Promotion Sensitivity Analysis" parameter = 1.05, but we do see a 180% increase in the AMEDD Operating Strength Deviation when the promotion rates increase only 5%.

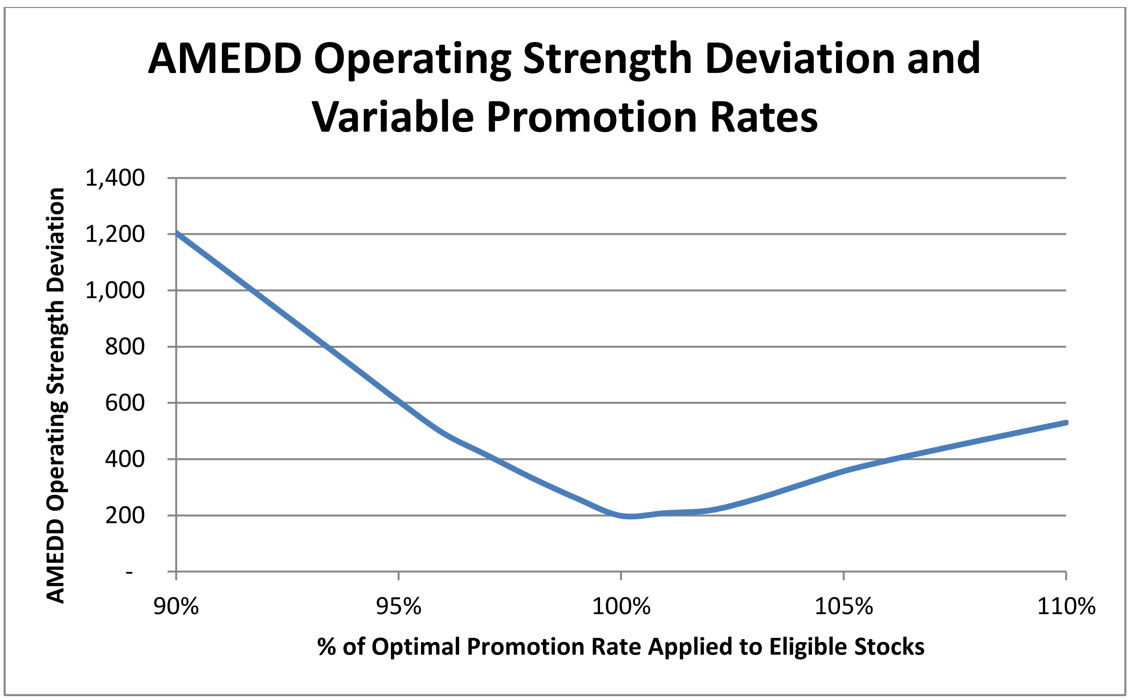


Figure 31 AMEDD Operating Strength Deviation and Variable Promotion Policies

At the individual corps, varying the promotion rates has the greatest effect on the four corps, AMSC, MSC, NC, and VC that are able to achieve a near perfect match between officer supply and officer demand. Small variations, a three percent decrease in the optimal promotion rate for officers causes the operating strength deviation of the Medical Services Corps and the Nurse Corps to sky rocket over 100. A one percent decrease in the optimal promotion rate causes the operating strength deviation to grow 30 units.

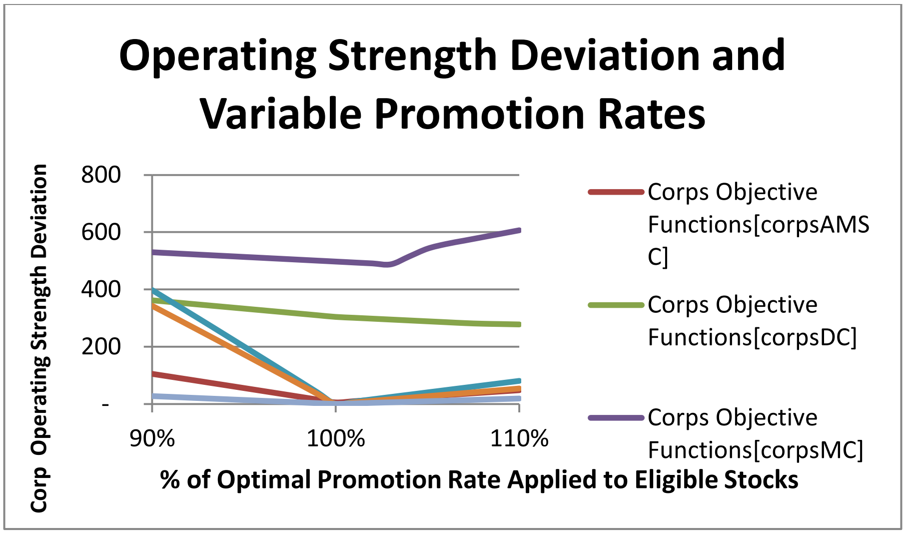


Figure 32 Corps Operating Strength Deviation and Variable Promotion Policies

Figure 33 shows the relationship between the system manpower requirements and the AMEDD operating strength deviation. The AMEDD operating system has a minimal operating strength deviation when there is a 1% reduction in the size of the manpower system requirements, all other parameters remaining the same.

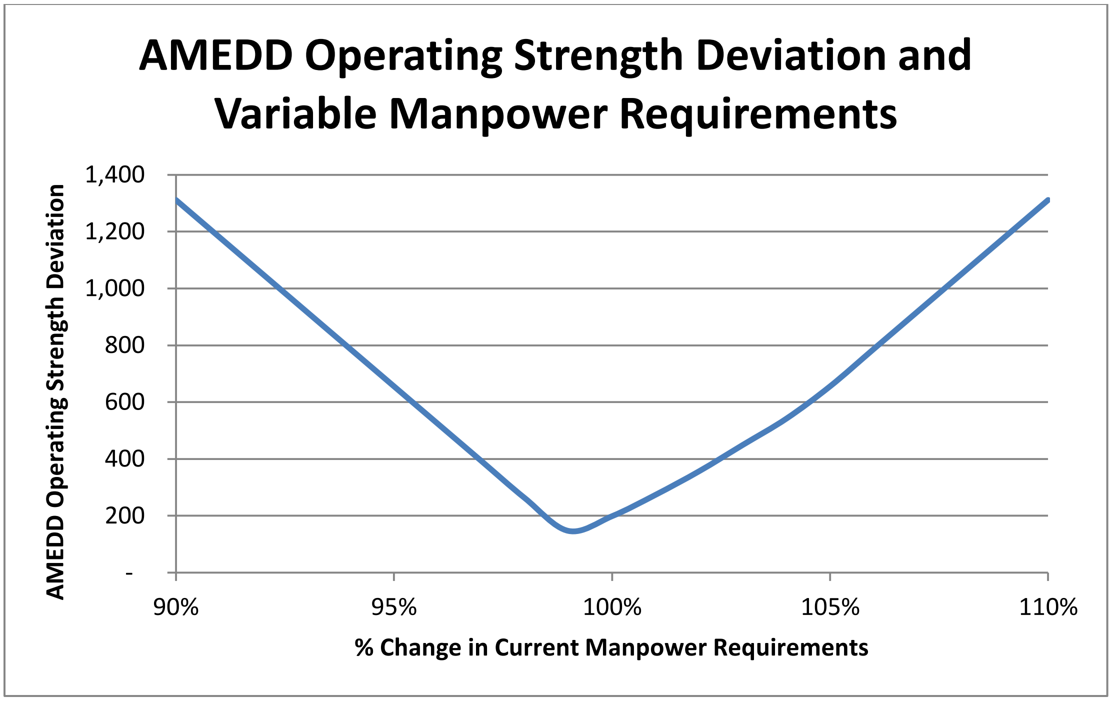


Figure 33 AMEDD Operating Strength Deviation and Variable Manpower Requirements

The corps operating strength deviation is more sensitive to changes in the manpower system requirements. Particularly, the operating strength deviation of the Army Medical Specialist Corps, the Medical Services Corps, the Nurses Corps, and the Veterinary Corps increases at dramatic rates as the percentage of requirements decreases. The change is the most dramatic in the Medical Services Corps. This is evident in examining the slope of the curves in Figure 34. A one percent decrease in the manpower system requirements causes an increase in the Medical Services Corps operating strength deviation of 34 units.

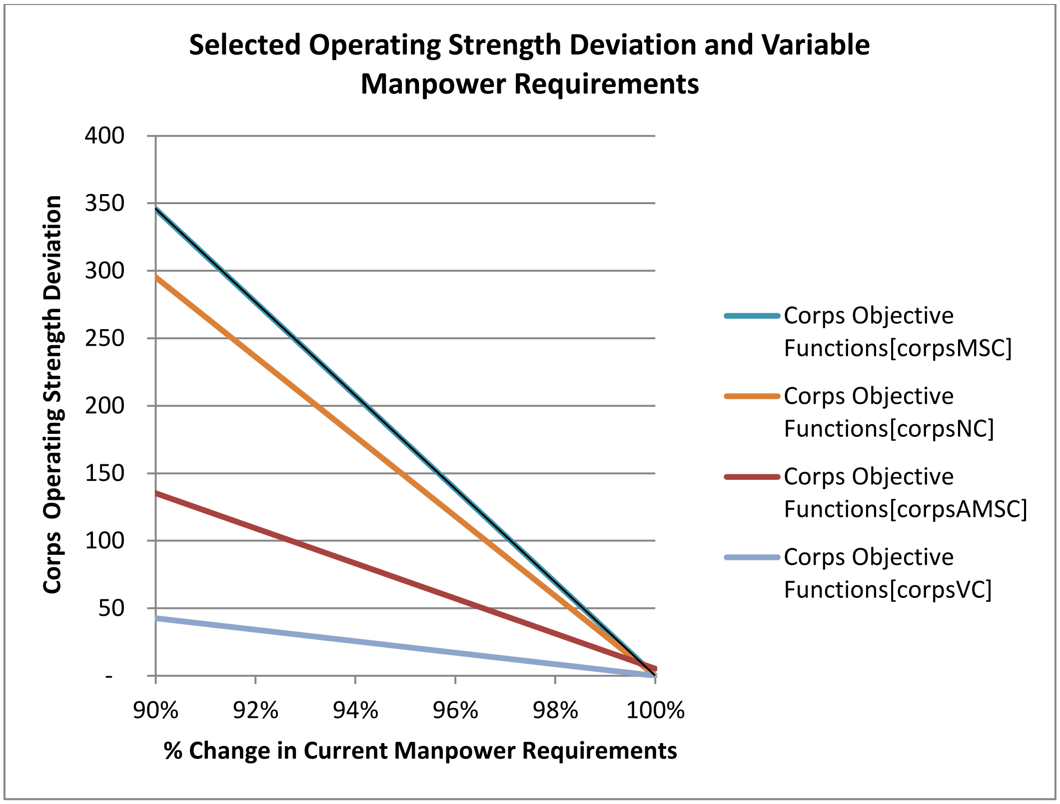


Figure 34 Selected Corps Operating Strength Deviation

In this section, we have explored the effect of varying critical simulation parameters and their effect on the system's operating strength deviation. In Chapter 7, we presented an alternate way to think of system deviations and presented a value scoring methodology that provides linear functions that can transform raw deviation in officer strength to value scores. These value scores range between [0,100]. The parameters needed to conduct this linear transformation were developed to make it more relevant to compare different components of the AMEDD manpower system. For example, the value score transformations make it more relevant to compare the value score of the Dental Corps to the Medical Corps than comparing sums of deviations.

In our simulation, we wanted to have a better understanding of the effect of varying manpower requirements. We have already presented the techniques required to conduct sensitivity analysis on varying parameters like the manpower system requirements. What was required additionally was the inclusion of function in Vensim to transform the raw deviations into value scores and then to multiply the value scores by the appropriate weights detailed in Chapter 7. This integration of value scoring methodology and the Vensim simulation environment that is so friendly to sensitivity analysis can be a very beneficial tool. We can quickly simulate different policies, in the following example we will change the number of requirements, and calculate what the effect of the varying manpower requirements will be on the total value of the manpower system. Equation 48 from Chapter 7 describes how we calculate the value score for Objective 2.0.

$$Maximize\ \Sigma_{t,corps,g}\gamma_{t,corps,g}(\phi_{t,corps,g}(pos\ dev_{t,corps,g} + neg\ dev_{t,corps,g}) +\ 100)$$

Equation 48 Calculating Objective 2.0

Figure 35 shows how Chapter 7's Objective 2.0 Sum of Corps Value Score is affected by varying levels of manpower system requirements. We varied each of the requirements from 80% of the current requirements to 120% of the current requirements. When there is no change to the manpower system requirements, intuitively the value score for Objective 2.0 is at its highest. Very small changes in the percentage of the requirements have a dramatic effect on the value score of Objective 2.0. A 1% decrease in the manpower system requirements across all specialties and grades costs the system 7 value points; just under 10%. A 1% increase in the manpower system requirements causes a 10% loss for the Objective 2.0 value score.

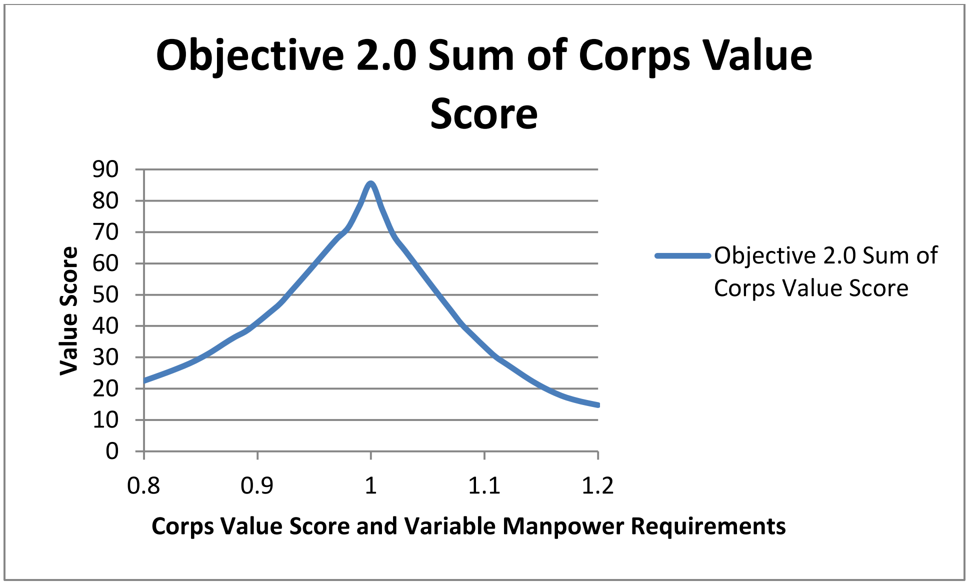


Figure 35 Objective 2.0 Value Score and Variable Manpower Requirements

8.5 Feedback Loops

A very important aspect of system dynamics modeling has not been included yet in our model. Sterman calls feedback "one of the core concepts of system dynamics". Our system dynamics model current captures the flow of officers from one inventory stock to another. But the optimization models and our initial system dynamics models do not model how the behavior of the officers in the manpower system will influence the system itself. The system dynamics model described here models the behavior of the individual officers and updates the officers' propensity to remain in the manpower system based on the overall performance of the system. The updated continuation rates have an impact on the manpower system objectives.

The AMEDD officer manpower system simulation has two feedback loops. The purpose of these two feedback loops is for the simulation to update the continuation rates based on the performance of the overall manpower system. Desired system performance is defined as minimizing the number of excess officers and the number of officers that the manpower system is short. The manpower system's objective is to minimize the total number of deviations (both positive and negative) from officer manpower requirements.

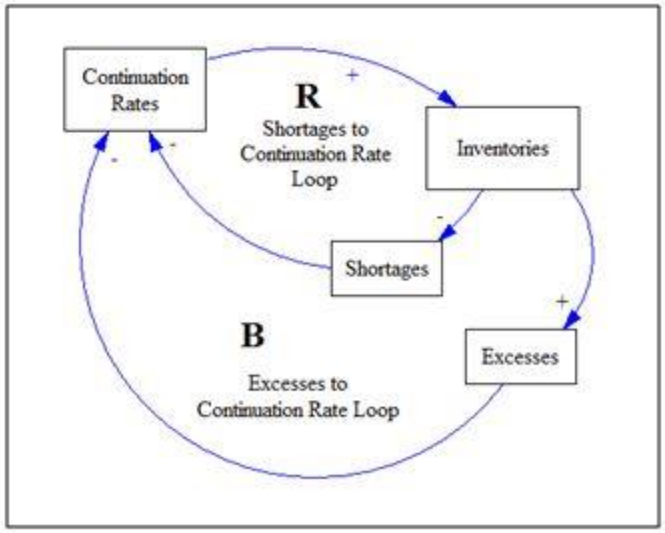


Figure 36 AMEDD Manpower System Feedback Loops

Schermerhorn(2010) defines effective teams and organizations as having three characteristics. The teams are successful – they perform well. The teams are viable and long lasting. Lastly, the members of the team value their association with the team, they positively identify with the team, and they are long lasting members of the organization. The value scoring methodology described in Chapter 7 values minimal officer shortages in the manpower system. Applying Schermerhorn's theory of team effectiveness, we see that shortages in the AMEDD officer system equates with decreased team effectiveness and could suggest that officers would choose to leave the system and the system would have higher instances of officer attrition.

The first of the two loops is the shortage to continuation rate loop. Increased continuation rates increase the inventories of officers in the system. Increased inventories decrease the number of shortages in the system. Decreased shortages means continuation rates for officers are going to increase - more officers are going to stay in (less officers are going to leave) the system because the overall performance or value of the system has improved. This is a positive or a reinforcing loop. The positive change in the continuation rate was propagated or reinforced by the changes it caused in the other parameters in the loop.

The second of the two loops is the excess to continuation rate loop. Again applying Schermerhorn's theory of team effectiveness, team effectiveness is decreased when there are an excess of officers. This excess causes officers to question whether their contributions are valuable in a population of so many others. Officers perceive they are part of an ineffective team, a team of lesser value – increased excess of officers causes a decrease in the value score of the manpower system. Increased continuation rates increase the inventories of officers in the system. Increased inventories increase the number of excess officers in the system. Increased excesses means continuation rates for officers are going to decrease - less officers are going to stay in (more officers are going to leave) the system because the overall performance of value of the system has regressed. This is a balancing loop. Increased continuation rates cause a series of events that results in an excess of officers in the system, which causes officers to leave the system, or a decrease in officer continuation rates.

8.6 Modeling the Feedback Loops

Figure 36 shows the feedback loops that are modeled in the system dynamics model. The figure is a simplification of the complex relationships in the system and the actual modeling structure that was created to create the effect of the feedback loops. What follows is a description of how these two feedback loops were modeled. We will then explore some of the results of the model and the insights we can gain from these feedback loops.

We will begin with a description of how the manpower system treats the phenomena of excess officers in the system. The number of excess officers is defined for each area of concentration and each grade combination. The number of excess officers is compared to the number of excess officers that were in the optimal work force structure in the optimization models described in Chapter 7. Even in the optimal AMEDD manpower system, there are going to be mismatches between the number of officers and the requirements for officers. Part of this mismatch is due to the fact that the optimization model minimized the number of total AMEDD grade deviations and the number of grade deviations in the six individual corps. The optimization program does not attempt to minimize the deviation between the area of concentration and grade requirements and the number of officers in those inventory stocks.

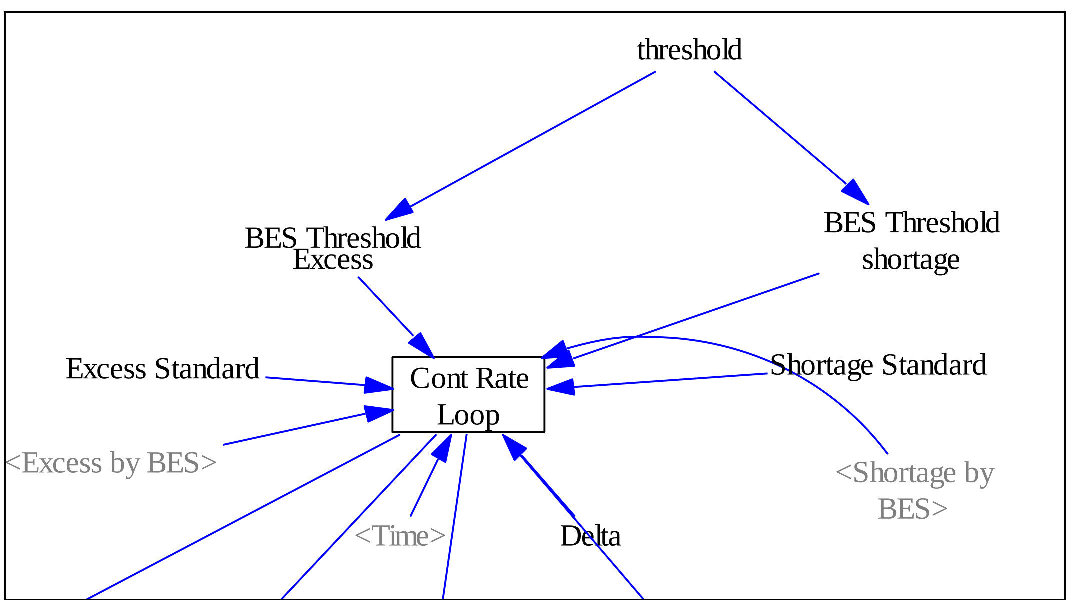


Figure 37 Effect of Excess and Shortages on Continuation Rates

If the number of excess officers in a particular area of concentration in a particular grade exceeds the number of excess officers in the optimal manpower system multiplied by a threshold factor, then there is going to be a decrease in the continuation rate for that area of concentration and grade combination. This threshold factor, a positive number, insures that the changes in the continuation rate are only propagated through the system if the change in the continuation rate is large enough to warrant a change in the number of officers in the system. These changes to continuation rates are not an attempt by the managers of the system to influence officer behavior. Though we could structure our model that way, our model here attempts to model the behavior the officers well demonstrate as a reaction to their assessment of the value and performance of the manpower system.

Starting in time period 31, when all of the manpower inventory stocks have been populated, if the excess number of officers in the system is greater than the threshold factor multiplied by the standard number of excess officers plus one, the continuation rate will be decreased by a factor of δ, represented in Figure 36 by the parameter "Delta". Adding one to the standard number of excess officers guards against the situation where the standard number of excess officers is zero, and any amount of excess officers in the inventory system would activate the penalty on the continuation rate.

If the amount of excess officers in the inventory system exceeds the threshold, then for each area of concentration and grade combination, the associated officer continuation rates will be penalized. In each subsequent time period, the continuation rates are subject to the same criteria. If the excess is corrected and it diminishes so that it is less than the product of the threshold factor and the excess standard, the continuation rate in time period t will be static and be equal to the continuation rate in time period $t-1$.

Otherwise, if the excess of officers remains in the system, than the continuation rate will continue to decrease by "Delta" percentage points.

A very similar formulation will cause a shortage of officers in an area of concentration and grade specialty to activate the penalty of size δ for the continuation rate if the shortage of officers exceeds the threshold factor and the shortage standard from the optimal work force size. The Continuation Rate Loop variable, which is indexed by area of concentration, years in service and grade, is inputted in the four variables for the continuation rates of the four most senior officer grades. The first two grades are ignored because officers only spend four years in those junior officer grades. Also, officers have a very high continuation rate in these grades because the officers have to stay in the system to meet their active duty service obligations. These officers must satisfy the commitment they have made to the Army. These relationships between "Threshold", the number of officers in excess and in shortage in the system, and the excess standard, and "Delta" is described in and is easily modeled in Vensim. "Delta" is represented by δ and is ≤ 0 because it is a penalty. "Delta" does not represent a planning or a policy decision to adjust the officer continuation rates. "Delta" represents the aggregated behavior of the officers in question as individual decision makers.

If Excess Officers(AOC, grade) $\geq$ Threshold * Excess Standard (AOC, grade)

Then $\text{Continuation Rate}_t = \text{Continuation Rate}_{t-1} + \delta$

If Shortage Officers(AOC, grade) $\geq$ Threshold * Shortage Standard (AOC, grade)

Then $\text{Continuation Rate}_t = \text{Continuation Rate}_{t-1} + \delta$

Figure 38 Relationship Between Excess / Shortage Officers and Continuation Rate Penalty

Use of the sensitivity simulation tool in Vensim made it possible to determine appropriate levels for the level of the two parameters described in Figure 37, "Threshold" and "Delta". "Threshold" is used to compare actual officer excesses and shortages to the excess and shortage standards. We multiply the excess and shortage standards by this factor "Threshold". If the manpower system's excesses and shortages exceeds the product of the "Threshold" and the standard level of shortages and excess, then a penalty is assessed to the continuation rate for that area of concentration and grade combination. The penalty is the parameter "Delta".

As described earlier, the sensitivity simulation feature will run the simulation for varying levels of parameters. First we used the sensitivity simulation tool to set the level for "Delta". Figure 39 shows how sensitive the AMEDD operating strength deviation is to very small changes in the officer continuation rates. In order for the penalty to be effective and an accurate representation of the current system, the penalty will have to cause the operating strength deviation of the manpower system to increase, but not a drastic or a dramatic increase.

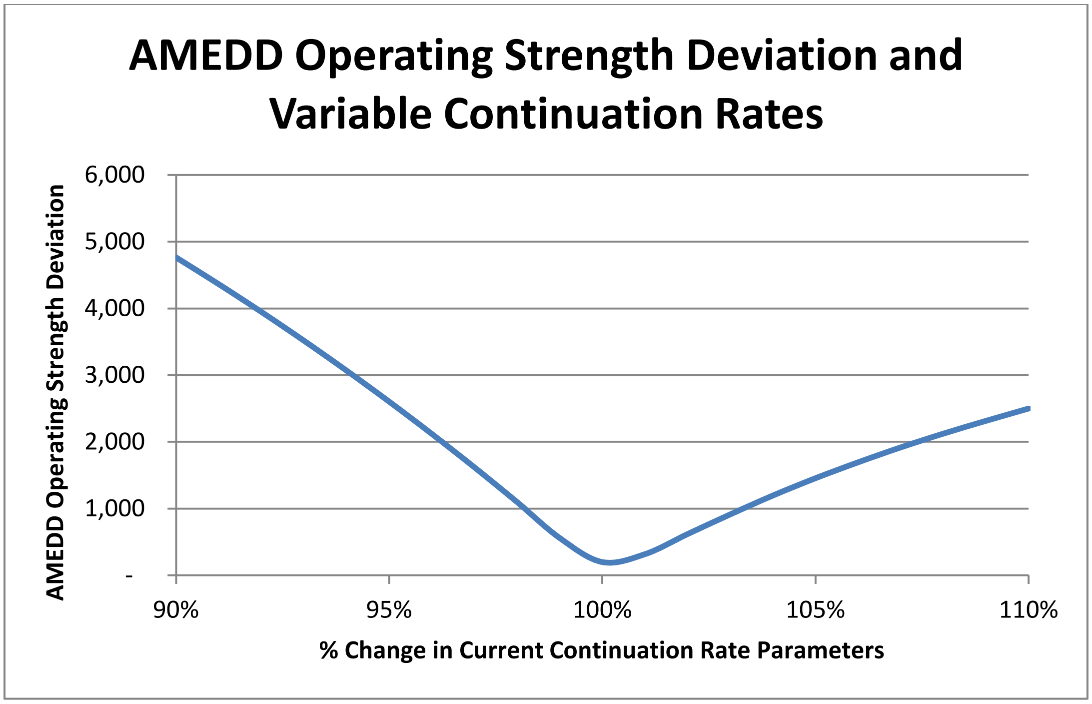


Figure 39 Sensitivity Analysis of AMEDD Operating Strength Deviation with respect to Continuation Rates

Figure 40 shows how the AMEDD Operating Strength Deviation changes with respect to the size of the penalty and the level of the excess and shortage threshold. We still see that the objective function is very sensitive to changes in the continuation rate. As the threshold increases, the level of sensitivity decreases. The effect a change in the size of the penalty has on the objective function decreases as the threshold increases. We will set delta to be 1% in the simulation. We know that the operating strength deviations for the entire manpower system and for the six corps are extremely sensitive to changes in the continuation rates. If the penalty is too large, than the effect it has on the objective functions will be too great. A penalty of 1% is large enough that the penalty causes a change in the continuation rate – as opposed to using a penalty a fraction of a percent.

But a 1% penalty does not have an unrealistic effect on the objective functions – the penalty is not too severe.

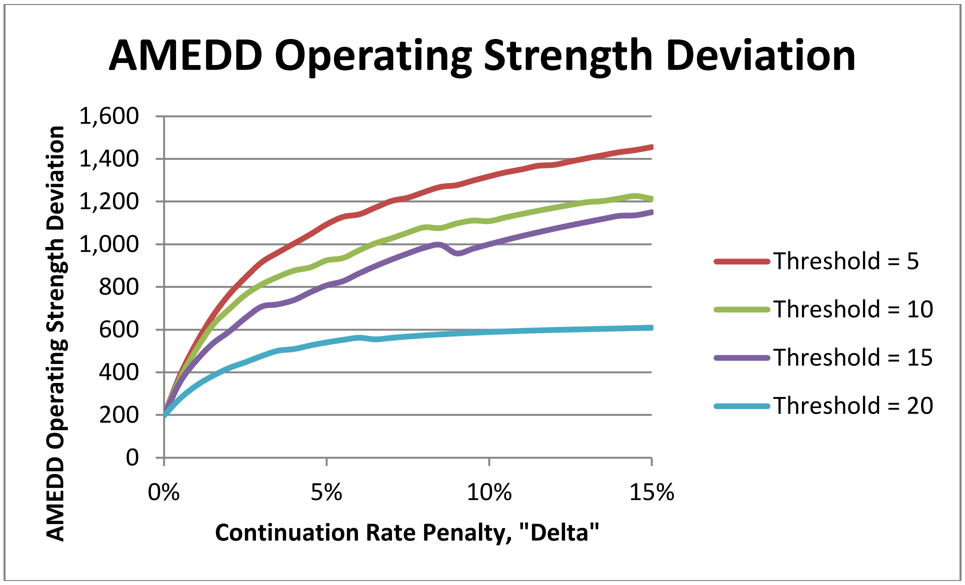


Figure 40 Sensitivity Analysis of AMEDD Operating Strength Deviation with respect to Sensitivity Analysis Parameters

The threshold factor level for excess and shortage levels can be set by examining how sensitive the AMEDD and corps operating strength deviations are to changes in the threshold level. Again, the intent is to set the threshold so that is has an effect, a measurable effect on the objective function, however it is not desirable that the effect be so dramatic that it is unrealistic or so large in terms of the scope and bounds of the normal levels of the objective functions.

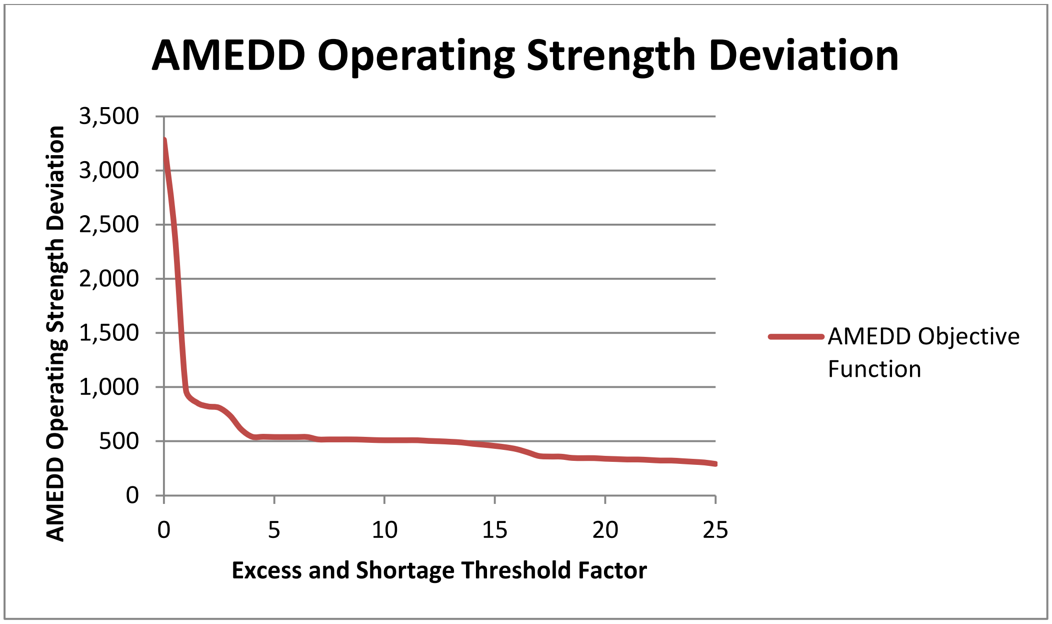


Figure 41 AMEDD Operating Strength Deviation and Threshold Factors

Figure 40 shows that when the parameter "Threshold" exceeds 20, the objective function of the AMEDD manpower system begins to resemble the AMEDD objective function without any feedback loops, described earlier in the chapter. The objective function is highly sensitive to lower levels of "Threshold" and begins to level off as "Threshold" increases. The AMEDD operating strength deviation before we began our sensitivity analysis was 199. As the threshold level increases, the AMEDD objective function is not sensitive to the "Threshold" Parameter. As the parameter increases, the right hand side of the inequalities described in Figure 38 increases, making it less and less likely that the actual number of excess officers or shortage officers would exceed the threshold. In turn, this makes it less and less likely that the continuation rates of officers will be penalized.

Level of “Threshold” Parameter	AMEDD Operating Strength Deviation
20	339
25	291
30	199

Table 52 Effect of "Threshold" Parameter on AMEDD Operating Strength Deviation - A Closer Look

As we continue to use the system dynamic model to assess the manpower system, we will set the value for the threshold parameter to be 20. This has the effect of increasing the AMEDD objective function by 70%.

Now that we have a simulation that will update the officer continuation rates based on the well-being or value of the system, it is appropriate to describe how this type of simulation can be used to help decision makers.

Recall that earlier in Chapter 8 we conducted sensitivity analysis on critical system parameters. We will do the same analysis here but will make the changes to the critical parameters and use the system dynamics simulation with feedback loops. The purpose of this analysis is to demonstrate the effect of these changing parameters. Our system with feedback loops models the manpower system more accurately because the officer continuation rates are updated based on the value of the system.

We vary each of the Sensitivity Analysis parameters for Hiring, Promotion, and for Manpower requirements. We can expect that the effect of the change is going to be more dramatic than it was earlier in Chapter 7. That is because, for example, if we are hiring less officers into the manpower system, then there will be shortages and the value of the manpower system is less. Officer continuation rates will decrease and we can expect officers to create additional shortages in the system by leaving the manpower system.

The Hiring Sensitivity Analysis Parameters as varied between a 90% policy reduction in the current hiring policies (derived from the optimization model in Chapter 4) and a 110% percent increase in the hiring policy. Figure 42 shows that the impact that changes in the hiring policies have a more dramatic effect on the operating strength deviation of the overall system when we incorporate the feedback loops in the model. The changes in the number of officers we hire in the manpower system has a much more dramatic effect on the manpower system because officer continuation rate is affected by the decreased continuation rates. We see similar behavior when we examine varying the promotion parameters and the actual number of officer requirements.

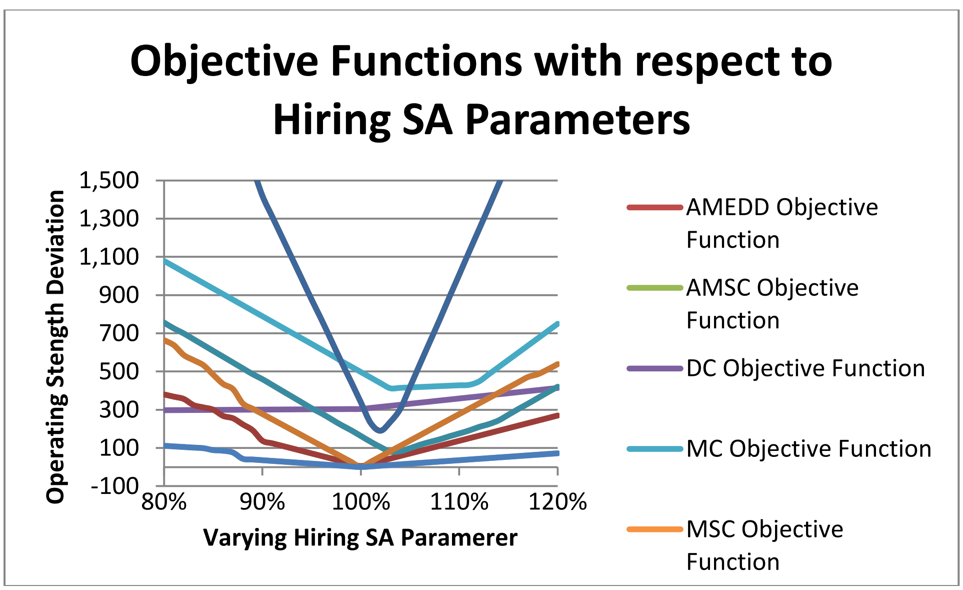
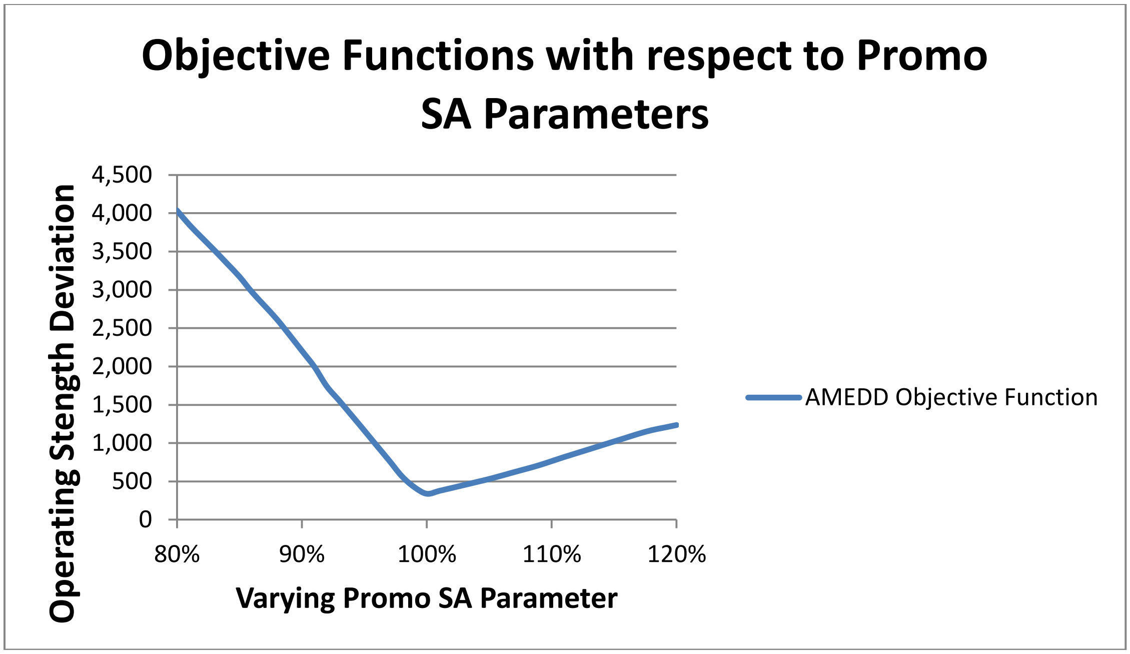


Figure 42 AMEDD and Corps Operating Strength Deviation and Variable Hiring Policies in a Feedback System



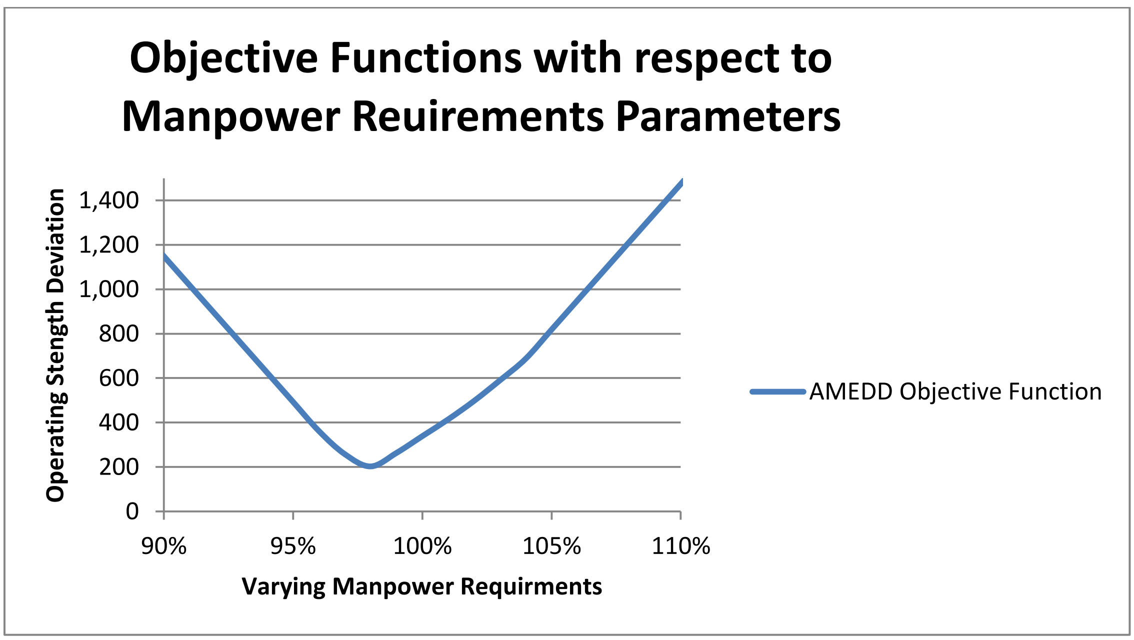


Figure 43 AMEDD Operating Strength Deviation and Variable Promotion Policies and Manpower Requirements

The system dynamics model updates the officer continuation rates. The updating of these continuation rates shows influences the number of officers that are in the system. Since there are both excess and shortages in the manpower system, the continuation rates are dynamically updated. But there is no economical method in Vensim to re-optimize important decision variables. These updated continuation rates can be formatted as inputs into the linear program manpower system model.

In Chapter 4, we identified that one of the weaknesses of the linear program was that it assumed that the continuation rates for officers remained static and officer behavior did not change over time. The Vensim system dynamics simulation has given us continuation rate matrix that now has the indices (*t,a,y,g*). We now have an estimate for an officer's probability of staying in the Army from one year to the next, for different time periods. This new continuation rate matrix now has a level of specificity that says the officers in time period t =1, might not have the same probability of staying in the Army in t = 2, as officers who are deciding whether to remain in the manpower system at a later time period.

The updated continuation rates were exported from Vensim and formatted so they could be inputted to the GAMS linear program model. We call them $cont\_rate\_prime_{t,a,y,g}$. The linear program that we will input these continuation rates into is the multi period, on hand inventory model, maximizing manpower system value score model 8. In this model, the continuation rates for officers had the index (*a,y,*g) and the rates remained static over the planning horizon. Each of the conservation of flow constraints was updated with the new parameter, continuation rate parameters. The number of officers in the inventory state *(t-1,a,y-1,g)* is multiplied by the updated continuation rate, *(t,a,y,g)*.

$$inventory_{t,a,y,g} = cont\_rate\_prime_{t,a,y,g} * inventory_{t-1,a,y-1,g}$$

Equation 49 Updated Conservation of Flow Equations

The optimal manpower value score solution is found as discussed in Chapter 7. The new optimal manpower solution has a very similar manpower value score. In fact, the optimization model with updated, dynamic, continuation rates produces a manpower system with a value score of 72.6 compared to the value score of 72 for the Chapter 7 model with static continuation rates. It is not important that the model with the dynamic continuation rates has a higher value score. What is important is that we have identified an optimal manpower policy for a model of the manpower system that we believe is more realistic, is more accurate compared to the model presented in Chapter 7.

In the original optimization models, we believed that the officer's continuation rates would remain static. It is clearly a false assumption, but one that was necessary because there was no method to update the continuation rate parameters from year to year. Our integration of the system dynamics model and the linear program makes it possible to relax this assumption because we are able to update our beliefs about how officers in the manpower system will behave. The result is a more realistic model and an optimal manpower policy, when implemented, that we expect to perform.

In this chapter, we built a system dynamics model of the AMEDD manpower system. The simulation models the flow of officers in the manpower system. The simulation models the flow of officers in the form of officers hired into the system, officers that are promoted, officers that transfer from one specialty to the next, and officers that progress in the system.

The simulations created here are capable of modeling the objective force model and the flow of the officers that are on hand in the manpower system. The Vensim system dynamics model does not have a powerful optimization package to optimize the decision variables that make up the optimal manpower policy. But, the system dynamics simulation does have a visual aspect that helps to graphically represent the flow of officers and the simulation can use the optimal manpower policy from the linear programs as inputs. The system dynamics model can then model the flow of officers through the system.

We were able to conduct sensitivity analysis of critical simulation parameters. The simulation can easily be modified to conduct the sensitivity analysis. Lastly, we modeled feedback loops, an essential component of system dynamics simulations. The manpower system simulation has two primary feedback loops. We are able to model how system performance will influence officer behavior in terms of the continuation rates. These continuation rates, dynamically updated based on the increased or decreased value of the system. The simulation output included a updated continuation rate parameters, indexed by *t*, that can be used now in the optimization models. The advantage of using these updated continuation rates in the linear program is that the rates no longer make the faulty, but required assumption in the earlier optimization models, that the rates are static. There is a great potential to continue to research how the system dynamics simulation and linear program can be continued to be integrated, especially in terms of simulating how the new optimal manpower policy would perform in a dynamic environment where feedback loops would influence future system performance and officer behavior.

9. Conclusions

This dissertation focused on operations management techniques that could be used to perform the modeling of the AMEDD manpower system. This is a specific manpower system, but the work presented here could be extended to other manpower systems, in and out of the military. The AMEDD manpower system has 15,000 officers, not a particularly large system, approximately 3% of the U.S. Army's size. But the size and complexity of manpower models is not related to the number of people in the system. It is related to the number of different specialties in the system, the number of different grades or positions in the manpower system hierarchy, how long people stay in the manpower system, and how many time periods you wish to study the system. The AMEDD manpower system is large and complex based on these criteria and the techniques presented here can be applied to other large manpower systems, even ones that have considerably more people.

The first of the three main contributions presented in this dissertation was the improvement of an existing manpower optimization model for a specific industry that can be extended to other manpower systems. The improvement was in three specific areas. First, this dissertation presents the transformation of a nonlinear optimization model to an equivalent, linear programming model. The AMEDD Personnel Planning Propnency and Directorate were able to take advantage of this transformation. They updated their working models of the manpower system to be linear and no longer had to purchase specialized, nonlinear programming solvers. They were able to solve the models with built in solvers in common spreadsheet programs.

This dissertation also describes the construction of a global linear programming model that AMEDD could use to model all six of its subordinate divisions. Previous models studied each of the six corps separately and failed to consider any of the interactions, interdependencies that exist between the six of them as possible levers to consider. Chapter 4 presents one such interaction and we describe how it could be leveraged to further minimize the manpower system's operating strength deviation.

Chapter 5 illustrates a third modeling improvement. AMEDD manpower models focused on determining the size of the optimal work force, but there were no existing optimization models to model the current work force. There were no models that looked at the current distribution of officers across all of specialties and grades and compared it with officer requirements. The model in Chapter 5 does just this and is constructed so that it can do it across multiple time periods. The model identifies the optimal manpower policy to minimize the gap between the numbers of officers on hand and requirements.

From the beginning, the simplest AMEDD optimization models looked at only one corps and did not consist of multiple time periods. These models had only four components to their objective function – the deviation between the number of colonels and the requirement for colonels, the deviation between the number of lieutenant colonels and the requirement for lieutenant colonels, the deviation between the number of majors and the requirement for majors, and the deviation between the number of company grade officers and the requirement for company grade officers. It was trivial for decision makers to assign weights to these four components. It was not hard for decision makers to understand the relationships and tradeoffs between the four components.

The problem became less trivial in Chapter 4 where we presented a global AMEDD model, a single optimization model of the six AMEDD corps. The objective function now had 24 components. As our modeling progressed and grew, the objective function continued to grow in terms of components. With the addition of multiple corps into the optimization model, we now had to ensure we found solutions to the optimization problems that did not optimize the global well-being of the AMEDD manpower system at the expense of one of the subordinate corps. Because we needed to ensure a solution did not optimize one component at the expense of another, we added the operating strength deviation for each corps to the objective function.

In Chapter 5 we presented the global, multi-period model. The model spans seven time periods and made the complexity of the objective function even larger when we minimized the operating strength deviation in each time period. We also sought to smooth the hiring and promotion policies which added more components to the objective function. In total, we created an optimization model that minimized the AMEDD operating strength deviation, the six corps' operating strength deviations, and the deviations between the number of officers hired and promoted each year – a total of 231 objective function terms.

It was no longer possible to assign weights to all of these objective function components. Incorporating a value hierarchy structure, Chapter 6 presents an efficient and a rational method to assign weights to each of these components. This is something that had not been done before to the AMEDD manpower system and had been ignored in other literature about multi-period, military manpower systems.

Besides describing a value hierarchy structure, Chapter 6 also describes how we converted the number of deviations in each component and converted it to a value score, on a scale between 0 and 100. A series of value functions converted deviations to a value score and, when utilizing the objective function weights, we were able to obtain a value score for each corps and for the entire solution. Lastly, we maximized this value score by replacing the previously used objective function that minimized the operating strength deviation, with an objective function that maximized the manpower system's value.

This value score makes it possible to compare the well-being of AMEDD corps relative to each other. It provides a sense of how costly a deviation is in one specialty relative to another specialty. It also allows you to compare the medical system to other systems in the Army. If we were to compare deviations, we are not comparing the manpower systems on an equal scale, akin to comparing to apples and oranges. One hundred deviations in the medical department would signify a significant loss of capability, but in larger Army sub systems, one deviation might represent a very small percentage of the system's budgeted end strength. The value score conversion allows us to compare the two systems in a much more consistent, appropriate manner.

The last contribution described in this dissertation was the creation of a system dynamics simulation of to capture the dynamic updating of continuation rates. Chapter 8 described the formulation and design of a system dynamics model of the AMEDD officer manpower system. The system dynamics model presented is not a standalone model. It relies on set of inputs from the optimization models presented in Chapters 6 and 7. These inputs are the optimal manpower policies – the optimal number of officers to hire, to promote, and to transfer from one specialty to the next. The system dynamics model allows us to simulate the performance of the optimal policy under varying conditions. In the system dynamic model, we study how sensitive the manpower system's operating strength deviation is to officer continuation rates.

For our purposes, the system dynamics model provides a much better modeling format for us to conduct this sensitivity analysis. Officer continuation rates are dynamic in our system dynamics model, from year to year, and they are influenced by the well-being and performance of the manpower system itself. At the end of Chapter 8, we see that our optimal policy does not perform as well as we had hoped it would, *if* the continuation rates evolve, transform, behave dynamically as they do in the system dynamics model.

As this dissertation comes to a close, there are two areas of research that come to mind that would be interesting methods to continue study this and other military manpower systems. The first area is the relationship between the optimization and system dynamics simulation. In this dissertation, the optimal manpower policy, the primary output of the optimization models described in Chapters 4-7, is the primary input to the system dynamics model. Chapter 8 provided a description of how we captured the updated officer continuation rates, an output of the system dynamics model, and used them as updated parameters in the optimization model.

It would be very interesting to continue along this line of research. One question to ask would be how many iterations would be appropriate to go through, how many times would we feed the outputs of one model as inputs into the other model. Unfortunately, this loop could continue forever. At this time, we can offer two possible answers. First, it may be possible to update the officer continuation rates in the optimization models, as we did in the system dynamics model. The continuation rates are parameters in the optimization model and could be updated from time period to time period based on the overall well-being of the system. One disadvantage of programming this in an optimization model would be the difficulty to see visually, as we are in a system dynamics model, the nature of the feedback loops and the relationship the loops have with the overall system and the system's performance.

The system dynamics software we used, Vensim, has a very limited optimization capability. This might be an avenue to pursue that would avoid all together the question of how many loops or iterations of the cycle of using the two models. An improved optimizer in Vensim or any other system dynamics software would provide us the opportunity to solve both of these models – find the optimal manpower policy and improve our estimates of officer continuation rates from year to year and update those continuation rates based on the state of the manpower system.

Another potential method to better understand the AMEDD manpower system and military manpower systems would be to consider an agent based model approach. In an agent based model, the system of interest is modeled as a collection of autonomous decision-making entities called agents. In our context, the AMEDD officers in the manpower system would be modeled as agents. The model could be expanded greatly, limited only by the ability to capture an acceptable level of model realism to characterize the system under study (Bradley, Hax, and Magnanti, 1977).

But AMEDD itself, the Army, the civilian, elected and non-elected, leadership of the Army, the American people, and foreign state and non-state actors could all be considered as agents. AMEDD would develop and implement manpower policies that would influence the behavior of the officers in the system. Foreign state and non-state actors could also be considered agents in the model because their behavior could cause civilian leadership to increase or decrease the size of the Army, having an effect on the required demand for AMEDD officers.

The agent based model is a comprised of repetitive competitive interactions between agents in the system. AMEDD officers would make decisions whether or not to stay in the manpower system, whether to switch from one specialty to the next. AMEDD and the Army would make decision about what percentage of officers to promote to higher ranks, what manpower requirements would be in the future if the Army were to shrink or to grow. The Army might decide to incentivize officers to stay in the Army with financial bonuses and AMEDD officers would have to take these offers into consideration when making decision about their future careers.

Agent based modeling can simulates all of these types of decisions and since the agent based model programs agents to make decisions that optimize their utility, the model can capture emergent phenomena, the result from the interactions of individual entities.

Agent based modeling has been used to study military manpower systems in the United States Navy and the United States Army. In fact, OpTek (www.opttek.com), an optimization software and services company, has developed sophisticated agent based models that help human resource managers do the following:

1. "Forecast human capital requirements (numbers, skill sets, locations, timing) given a range of possible business scenarios, and respond in real-time to changes in the assumptions behind those scenarios;
2. Identify the recruitment channels that will be most effective in meeting those requirements;
3. Forecast the impact of various HR programs/practices on attraction and retention, and identify how that varies based on demographics, job level, and performance;
4. Model the impact of turnover and employee movement within the organization;
5. Understand trade-offs between readiness and HR costs;
6. Achieve objectives with respect to workforce representation;
7. Quantify the financial impact of HR decisions."(OpTek, 2011)

Addressing these seven items would provide a deeper understanding of the AMEDD manpower system. Most importantly, it would provide AMEDD manpower system managers, not only a tool to optimally manage their system, which this dissertation has constructed, described, and provided, but these seven agent based modeling capabilities would provide AMEDD manpower managers the ability to optimize their manpower system within the larger Army and military manpower systems.

In our introduction, we described manpower system problems as an attempt to identify the optimal policies to place the appropriate and accurate numbers of the correct types of people in the right jobs at the necessary time. In this dissertation, we have explored techniques to do just that and in this chapter specifically, we have identified possible new techniques, methods, and possible area of research to continue to research how we can continue to improve upon how we solve these manpower problems. One vital area to include in these operations management techniques would be to include a behavioral science approach to the study of the organization. This dissertation focuses on models that are descriptive and tell manpower policy decision makers what policies to implement. But the success of these policies is heavily dependent on how the policies are executed. Integrating a behavioral science and organization behavior approach would be another area to continue to research and could result in interesting, yet more realistic results.

Appendix A – AMEDD Value Hierarchy Weights and Objective Function Coefficients

Weights Supporting Objective 1.0

		α_g			
$Weight_{1.0}$	0.34	Co_Grade	O-4	O-5	O-6
Time period *t*	α_t	47%	32%	8%	13%
1	3%	0.4%	0.3%	0.1%	0.1%
2	6%	1.0%	0.7%	0.2%	0.3%
3	25%	4.0%	2.7%	0.7%	1.1%
4	25%	4.0%	2.7%	0.7%	1.1%
5	19%	3.0%	2.0%	0.5%	0.8%
6	13%	2.0%	1.3%	0.3%	0.6%
7	10%	1.6%	1.1%	0.3%	0.4%

Weights Supporting Objective 2.0

$Weight_2$	0.32	β_g			
AMSC	14.1%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	54%	32%	8%	5%
1	3%	0.06%	0.04%	0.01%	0.01%
2	6%	0.15%	0.09%	0.02%	0.02%
3	25%	0.61%	0.37%	0.09%	0.06%
4	25%	0.61%	0.37%	0.09%	0.06%
5	19%	0.46%	0.27%	0.07%	0.05%
6	13%	0.30%	0.18%	0.05%	0.03%
7	10%	0.24%	0.15%	0.04%	0.02%

$Weight_2$	0.32	β_g			
DC	17.9%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	25%	21%	25%	29%
1	3%	0.04%	0.03%	0.04%	0.04%
2	6%	0.09%	0.07%	0.09%	0.11%
3	25%	0.36%	0.30%	0.36%	0.42%
4	25%	0.36%	0.30%	0.36%	0.42%
5	19%	0.27%	0.22%	0.27%	0.32%
6	13%	0.18%	0.15%	0.18%	0.21%
7	10%	0.14%	0.12%	0.14%	0.17%

$Weight_2$	0.32	β_g			
MC	25.6%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	47%	40%	9%	5%
1	3%	0.10%	0.08%	0.02%	0.01%
2	6%	0.24%	0.20%	0.05%	0.02%
3	25%	0.95%	0.81%	0.19%	0.10%
4	25%	0.95%	0.81%	0.19%	0.10%
5	19%	0.72%	0.61%	0.14%	0.07%
6	13%	0.48%	0.41%	0.10%	0.05%
7	10%	0.38%	0.32%	0.08%	0.04%

		β_g			
MSC	20.5%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	42%	29%	25%	4%
1	3%	0.09%	0.05%	0.01%	0.01%
2	6%	0.22%	0.13%	0.03%	0.02%
3	25%	0.89%	0.53%	0.13%	0.09%
4	25%	0.89%	0.53%	0.13%	0.09%
5	19%	0.67%	0.40%	0.10%	0.07%
6	13%	0.44%	0.27%	0.07%	0.04%
7	10%	0.35%	0.21%	0.05%	0.04%

$Weight_2$	0.32	β_g			
NC	15.4%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	44%	39%	12%	5%
1	3%	0.03%	0.03%	0.03%	0.04%
2	6%	0.08%	0.06%	0.08%	0.09%
3	25%	0.31%	0.25%	0.31%	0.36%
4	25%	0.31%	0.25%	0.31%	0.36%
5	19%	0.23%	0.19%	0.23%	0.27%
6	13%	0.15%	0.13%	0.15%	0.18%
7	10%	0.12%	0.10%	0.12%	0.14%

$Weight_2$	0.32	β_g			
VC	6.4%	Co_Grade	O-4	O-5	O-6
Time period *t*	β_t	42%	29%	21%	8%
1	3%	0.02%	0.02%	0.00%	0.00%
2	6%	0.06%	0.05%	0.01%	0.01%
3	25%	0.24%	0.20%	0.05%	0.02%
4	25%	0.24%	0.20%	0.05%	0.02%
5	19%	0.18%	0.15%	0.04%	0.02%
6	13%	0.12%	0.10%	0.02%	0.01%
7	10%	0.10%	0.08%	0.02%	0.01%

Calculation of Weights Supporting Objective 3.0

$Weight_{3.0}$	17%	
Time period *t*	β_t	$Weight_3 * \beta_t$
1	7%	1%
2	7%	1%
3	11%	2%
4	19%	3%
5	19%	3%
6	19%	3%
7	19%	3%

Calculation of Weights Supporting Objective 4.0

$Weight_4$	17%	κ_g			
		Co_Grade	O-4	O-5	O-6
Time period *t*	κ_t	42%	29%	21%	8%
1	16%	1.15%	0.81%	0.58%	0.23%
2	3%	0.18%	0.12%	0.09%	0.04%
3	13%	0.89%	0.62%	0.44%	0.18%
4	11%	0.80%	0.56%	0.40%	0.16%
5	13%	0.89%	0.62%	0.44%	0.18%
6	25%	1.77%	1.24%	0.89%	0.35%
7	20%	1.42%	0.99%	0.71%	0.28%

Appendix B - Calculating Mean Absolute Deviation of Officers Hired Annually to Measure Policy Stability

	Case One		Case Two		Case One		Case Two	
	Number of 65A Hired	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65A Hired**	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65B Hired**	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65B Hired**	**Absolute Deviation from Average Annual Officers Hired**
1	6.46	11.91	7.71	0.25	13.08	20.55	67.957	21.46
2	6.60	11.77	7.71	0.25	25.528	8.10	67.957	21.46
3	85.69	67.32	7.71	0.25	49.616	15.99	48.728	2.23
4	0.00	18.37	7.71	0.25	0	33.63	48.728	2.23
5	0.00	18.37	7.71	0.25	147.169	113.54	48.728	2.23
6	0.00	18.37	6.83	0.63	0	33.63	21.69	24.81
7	29.85	11.48	6.83	0.63	0	33.63	21.69	24.81
Average	18.37	22.51	7.46	0.36	33.63	37.01	46.50	14.18

	Case One		Case Two		Case One		Case Two	
	Number of 65C Hired	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65C Hired**	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65D Hired**	**Absolute Deviation from Average Annual Officers Hired**	**Number of 65D Hired**	**Absolute Deviation from Average Annual Officers Hired**
1	0	11.28	11.411	0.00	180.98	96.78	78.995	0.00
2	11.582	0.30	11.411	0.00	101.826	17.63	78.995	0.00
3	15.337	4.05	11.411	0.00	0	84.20	78.995	0.00
4	14.106	2.82	11.411	0.00	145.366	61.17	78.995	0.00
5	10.08	1.20	11.411	0.00	0	84.20	78.995	0.00
6	27.878	16.59	11.411	0.00	83.987	0.21	78.995	0.00
7	0	11.28	11.411	0.00	77.219	6.98	78.995	0.00
Average	11.28	6.79	11.41	0.00	84.20	50.17	79.00	0.00

References

Abrams, J. (1957). Military Applications of Operations Research. Operations Research , 434-440.

Ahuja, R., Magnanti, T., & Orlin, J. (1993). *Network Flows.* Upper Saddle River: Prentice Hall, Inc.

Anbil, R., Gelman, E., Patty, B., & Tanga, R. (1991). Recent Advances in Crew-Pairing Optimization at American Airlines. *Interfaces* , 62-74.

April Jay. (2011). Strategic Workforce Optimization: Ensuring Workforce Readiness with OptForceTM. Annals of Optimization.

Armacost, A. L. (2005). Decision Support for the Career Field Selection Process at the United States Air Force Academy. European Journal of Operational Research , 839-850.

Belton, V. S. (2002). Multiple Criteria Decision Analysis. Boston: Kluwer Academic Publishers.

Bertsekas, Dmitri. (1999) Nonlinear Programming: 2nd Edition. Nashua, New Hampshire: Athena Scientific.

Bradley, Stephen P., Hax, Arnoldo C., Maganti, Thomas L. (1977) Applied Mathematical Programming. North America: Addison-Wesley Publishing Company.

Cashbaugh, D. A. (2007). Manpower and personnel. In A. L. L. Rainey, Methods for Conducting Military Operational Analysis. Military Operations Research Society.

Cavana, R. Y. (2004). A Systems Thinking Study of the New Zealand Arm Electronic Technician Group. 22nd International Conference of the System Dynamics Society. Oxford, England.

Charnes, A., Cooper, W., & Ferguson, R. (1955). Optimal Estimation of Executive Compensation by Linear Programming. Management Science , 138-151.

Coates, H. R., Silvernail, T. S., Fulton, L. V., & Ivanitskaya, L. (2011). The Effectiveness of the Recent Army Captain Retention Program. *Armed Forces & Society* , 5-18.

De Feyter, T. (2007). Modeling Mixed Push and Pull Promotion Flows in Manpower Planning. Annals of Operations Research , 25-39.

Fulton, L., & McMurry, P. (2014). The AMEDD Uses Goal Programming to Optimize Workforce Planning Decisions. Interfaces.

How the Army Runs - A Senior Leader Reference Notebook 2013 - 2014. (2013). U.S. Army War College, Carlisle Barracks.

Garza, A. K. (2014). System Dynamics Based Manpower Modeling. 2014 Industrial and Systems Engineering Research Conference.

Gass, S. I. (1991). Military Manpower Planning Models. Computers and Operations Research , 65-73.

Gass, S. I., Collins, R. W., Meinhardt, C. W., Lemon, D. M., & Gillette, M. (1988). The Army Manpower Long Range Planning System. Operations Research , 5-17.

Geoffrion, A. G. (1971). Multicommodity Distribution System Design by Benders Decomposition. Management Science , 822-844.

Grinold, R. C., & Marshall, K. T. (1977). *Manpower Planning Models.* Amsterdam: North-Holland Publishing Company.

Hall, A. (2009). *Simulating and Optimizing: Military Manpower Modeling and Mountain Range*

Henry, T. M., & Ravindrian, A. R. (2005). A Goal Programming Application for Army Officer Accession Planning. INFOR , 111-119.

Hillier, F. S. (1986). Introduction to Operations Research. New York: McGraw Hill Publishing Company.

Jacobs, F. R., & Chase, R. B. (2014). Operations and Supply Chain Management. New York: McGraw Hill Publishing.

Jensen, P. A. (2003). Operations Research Models and Methods. Hoboken: John Wiley &Sons, Inc.

Khoong, C. (1999). Some Optimization Models for Manpower Planning. Systems Management , 159-167.

Luenberger, D. (1984). Linear and Nonlinear Programming. Menlo Park: Addison-Wesley Publishing Company.

McMurry, P., Fulton, L., Brooks, M., & Rogers, J. (2010). Optimizing Army Medical Department Officer Accessions. Journal of Defense Modeling and Simulation .

Mutingi, M. (2012). Dynamic Simulation for Effective Workforce Management in New Product Development. Management Science Letters .

Mutingi, M. M. (2012). Fuzzy System Dynamics and Optimization with Application to Manpower Systems. International Journal of Industrial Engineering Computations .

Parnell, G. S., Driscoll, P.J., Henderson, D.L. (2008). Decision Making in Systems Engineering and Management. Hoboken, New Jersey: John Wiley & Sons, Inc.

Parnell, G. and Trainor, T., "Using the Swing Weight Matrix to Weight Multiple Objectives." Proceedings of the INCOSE International Symposium, Singapore, July 1923, 2009.

Price, W. (1978). Goal-Programming Manpower Models Using Advanced Network Codes. The Journal of the Operational Research Society , 1231-1239.

Price, W., & Piskor, W. (1972). Application of Goal Programming to Manpower Planning. INFOR , 221-231.

Rosenthal, R. E. (2011). *GAMS - A User's Guide.* Washington, D.C.

Schermerhorn Jr., J. R. (2010). Management. Hoboken: John Wiley & Sons, Inc.

Shrimpton, D., & Newman, A. M. (2005). The U.S. Army Uses a Network Optimization Model to Designate Career Fields for Officers. Interfaces , 230-237.

Sterman, John D. (2000). *Business Dynamics Systems Thinking and Modeling for a Complex World.* Boston: Irwin McGraw Hill.

Vita

Patrick McNally Downes is a career United States Army officer. In 1993, he graduated from the United States Military Academy at West Point, New York. He earned a B.S. in Systems Engineering and was commissioned a Second Lieutenant in the Infantry. LTC Downes served as a lieutenant with the 25th Infantry Division (Light) at Schofield Barracks, Hawaii and as a captain with 1st Armored Division at Fort Riley, Kansas, where he commanded an infantry company.

In 2002, Pat graduated from the University of Virginia with a Master's of Science in Systems and Information Engineering. His thesis research focused on building simulations to determine how well infantry fighting systems improved Soldiers' situational awareness. Upon earning his degree, Pat taught in West Point's Department of Systems Engineering from 2002 to 2005.

After his three year teaching assignment, Pat graduated from the United States Army's Command and General Staff College. He was then stationed in Vicenza, Italy, where he was assigned to the Southern European Task Force and later the 173rd Airborne Brigade Combat Team. He deployed with the 173rd to Afghanistan in 2007 where he served as a battalion executive officer. Pat's current assignment is as an assistant professor in the Department of Behavioral Sciences and Leadership at USMA.

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This dissertation was typed by Patrick Downes.