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A Robust, Multi-criteria Modeling Approach for Optimizing Aeromedical Evacuation Asset Emplacement

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Abstract

According to current force health protection policy, the U.S. Army's Health Service Support system is designed to maintain a healthy force and to conserve the combat strength of deployed soldiers. Specifically, this system remains particularly effective by employing standardized aeromedical evacuation assets and providing a responsive field-sited medical treatment facility for the wounded soldiers evacuated from the battlefield. Since the beginning of Operation Enduring Freedom, military commanders have faced a significant combinatorial challenge integrating these life-saving yet limited air evacuation assets into a fully-functional, comprehensive system for the entire theatre, which deserves thorough analysis for decision-making. This work describes a robust, multi-criteria decision analysis methodology using a scenario-based, stochastic optimization goal-programming model that U.S. Army medical planners can use as a strategic and tactical aeromedical evacuation asset-planning tool to help bolster and improve the current air evacuation system in Afghanistan. Specifically, this model optimizes over a set of expected scenarios with stochastically-determined casualty locations to emplace the minimum number of helicopters at each medical treatment facility necessary to maximize the coverage of the theatre-wide casualty demand and the probability of meeting that demand, while minimizing the maximal medical treatment facility evacuation site total vulnerability to enemy attack.

Keywords

goal programming, optimization, stochastic modeling, decision analysis, medical evacuation

1 Introduction

1.1 Background

The U.S. Army is making remarkable strides in its systematic approach to delivering health care across a continuum of combat operations. According to current force health protection policy, the U.S. Army's Health Service Support (HSS) system is designed to maintain a healthy force and to conserve the combat strength of deployed soldiers. Specifically, the HSS system remains particularly effective by providing prompt medical treatment to prepare patients for evacuation, employing standardized air and ground medical evacuation assets, providing a responsive field hospital for the wounded soldiers evacuated from the battlefield, and providing various other health and preventive medicine services. Furthermore, the HSS system incorporates the maximum use of emerging technology to improve battlefield survivability.[1]

According to the Operation Enduring Freedom (OEF) U.S. casualty status report as of May 4, 2009, there have been 452 killed-in-action (KIA) casualties and 2807 wounded-in-action (WIA) casualties since the inception of the war in 2001.[2] Therefore, although more soldiers survive compared to previous operations and wars, the U.S. Army can still greatly improve its systematic approach to treat and evacuate casualties from combat zones. As a pillar of military medical doctrine, air ambulance helicopters serve as the primary means for evacuating casualties during combat

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because of the in-transit medical care provided to the soldier. During military stability operations, however, the availability of these aeromedical evacuation (MEDEVAC) assets is likely to be fixed for a set duration. Nonetheless, optimizing the emplacement of these MEDEVAC assets at a set of medical treatment facility (MTF) evacuation sites can greatly increase casualty survivability, despite the constrained military resources.

Since the beginning of OEF in Afghanistan, military commanders have faced a significant challenge integrating coalition medical assets into a fully-functional, interconnected HSS system for the entire OEF theatre. In 2006, OEF battlefield responsibilities transitioned from a U.S. military command to a North Atlantic Treaty Organization (NATO) military command. As per this changeover of command, the Combined Security Transition Command – Afghanistan (CSTC-A) desired an integration of limited MEDEVAC assets from each contributing NATO country into a comprehensive MEDEVAC system. Moreover, CSTC-A faced an immense combinatorial problem given the number of potential MEDEVAC helicopter locations, the number of different aircraft models for employment and their associated constraints, the potential sites for casualty sustainment, and the number of supporting MTF evacuation site locations.

Therefore, the thorough investigation and development of improved analytical solutions concerning the optimization of casualty coverage, air ambulance helicopter utilization, and vulnerability to enemy attack measures directly supports the military medical mission, especially because these assets are the most important mechanism for saving lives in combat. Despite the long-term and strategic nature of military stability operations, MEDEVAC assets can be tactically re-distributed across the possible MTF evacuation sites as increases in insurgent activity and other factors cause a greater number of casualties in the entire theatre of operations. Hence, this research and work is important as it provides a robust, multi-criteria modeling approach for optimizing MEDEVAC asset emplacement.

1.2 Problem Definition

CSTC-A and the Central Command (CENTCOM) requested an analytical methodology to tackle the following problem:

> *Given a distribution of MEDEVAC missions, where do coalition forces position several different model types of helicopters amongst various possible locations to minimize the time from injury occurrence to arrival at a MTF? Given that positioning, what percent of MEDEVAC missions can be supported in less than or equal to two hours from the time of soldier injury to arrival and patient drop-off at the closest MTF site?*

1.2.1 Complexity

This problem falls under the category of discrete facility location modeling, where demands arise on distinct nodes and the facilities are restricted to a finite set of candidate locations.[3] Here, this problem is classified as a covering-based model, because there is a coverage time (two hours) within which casualties (at specific casualty-demand nodes) must be evacuated in order to be considered covered. Furthermore, Daskin[3] suggests three prototypical problems under the class of covering models: the set covering model, the maximal covering model, and the *p*-center model. Although some instances of these problems can be solved in polynomial time using mixed integer programming techniques where the linear programming relaxation is an integer solution, each of these covering-based models is classified as non-deterministic polynomial-time hard (*NP*-hard). Therefore, the problem concerning the optimization of MEDEVAC asset emplacement is also classified as *NP*-hard, as it falls under the class of discrete location coverage modeling.

1.2.2 Literature Review

This problem and its variants were researched and tackled by Zeto et al.[4] at the U.S. Army Center for Army Analysis (CAA) and Fulton et al.[5] at the U.S. Army Center for Army Medical Department Strategic Studies (CASS). Zeto et al.[4] employed a three-phase methodology emulating work done by Alsalloum and Rand[6] to tackle this problem concerning the optimal emplacement of scarce resources to maximize the expected coverage of a geographically variant demand function. The first phase consisted of a multivariate hierarchical cluster analysis of empirical data to determine the geographically variant demand, the second phase executed a Monte Carlo simulation for parameter and variable quantification, and the final phase formulated and solved the problem using a dual-criteria optimization model.[4] In particular, Alsalloum and Rand[6] extend the maximal covering location problem and suggest a goal-programming approach to solving the problem of identifying the optimal locations of a pre-specified number of emergency medical service stations. Their first objective sought to locate these stations such that the maximum expected demand is covered within a pre-specified target time. Unlike a typical set covering problem, however, Alsalloum and Rand[6] re-defined coverage as the probability of covering a demand within the threshold time. In addition, their second objective was to ensure that any demand located within the target time could find at least one available ambulance. Therefore, Zeto et al.[4] sought to maximize theatre-wide coverage while balancing asset reliability.

Fulton et al.[5] proposed a two-stage stochastic optimization model for the relocation of deployable military hospitals, the reallocation of hospital beds and commensurate staff, and the emplacement of tactical evacuation assets (medical evacuation helicopters and ground ambulances) during steady-state military combat operations. He employed a two-phase methodology consisting of a simulation and a mixed integer programming model. The simulation output the mobile hospital components and feasible locations, the evacuation components and feasible locations, and the distribution of casualties around areas that were likely to experience significant combat. Fulton et al.[5] generated various expected scenarios using a 3^{4-2} factorial design due to the uncertainty of future casualty locations, numbers, and patient severities. Therefore, the optimization phase minimized the sum of the penalty-weighted time traveled over all scenarios from potential evacuation sites to the casualty locations onward to the mobile hospital sites, where the objective function was weighted by patient injury severity scores. The model solution output the number of air and ground ambulances and the hospital beds of each type required at each selected site.

Although the research and work conducted by Zeto et al.[4] and Fulton et al.[5] suggested different solution techniques to tackle this problem and its variants, both methodologies had limitations and areas for further development. For example, Zeto et al.[4] determined his geographically variant demand function solely using empirical data and did not consider the stochastic effects due to uncertainty. In addition, the goal program neither optimized over a set of probabilistic scenarios nor contained goal priority weights. Furthermore, Fulton et al.[5] did not capture the effects due to competing objective functions that could better aid the decision maker. Neither of the analyses examined the vulnerability of enemy attack associated with air and/or ground movement in and out of the evacuation sites and mobile hospitals. Moreover, their analyses did not consider the three-dimensional distances and other effects on ground/air movement when calculating traveling times. Therefore, this work combines and extends the solution methodologies from Zeto et al.[4] and Fulton et al.[5] in order to provide further analytical investigation of this problem.

1.2.3. Motivation

Firstly, we expand the goal program established by the CAA to account for MTF site vulnerability associated with the amount of enemy activity per Afghan province where MEDEVAC operations are conducted to and from each MTF evacuation site, and we incorporate goal priority weights into the modeling objective. Secondly, we reformulate this multi-criteria optimization model to account for future uncertainty by optimizing over a set of expected scenarios based on specific Design of Experiments (DOE) factors, making the model robust and keen for both strategic and tactical MEDEVAC asset planning and decision making. Thirdly, we incorporate a stochastic modeling approach to capture the uncertainty involved with forecasting future casualty demand locations and respective monthly casualty demand in order to better determine the optimal emplacement of MEDEVAC assets; we also modify the original data parameters to account for various stochastic factors. Fourthly, we expand the model by integrating a multi-use, decision-analysis tool with statistical analyses of the modeling results in order to assist the user in his or her decision-making process. A fifth area of motivation concerns developing a model with a high level of variety constraint aggregation, allowing computationally fast solutions – the modeling tractability goal is find an optimal solution within one minute – which is especially important when using the model as a decision-making instrument for tactical MEDEVAC asset planning. Lastly, we develop a three-dimensional shortest helicopter path algorithm to more accurately compute the probability of successfully evacuating patients from a casualty demand location to the closest MTF site within two hours. In order to determine the optimal flight route and respective helicopter flight time, this algorithm considers the effects of terrain obstacles, known enemy locations, air traffic control regulations, limitations due to patients' pulmonary conditions, helicopter performance at high altitudes, and the dependence of helicopter velocity on density altitude.

1.2.4 Purpose

Therefore, this work describes a robust, multi-criteria modeling approach for optimizing MEDEVAC asset emplacement using a scenario-based, stochastic optimization goal-programming model that U.S. Army medical planners can use as a strategic and tactical MEDEVAC asset-planning tool to help bolster and improve the current HSS system within Afghanistan to support OEF. Specifically, this model optimizes over a set of expected scenarios to determine the optimal emplacement of MEDEVAC assets (including MEDEVAC helicopter sites and the type and quantity of aircraft at each site) in Afghanistan based on stochastically-determined casualty locations and three optimization goal criterion: maximize the aggregate expected casualty demand coverage, minimize MEDEVAC helicopter spare capacities, and minimize the value of the maximal MTF evacuation site total vulnerability to enemy attack.

1.3 Approach

The remainder of this work is organized as follows. Section 2 explains the theoretical methods used, particularly the optimization methodologies incorporated into the model, the mixed integer programming formulations, and our three-dimensional shortest helicopter path algorithm. Section 3 discusses our modeling experiment, specifically explaining the Afghanistan MEDEVAC asset optimization context, model data parameter quantification and assumptions, model implementation and solutions, and the final results and sensitivity analyses that are useful for the decision maker. Concluding remarks, model limitations, and areas for further research are presented in Section 4. Acknowledgments are given after the reference section.

2 Theoretical Methods

2.1 Modeling Methodologies

The following modeling techniques are incorporated in this robust, multi-criteria modeling approach for optimizing MEDEVAC asset emplacement.

2.1.1 Goal Programming

Goal programming is a traditional multi-criteria decision analysis technique that provides an analytical framework through which decision makers can systematically explore and examine different optimization problem alternatives. Moreover, the decision maker defines goals for the different optimization objectives considered and evaluates the effects each of these criterion have on the overall optimal solution for the system.[7] This methodology is particularly useful for strategic planning when incorporated with goal priority weights determined by the decision maker. In the following solution methodology, our goal-programming model consists of three different criteria seeking to maximize the aggregate expected casualty demand coverage, while minimizing both MEDEVAC helicopter spare capacities and the maximal MTF evacuation site total vulnerability.

2.1.2 Scenario Planning

Scenario planning methods take into account future uncertainty and randomness involved in strategic decision making. These scenarios are developed in an approach that focuses on underlying factors causing uncertainty within the system. Specifically, this approach aims to identify robust alternatives over the set of probabilistic scenarios.[7] DOE is a mathematical process used for identifying these different modeling alternatives, as it provides solution designers with a systematic method for modeling the interactive effects of various experimental design factors. Models designed using DOE are called 2^f factorial designs, where f refers to the number of factors considered in each scenario.[8] In the following solution methodology, a 2^3 design scenario approach is utilized to capture uncertainty for better decision making; the specific scenario DOE factors are discussed in Section 2.2.6. In addition, the model provides sufficient statistical analyses for each solution found across the given set of scenarios.

2.1.3 Stochastic Optimization

Stochastic optimization methods incorporate random elements into the model objective function, model constraints, and/or model data parameters, which serve a similar function to scenario planning in aiding decision makers when optimizing in the presence of uncertainty. Furthermore, stochastic programming is frequently used to model probabilistic scenario-based problems.[9] The following solution methodology describes a stochastic optimization goal program – where the casualty demand locations are stochastically determined and MEDEVAC helicopters are optimally emplaced at a subset of the feasible MTF evacuation sites based on these casualty demand sites – that optimizes the expected value of the objective function (i.e., minimizes over a set of probabilistic scenarios), and many of the model data parameters are quantified using stochastic calculations rather than deterministic (see Section 3.2 for more details).

2.2 Model Development

The following goal-programming model optimizes over a set of expected scenarios generated from different experimental design factors, providing a robust, multi-criteria decision-analysis mechanism to tackle the Afghanistan MEDEVAC asset optimization problem. The following sets, data parameters and decisions variables are defined to formulate the model.

2.2.1 Sets

- W = experimental design scenarios for evaluation with index $w \in W$.
- I = monthly casualty demand locations with index $i \in I$.
- J = feasible MTF sites for helicopter emplacement with index $j \in J$.
- K = aircraft model types with index $k \in K$.
- S = number of aircraft to be co-located at MTF evacuation site j with index $s \in S$.
- G = goals/criteria considered in the goal program with index $g \in G$.
- T = number of Monte Carlo simulation trials, not in the formulation, with index $t \in T$.

2.2.2 Data Parameters

- a_{iw} = the proportion of monthly demand originating at casualty site i such that the summation of a_{iw} for all i equals 1 in each scenario w.
- P_{ijkw} = the probability of successfully evacuating patients from casualty location i to MTF site j with aircraft type k in scenario w within two hours, where MEDEVAC assets are co-located with and dispatched from the closest MTF evacuation site.
- r_{jksw} = the average maximum number of casualties that can be supported from MTF evacuation site j with s number of aircraft type k in scenario w.
- λ_{iw} = the actual monthly casualty demand emanating from casualty location i in each scenario w.
- c_k = the number of aircraft of model type k available in the OEF theatre.
- v_{jw} = the vulnerability associated with each MEDEVAC route in/out of each MTF site j in scenario w.
- vc_{jw} = the total vulnerability threshold level for each MTF evacuation site j in scenario w.

$occur_w$ = the expected probability that scenario w occurs, in the objective function.

pri_{gw} = the priority weight of goal g in scenario w, in the objective function.

2.2.3 Decision Variables

Binary Variables

Y_{ijk} = the binary variable for MEDEVAC assets, equals 1 if the evacuation from casualty location i with aircraft type k dispatched from MTF site j is equal to or greater than the pre-specified probability and j is the nearest emplaced MTF evacuation site that facilitates evacuation within two hours, or 0 otherwise.

X_{jks} = the binary variable for positioning of aircraft, equals 1 if s number of aircraft type k are to be considered for positioning at MTF evacuation site j, or 0 otherwise.

Positive Variables

$dmiv_{1w}$ = underachievement deviation for Goal 1 in each scenario w.

$dplus_{2jkw}$ = overachievement deviation for Goal 2 for each j, k, and w.

$dplus_{3w}$ = overachievement deviation for Goal 3 in each scenario w.

V = the value of the maximal MTF evacuation site total vulnerability over all scenarios.

Q = the value of the maximum expected sum of the weighted goal deviations over all scenarios.

2.2.4 Mixed Integer Programming Model Formulations

Model Formulation #1: The first model formulation consists of a super goal program (with the three optimization goals) that optimizes over a set of expected scenarios. The objective function here in (1) seeks to minimize over the set of scenarios the expected sum of the weighted goal deviations. Constraints (2), (4), and (7) refer to the objective functions of each of the three original optimization goals (see Section 2.2.5) with their respective under/over achievement deviations from their desired goal target values. Constraints (3) suggest that each casualty demand location can be covered by no more than one in-theatre MEDEVAC asset of a certain type k emplaced at a MTF evacuation site j. Constraints (5) mean that only s number of type k aircraft can be located at each MTF site, and constraints (6) dictate that the total number of helicopters of type k positioned cannot exceed the MTF's in-theatre capacity. Furthermore, constraints (8) ensure that the total vulnerability of each MTF site j does not exceed its pre-decided enemy vulnerability threshold level, and constraints (9) define the value of maximal vulnerability V as greater than or equal to the total vulnerability of the MTF site with the highest total vulnerability over all scenarios. Lastly, constraints (10) and (11) refer to the binary and positive decision variables, respectively.

$$\text{Min} \quad \sum_w occur_w \left(pri_{1w} dmiv_{1w} + pri_{2w} \sum_j \sum_k dplus_{2jkw} + pri_{3w} dplus_{3w} \right) \tag{1}$$

$$\text{subject to} \quad \sum_i \sum_j \sum_k a_{iw} P_{ijkw} Y_{ijk} + dmiv_{1w} = 1 \qquad \forall w \tag{2}$$

$$\sum_j \sum_k Y_{ijk} \leq 1 \qquad \forall i \tag{3}$$

$$\sum_s r_{jksw} X_{jks} - \sum_i \lambda_{iw} Y_{ijk} - dplus_{2jkw} = 0 \qquad \forall jkw \tag{4}$$

$$\sum_s X_{jks} \leq 1 \qquad \forall jk \tag{5}$$

$$\sum_s \left(s \sum_j X_{jks} \right) \leq c_k \qquad \forall k \tag{6}$$

$$V - dplus_{3w} = 0 \qquad \forall w \tag{7}$$

$$\sum_i \sum_k v_{jw} Y_{ijk} \leq vc_{jw} \qquad \forall jw \tag{8}$$

$$V \geq \sum_w \sum_i \sum_k v_{jw} Y_{ijk} \qquad \forall j \tag{9}$$

$$X_{jks} \in \{0, 1\}, \quad Y_{ijk} \in \{0, 1\}, \qquad \forall ijks \tag{10}$$

$$V, \; dmiv_{1w}, \; dplus_{2jkw}, \; dplus_{3w} \geq 0 \qquad \forall jkw \tag{11}$$

Model Formulation #2: The second model formulation also combines the three optimization goals into a super goal program, but with a different objective than the previous formulation. The objective function in (12) seeks to minimize Q, where constraints (13) define the value of Q as greater than or equal to the maximum expected sum of the weighted goal deviations over all scenarios – a min–max objective function. All other constraints are equivalent to the previous.

$$\text{Min} \quad Q \tag{12}$$

$$\text{subject to} \quad Q \geq occur_w \left(pri_{1w} dmiv_{1w} + pri_{2w} \sum_j \sum_k dplus_{2jkw} + pri_{3w} dplus_{3w} \right) \forall\, w \tag{13}$$

2.2.5 Multi-criteria Optimization Goals

Optimization Goal #1: The first goal seeks to maximize the aggregate expected casualty demands covered.

$$\text{Max} \quad \sum_i \sum_j \sum_k a_i P_{ijk} Y_{ijk}$$

Optimization Goal #2: The second goal seeks to minimize the spare capacities of MEDEVAC helicopters for each type k emplaced at each MTF site j, ensuring a sufficient level of pre-determined reliability that an aircraft will be available when casualties occur.

$$\text{Min} \quad \sum_s r_{jks} X_{jks} - \sum_i \lambda_i Y_{ijk}$$

Optimization Goal #3: The third goal seeks to minimize the value of the maximal MTF evacuation site total vulnerability to enemy attack.

$$\text{Min} \quad V$$
$$V \geq \sum_i \sum_k v_j Y_{ijk} \qquad \forall\, j$$

2.2.6 Modeling Scenarios

This work uses the DOE mechanism for determining the optimization modeling scenarios. Specifically, the solution methodology has a 2^3 design, which means three different design factors are explored to generate eight different modeling scenarios. These scenario design factors consist of the goal priority weights (pri_{1w}, pri_{2w}, and pri_{3w}), the maximum Areas of Operation (AO) 'hotbed' casualty radius (mag_{iw}), and the total vulnerability threshold level for each MTF evacuation site (vc_{jw}). In addition, although not one of the specific design factors, each scenario has a respective expected probability of occurrence ($occur_w$) set by the decision maker.

2.3 Three-dimensional Shortest Helo-path Algorithm

The algorithm presented in this section computes a nearly optimal (i.e., almost fastest) helicopter flight route with respective flight time between an origin (e.g., MTF evacuation site) and a destination (e.g., casualty demand location), which considers the effects of:

(1) terrain obstacles within the operating environment;
(2) known enemy hotspots;
(3) air traffic control regulations;
(4) limitations due to patients' pulmonary conditions;
(5) helicopter performance at high altitudes;
(6) dependency of the helicopter velocity on density altitude.

2.3.1 Algorithm Conditions

Before diving into the specifics of our algorithm, it is important to describe some of the conditions affecting a real-world, nearly optimal helicopter path during combat operations. Condition (1) is important when determining a helicopter flight route in the three-dimensional space where helicopters must fly over, around, or between terrain obstacles such as mountains, which is particularly important in an operating environment such as Afghanistan. Condition (2) is necessary so that helicopters avoid probable enemy attacks during the flight route, thereby safely transporting soldiers and evacuating those WIA casualties requiring medical assistance at the closest MTF site. Condition (3) is essential because there are some flight routes where helicopters are not allowed to fly, such as over field artillery and mortar units or other 'No Fly' zones. In addition, there are some flight routes that air traffic controllers' deem un-flyable due to frequently poor weather in terms of visibility and cloud ceiling conditions. Condition (4) is vital such that WIA soldiers suffering from cardiac arrests or other pulmonary injuries cannot fly over 10,000 feet, where patients do not receive oxygen supplements at the higher altitudes. These first four conditions are utilized during the preprocessing phase of our algorithm to determine if the three-dimensional flight route is feasible, where the final two conditions greatly impact the actual helicopter flight time.

Condition (5) suggests that the helicopter performance at high altitudes – assuming that the helicopter engine and all components are operating satisfactorily – is heavily influenced by the density altitude, gross weight, and wind velocity during takeoff, hovering, and landing. Gross weight is the only factor that the pilot of the helicopter can control (i.e., changing fuel amounts, number of passengers, or baggage loads). If a helicopter must fly over a mountain against the violent wind downdrafts (although this creates an easy target for the enemy with a silhouette of the helicopter in the sky), it is advisable for a pilot to allow extra distance to safely clear the mountainous terrain. In addition, there are distinct helicopter airspeed limitations such that as the altitude increases, the never-exceed airspeed (V_{ne}) for most helicopters decreases. For example, at sea level V_{ne} is 86 miles per hour (MPH): at 6000 feet and 2500 rotor blade rotations per minute (RPM), it is 65 MPH; and at 6000 feet and 2700–2900 RPM, it is 78 MPH. Above 2000 feet, V_{ne} decreases by 3 MPH per 1000 feet, and above 6000 feet, V_{ne} decreases 5 MPH per 1000 feet. Therefore, as the density altitude, gross weight, and/or wind velocity increases, the helicopter performance diminishes.[10]

Lastly, condition (6) is also important for the actual flight time calculation where helicopter velocity depends on density altitude. In particular, as the density altitude increases during flight, then the greater the velocity decrement (i.e., decrease in the rate of climb) for any helicopter. The four factors affecting density altitude within the operating environment include the elevation, atmospheric pressure, temperature, and moisture content of the air. As elevation increases, the atmospheric pressure decreases, the air becomes less dense, which increases the density altitude. A specific chart is used to determine density altitude based on the temperature and the pressure altitude, where the pressure altitude is read directly from the altimeter in the cockpit when adjusted to a certain atmospheric pressure (such as 29.92 inches of mercury). Great changes in temperature cause major changes in air density, even when elevation and pressure remain constant. Therefore, as temperature increases, the air becomes less dense and the density altitude increases. Although this density altitude chart does not consider the moisture content of the air, increases in air moisture lead to less dense air and, thus, a greater density altitude, when temperature and pressure are constant. Moreover, as the temperature increases, the air can hold a greater amount of moisture. Therefore, the actual density altitude could be much higher then what is computed by the chart if the air contains high moisture content. After computing the density altitude for the temperature and pressure altitude conditions using the density altitude chart, pilots use another chart in the flight manual to compute the helicopter rate of climb and best rate of climb speed. This velocity decrement as density altitude increases is essential for calculating the helicopter flight time in our algorithm.[10]

2.3.2 Algorithm Description

We use an approximate dynamic programming algorithm to solve the three-dimensional fastest helicopter-path problem. Here, 'approximate' regards the fact that the originally continuous problem is discretized. Due to this discretization, the algorithm does not return an optimal solution to the continuous problem, but a solution of the flight time at most α times the continuous optimum. The discretization is made in a straightforward way: instead of the continuous operating scene in three-dimensional space, we only consider integer points in some parallelepiped that approximates the operating scene. More specifically, if the operating scene is defined in R^3_+ with $0 \le x \le X$, $0 \le y \le Y$, $0 \le z \le Z$, we take into consideration only the integer points in this parallelepiped $S = Z^3_+ \bigcap \{(x,y,z) \in R^3_+ \colon 0 \le x \le X, 0 \le y \le Y, 0 \le z \le Z\}$. Further, we assume that the helicopter flies only piece-wise linearly from point to point in S. Deviation from the optimal continuous curve defines the multiplicative error of the discrete solution. On the other hand, any continuous partially differentiable curve in three-dimensional space can be approximated by a piece-wise linear curve with arbitrary precision. Therefore, making the discretization scale dense enough, we can achieve $\alpha \le 1 + \varepsilon$ for any given $\varepsilon > 0$.

Given two points $p = (x, y, z) \in S$ and $p' = (x', y', z') \in S$, the helicopter flight time between p and p' is defined as follows:

$$f(p,p') = \frac{d(p,p')}{|z - z'|}\left|\int_{z}^{z'} \frac{dh}{v_o - h \cdot c}\right| = d(p,p')\left|\frac{\ln(v_o - zc) - \ln(v_o - z'c)}{zc - z'c}\right| \tag{14}$$

where $d(p,p')$ is the Euclidean distance (nautical miles) between p and p', v_o is the flight speed of the helicopter at sea level (nautical MPH), and c is the helicopter speed decrement of the density altitude (where the necessary density altitude conversions are made depending on elevation, atmospheric pressure, and temperature factors).

In the preprocessing phase of the algorithm, for any two points p and p' from S, we compute $f(p,p')$ using Equation (14). Moreover, for any two points p and p' we test whether the straight-line flight route from p to p' satisfies conditions (1) through (4). If the feasibility conditions are not satisfied, we re-define $f(p,p') = +\infty$. For completeness, we define $f(p,p') = 0$ for any $p \in S$. Now, quadruple (S, F, s, d), where $F = \{f(p,p') \colon p,p' \in S\}$, $s, d \in S$ specifies the input of the discrete fastest helicopter-path problem. Here, vertex s denotes the origin and vertex d denotes the destination of the helicopter flight route. Let K be a clique on the vertex set S. Let the length $(p,p') \in E(K)$ be determined by $f(p,p')$. Therefore, it is obvious that the straightforward Dijkstra's dynamic programming algorithm for the shortest sd-path in

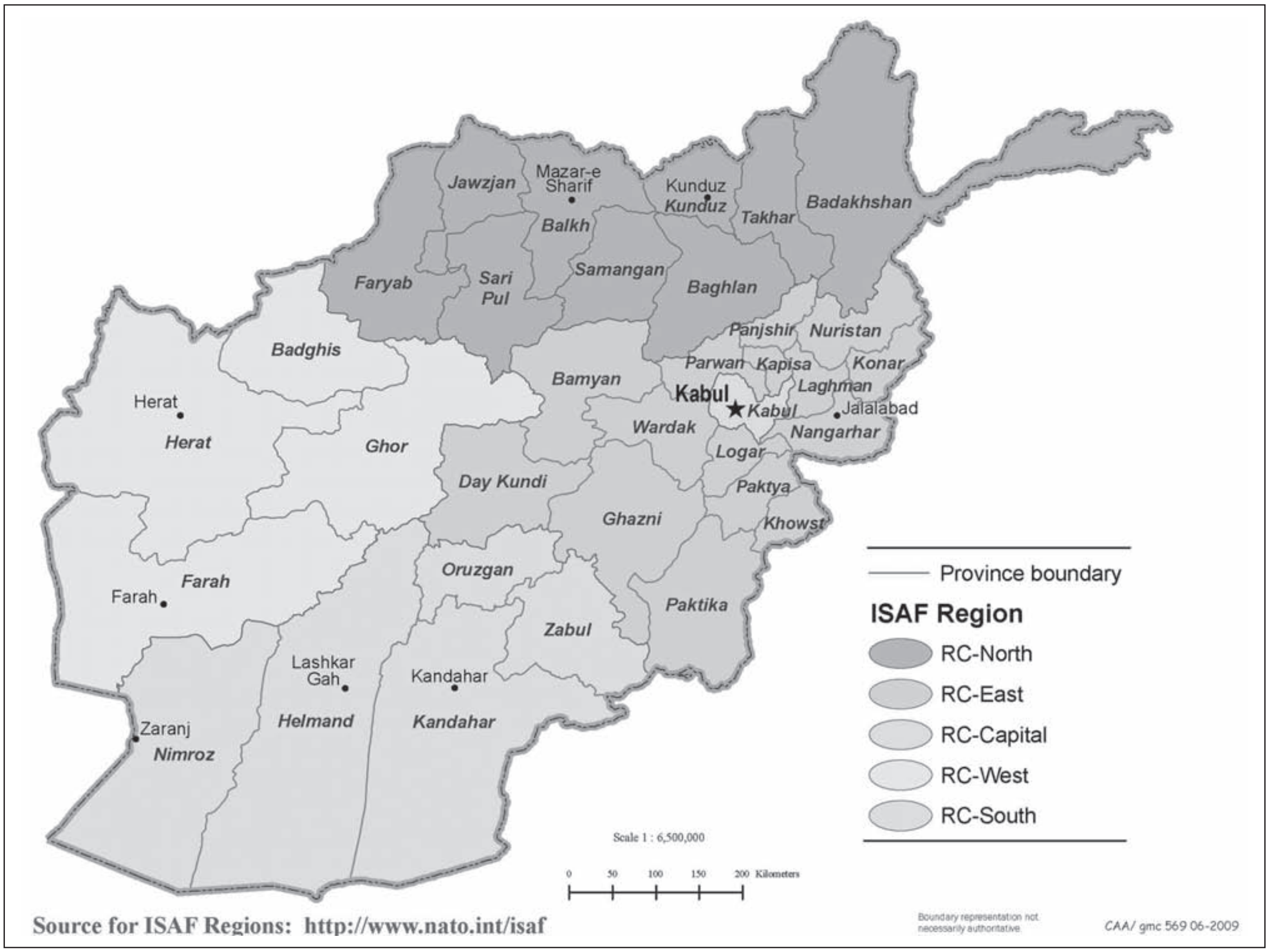

Figure 1. ISAF operating regions and Afghan provinces

K solves the discrete fastest helicopter-path problem. Refer to Dijkstra[11] for the pseudo-code.

3 Experiment

3.1 Problem Context

The following real-world experiment uses our proposed solution methodology to tackle the combinatorial problem defined by CSTC-A and CENTCOM in 2006, which specifically concerns optimizing the U.S. Army's MEDEVAC system in Afghanistan.

3.1.1 Afghanistan MEDEVAC System Optimization

Military commanders have faced significant obstacles since the inception of OEF to holistically integrate MEDEVAC assets within Afghanistan to provide a fully-functional HSS system that ensures WIA soldiers are efficiently air evacuated to receive effective medical care at field-sited MTF sites. Figure 1 depicts Afghanistan with its respective provinces and the five International Security Assistance Force (ISAF) operating regions in which both U.S. and NATO combat forces conduct operations.

3.1.2 Medical Treatment Facility Evacuation Sites

In order to improve patient survivability in-theatre, combat soldiers who are WIA must be efficiently evacuated by either air or ground medical evacuation assets where highly trained medics provide in-route medical care before arrival at the closest MTF. Here, the model provides a strategic and tactical solution for the optimal emplacement of MEDEVAC assets at MTF evacuation sites, where all MTFs serve as feasible MEDEVAC helicopter positioning sites. In Figure 2, 21 MTF sites serve as feasible MEDEVAC helicopter emplacement locations; with the assumption that MEDEVAC assets are co-located at the MTF sites (i.e., MEDEVAC helicopters evacuate WIA casualties to and from the same closest MTF evacuation location). Moreover, these MTF evacuation sites are restricted to pre-determined locations in the OEF theatre due to sustainability requirements such as logistics, maintenance, and security. These feasible MTF evacuation sites are plotted by red crosses on a 540 × 864 nautical-mile grid coordinate system to account for MEDEVAC flight times where helicopter velocities are calculated in knots (nautical MPH). Although these 21 MTF sites are pre-assigned due to sustainment capabilities,

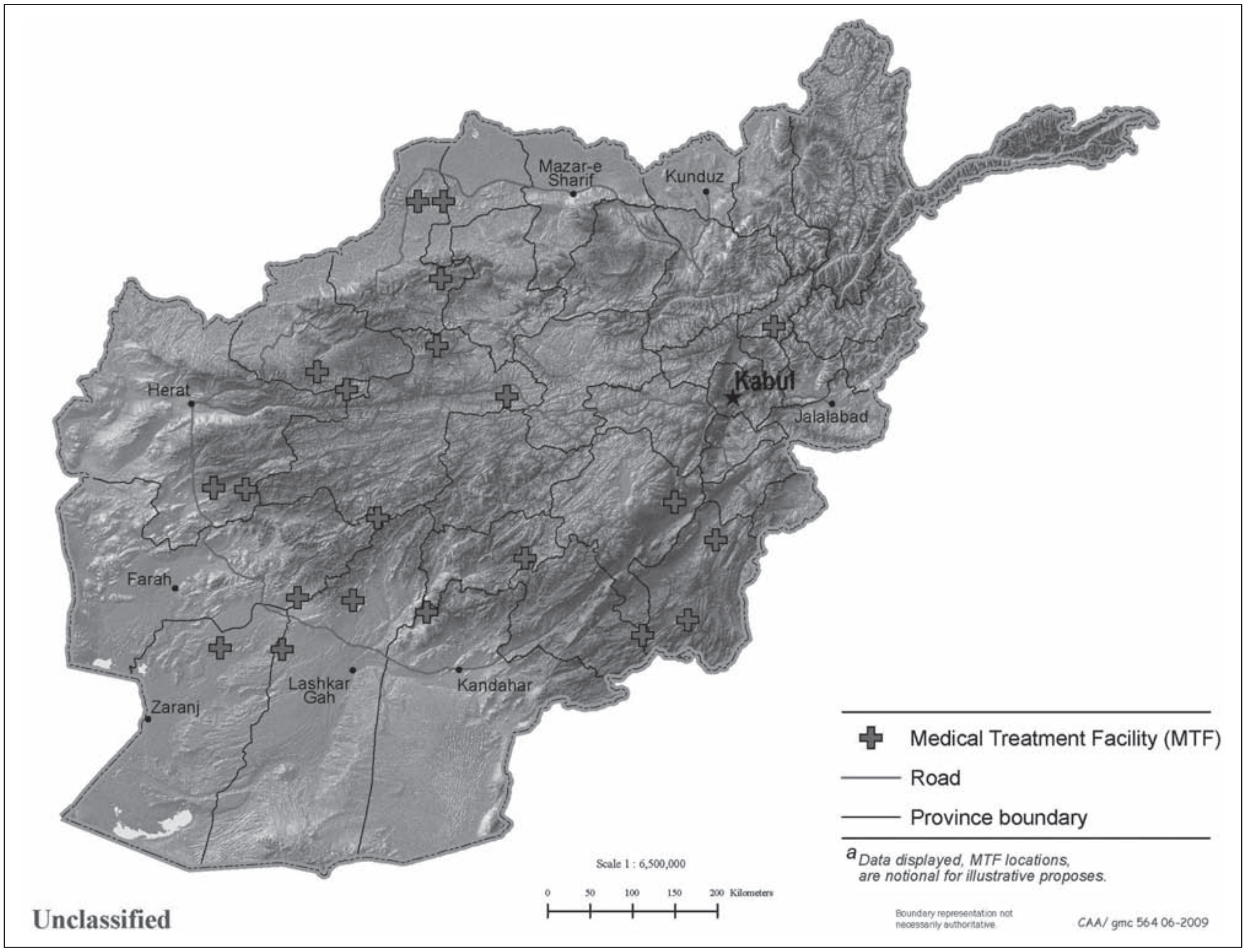

Figure 2. Feasible Medical Treatment Facility evacuation sites in Afghanistan

some of them are more susceptible to uncertain enemy insurgent attack than others. Therefore, the model captures the additional importance of optimizing MTF site total vulnerability, ensuring that each evacuation site does not exceed the pre-determined total vulnerability threshold level assigned by the decision maker. In addition, the quantity of each MEDEVAC helicopter type in-theatre is fixed due to the long-term nature of steady-state combat operations. Despite this, the decision maker can utilize this model tactically to re-distribute and re-emplace the MEDEVAC assets available on a monthly basis among the feasible MTF evacuation sites to continually optimize the MEDEVAC system based on the three goal program optimization criteria.

3.1.3 U.S. Army Areas of Operation Hotbeds Based upon the ISAF regions from Figure 1, the U.S. Army had main operating units in both RC-East and RC-South zones. In particular, the U.S. Army 3rd Brigade 1st Infantry Division and 4th Brigade 101st Airborne Division were situated in RC-East – the Afghan provinces of Nangarhar and Khost, respectively – and the U.S. Army Company D 1st/4th Regiment was located in RC-South – the Afghan province of Zabul.[12] Moreover, U.S. President Barack Obama announced that new U.S. Army Brigade Combat Teams (BCTs) would deploy to Afghanistan in support of OEF. Due to the influx of insurgent and Taliban activity in the southern part of Afghanistan bordering Pakistan, we assume in this experiment that the newly deployed BCTs were positioned in the Afghan provinces of Farah (RC-West) and Kandahar (RC-South). Figure 3 illustrates the five locations of these US Army operating units, which will serve as AO 'hotbeds'. These AO locations are also plotted on the 540 × 864 nautical-mile coordinate system, giving the following grid points ({108, 189}, {378, 162}, {270, 162}, {567, 324}, {540, 243}). The AO hotbed locations are used later in the experiment to stochastically generate casualty demand sites i and the actual monthly casualty demand (λ_{iw}) within the Afghanistan theatre (see Section 3.2.1). Although the war in Afghanistan is a very fluid situation

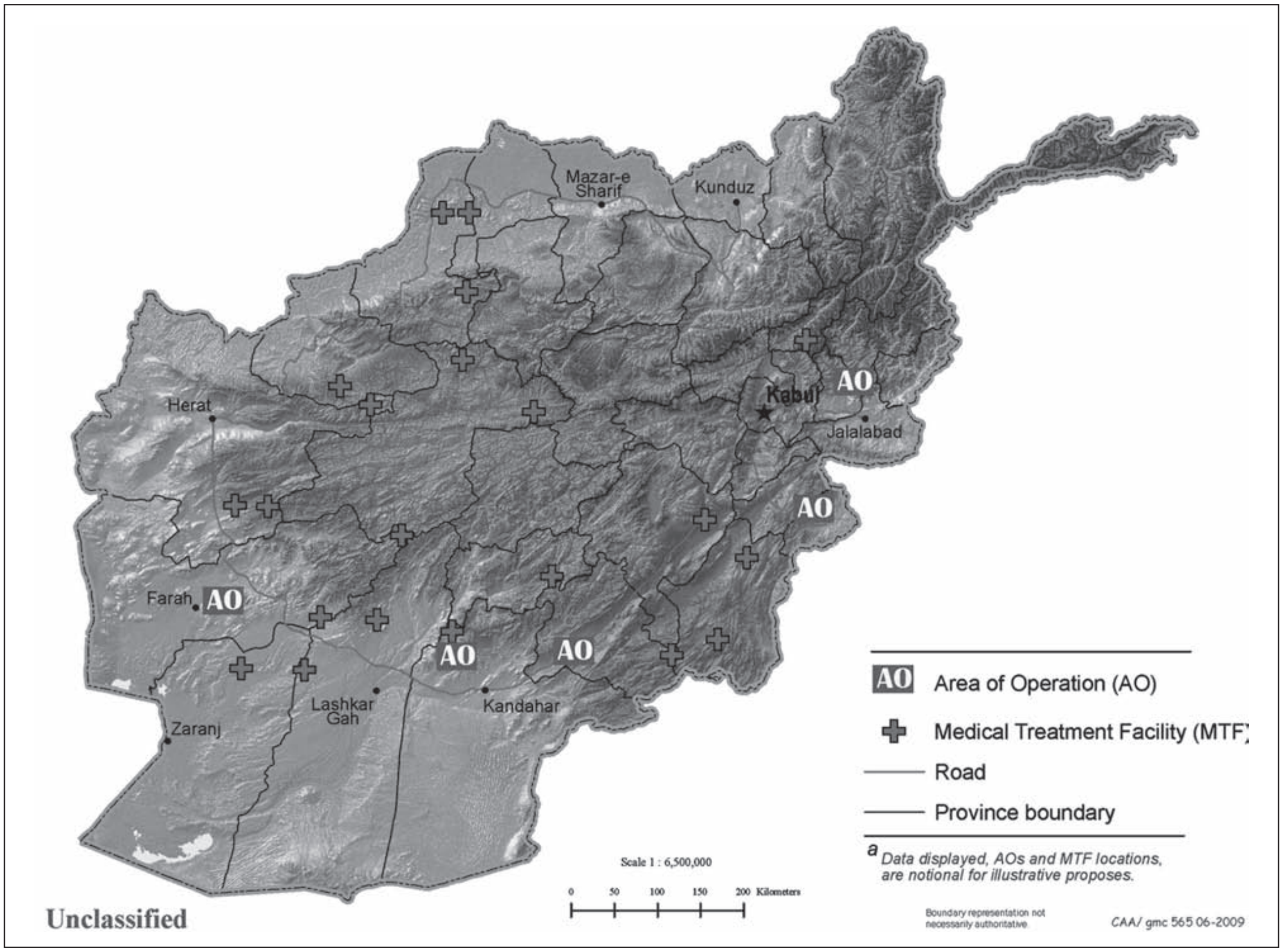

Figure 3. U.S. Army operating units in Afghanistan

with great potential for increased forces, our experiment only analyzes the situation as it was in 2006.

3.2 Data Parameter Quantification

Inherent in the stochastic optimization goal-programming model is the necessity to quantify the geographically variant casualty demand and respective demand locations in Afghanistan, the probability of successfully evacuating WIA casualties within two hours from each demand location, the maximum supportable MEDEVAC demand from helicopters emplaced at MTF evacuation sites, and the vulnerability level of each MTF evacuation site within the different Afghan provinces associated with MEDEVAC routes in and out of each MTF.

3.2.1 Casualty Generation Due to uncertainty involved with Taliban and insurgent activity within Afghanistan, future casualty demand numbers and locations must not be determined from purely historical casualty patterns. Instead, U.S. Army medical planners must combine both empirical and stochastic data to best forecast future geographically variant casualty demand. According to OEF casualty statistics posted by the U.S. Department of Defense (DoD), there have been 2806 WIA soldiers as of May 4, 2009, since the inception of OEF on October 7, 2001, which averages roughly 30 WIA casualties per month.[2] For experimental purposes, we assume that all WIA casualties were air evacuated to a mobile hospital, where roughly one patient was air evacuated per injury location. Therefore, the model stochastically forecasts monthly geographically variant casualty demand with 30 different casualty demand locations, which proves useful for tactical MEDEVAC asset planning each month during steady-state combat operations. Moreover, this experiment assumes that U.S. Army medical planners have selected the five U.S. Army AO hotbeds as prime locations or 'casualty centers' for likely enemy attacks due to the ongoing combat operations and, therefore, casualty demand can be estimated near the Afghan provinces of Nangarhar, Khost, Zabul, Farah, and Kandahar. Furthermore, a frequency distribution then assigns the percentage of casualties occurring within each predetermined AO hotbed location, which is depicted in Table 1.

Table 1. Pre-determined locations of casualty centers

Locations of casualty centers		
Grid	Casualties (%)	
{108, 189}	0.073	**CDF**
{378, 162}	0.180	0.252
{270, 162}	0.180	0.432
{567, 324}	0.284	0.716
{540, 243}	0.284	1.000

In Table 1, each AO hotbed grid coordinate is located in one of the Afghan operating regions classified by the ISAF. In fact, two of the AOs are co-located in RC-South and another two AOs are co-located in RC-East. Moreover, this casualty frequency distribution using data from Campbell and Shapiro[12] was determined by dividing the number of Taliban incidents in the AO hotbed region by the total number of Taliban incidents that occurred in RC-East, RC-West, and RC-South. For the two sets of four AOs co-located in the same regions, each casualty center was assigned half of the overall percentage of casualties within its respective region. The distribution in Table 1 provided the baseline for this experiment, even though an actual casualty frequency distribution would be determined more precisely by U.S. Army medical planners. Due to the nature of the ongoing U.S. Army combat operations in the OEF theatre, however, the actual empirical distributions are inaccessible for security purposes.

Despite this, a stochastic mechanism exists for determining casualty demand sites based on these AO hotbed locations and applying uniform randomness to the identified casualty centers. The first step is to assign a random casualty radius around each AO hotbed location. From the 2008 OEF MEDEVAC After Action Review (AAR), the coverage radius for each MEDEVAC aircraft was set at 74 nautical miles for planning purposes.[13] Therefore, this experiment assumes a random uniform casualty generation radius around each AO hotbed location, where $mag_{iw} = uniform(-d, +d)$ and d is one of the DOE scenario factors set at values of 50 or 100 nautical miles. The second step is to generate random uniform angles [$ang = uniform(0, 2\pi)$] from the AO hotbed location in the direction in which these casualties are generated. Based on a uniform random number (0, 1) and the casualty cumulative distribution value for the AO casualty center from Table 1, the 30 casualty demand locations are stochastically determined: $i\,(x_{\text{coord}}) = \text{AO site}\,(x_{\text{coord}}) + mag_{iw} \times \cos(ang)$ and $i\,(y_{\text{coord}}) = \text{AO site}\,(y_{\text{coord}}) + mag_{iw} \times \sin(ang)$.[5]

Based on this stochastic method for casualty location generation, Figure 4 illustrates the total number of casualties generated over all eight modeling scenarios, which contains a total of 240 casualty demand locations (represented by triangles that clearly surround the five AO hotbed locations and are denser in the RC-East region).

In addition to stochastic generation of the casualty demand locations, another stochastic element engenders the actual monthly casualty demand originating at each of these locations. We model uncertainty regarding enemy capability in the AO hotbed area by applying a lethality factor to the number of casualties generated at each location. Based on 2008 data from Campbell and Shapiro[12] for Taliban incidents, the maximum and minimum lethality factors were determined by the following equation: 1+ (number of Taliban incidents in the Afghan province divided by the total number of Taliban incidents in all Afghan provinces), giving a minimum value of 1.00 and a maximum value of 1.154. This lethality factor is applied as a uniform random distribution from the minimum to the maximum value [$leth_{iw} = uniform(1.0, 1.154)$]. The application of this lethality factor serves to evaluate the lethal sensitivity of the casualty location and the uncertain enemy capabilities. Based on Operation Iraqi Freedom MEDEVAC flight logs from the Army Medical Evacuation Proponency Directorate and then adjusted to the OEF casualty situation with 30 WIA soldiers per month, Table 2 provides an approximate probability mass function for determining the number of casualties at a given casualty demand location.[13]

Table 2. Number of casualties evacuated at the same casualty demand location

Casualties at same location		
# Patients	$P(X = x)$	**CDF**
1	0.874	
2	0.086	0.96
3	0.03	0.99
4	0.01	1

Note: Based on 30 WIA/month

To assign distributions for actual monthly demand at each casualty location (λ_{iw}), we use a uniform random number (0, 1) and the probability mass function from Table 2 for casualties at the same location and apply a lethality factor to the casualties generated at each location. For instance, for every casualty location i and scenario w, $\lambda_{iw} = round(\#\text{ Patients Evacuated at Same Location} \times leth_{iw})$ and cas_d_w = sum over all λ_{iw} for each scenario w. In addition, to assign the proportion of monthly demand originating at each casualty demand location such that the summation of a_{iw} for all i equals 1 for each scenario w, we assign $a_{iw} = \lambda_{iw} / cas\_d_w$. For further information regarding stochastic casualty generation, please refer to Fulton et al.[5]

3.2.2 MEDEVAC Time Monte Carlo Simulation

Another essential aspect of this experiment involves quantification of the probability (P_{ijkw}) of successfully evacuating casualties from each of the 30 stochastically-determined casualty demand locations within two hours: this is calculated for each scenario. Moreover, MEDEVAC helicopters

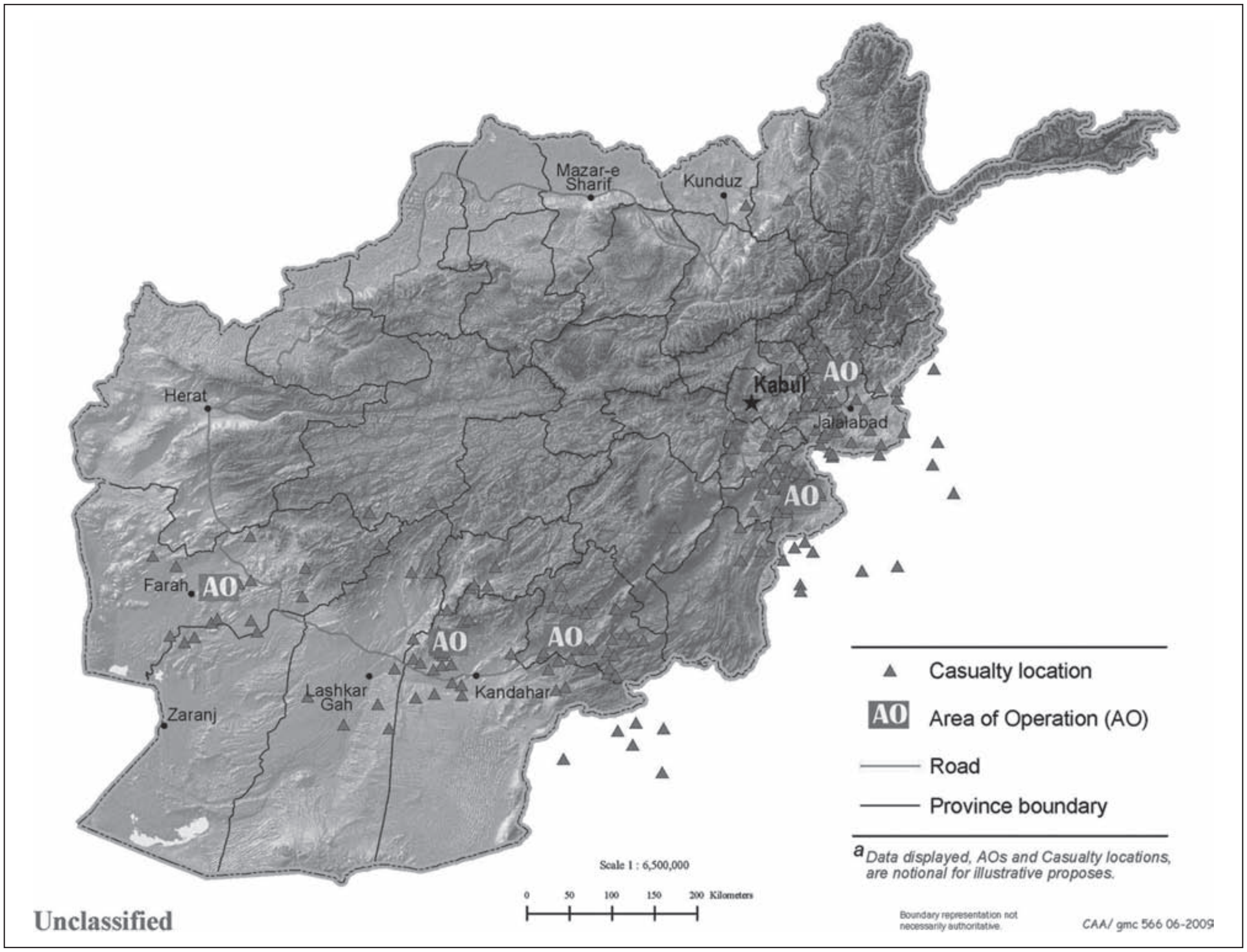

Figure 4. Stochastically generated casualty demand locations

are dispatched from the closest MTF evacuation site where aircraft are positioned and are available to retrieve the WIA soldiers and transport them to the closest MTF. In general terms, this data parameter measures the probability of success for each Y_{ijk} 'arcbird' (where the total number of arcbirds represent the product of the 30 casualty demand locations, the 21 potential MTF evacuation sites, and the three aircraft models for emplacement). In order to quantify this data parameter for the goal program, the model conducts a Monte Carlo simulation for a set number of trials per arcbird (the fewer the number of trials the faster the computational running time), where each trial sampling calculates the total MEDEVAC time per trial and scenario ($trial_{ijkwt}$). This data parameter equals the sum of six different MEDEVAC times.

1. *The time in each trial from injury at the casualty demand location to notification of a supporting MEDEVAC helicopter in each scenario ($time\_inj_{ijkwt}$).* Based on the CAA's analysts who queried in-theatre MEDEVAC pilots, this variable is stochastically calculated using their subject matter expertise via a triangular distribution in the simulation with a minimum of five minutes, a maximum of 15 minutes, and a most likely value of 10 minutes (the model computes in hours rather than minutes).
2. *The time in each trial from notification to MEDEVAC helicopter wheels up in each scenario ($time\_wup_{ijkwt}$).* Based on the 2008 MEDEVAC AAR, in-theatre subject-matter experts estimated a mean time of 20 minutes.[13] From personal MEDEVAC experience, a standard deviation of five minutes is deemed appropriate. Therefore, this variable is computed using a normal distribution using the estimated mean and estimated standard deviation (the model computes in hours rather than minutes).
3. *The flight time in each trial to pickup casualties with a helicopter dispatched from the closest MTF evacuation site in each scenario ($time\_pup_{ijkwt}$).* This variable was stochastically calculated from

dividing the Euclidean distance between the casualty demand location and the closest MTF evacuation sites (*dist_pu*$_{ijkw}$) by a random uniform distribution of MEDEVAC helicopter speeds from 120 to 193 nautical MPH (*vel*$_{ijkwt}$). Note that this range of helicopter speeds was based on the assumption that aircraft type K1 is a HH60 Pavehawk, aircraft type K2 is a UH60A-L Blackhawk, and aircraft type K3 is a UH60Q MEDEVAC with normal operating speeds between 120 and 193 knots.[14] In addition, this MEDEVAC time can be replaced by the value computed from our three-dimensional shortest helicopter path algorithm (Section 2.3).

4. *The patient load time in each trial at the casualty pickup location in each scenario (time_ld*$_{ijkwt}$*).* Similar to the time in each trial from injury to notification of the supporting MEDEVAC helicopter in each scenario, in-theatre MEDEVAC pilots provided stochastic data to model this variable in the simulation using a triangular distribution with a minimum of five minutes, a maximum of 15 minutes, and a most likely value of 10 minutes (the model computes in hours rather than minutes).[13]
5. *The flight time in each trial from the casualty location to drop-off patients at the closest MTF evacuation site in each scenario (time_drop*$_{ijkwt}$*).* Similar to the flight time in each trial to pickup casualties with a helicopter dispatched from the closest MTF evacuation site in each scenario, this variable was stochastically calculated by the same means; divide the Euclidean distance between the casualty demand location and the closest MTF evacuation site (*dist_pu*$_{ijkw}$) by a random uniform distribution of MEDEVAC helicopter speeds (*vel*$_{ijkwt}$). Note that in this experiment MEDEVAC helicopters only conduct evacuation missions to and from the same MTF evacuation site, which permits use of the same previously determined distance calculation. Again, this MEDEVAC time can be replaced by the value computed from our three-dimensional shortest helicopter path algorithm (Section 2.3).
6. *The patient off-load time at the MTF evacuation site in each trial and each scenario (time_offld*$_{ijkwt}$*).* Based on the 2008 MEDEVAC AAR, in-theatre subject-matter experts assumed a mean off-load time of five minutes.[13] From personal MEDEVAC experience, a standard deviation of two minutes is deemed appropriate. Therefore, this variable is computed using a normal distribution using the estimated mean and estimated standard deviation (the model computes in hours rather than minutes).

Again, each trial of the Monte Carlo simulation sums these six essential MEDEVAC times and keeps a count of the number per Y_{ijk} arcbird that meets the two-hour time threshold. From this, the probability of successfully evacuating patients within two hours for all *i, j*, and *k* combinations (P_{ijkw}) is calculated by taking the number of trials meeting the threshold divided by the total number of simulation trials; this is executed for each scenario.

3.2.3 Average Maximum Supportable MEDEVAC Demand

The stochastic optimization goal-programming model requires the actual quantity of each helicopter model available in-theatre for emplacement at MTF evacuation sites (c_k). In this experiment we assume that two K1s, three K2s, and twelve K3s are available to support OEF MEDEVAC operations. Furthermore, another important data parameter is the average maximum supportable MEDEVAC demand from each type and quantity of MEDEVAC helicopters emplaced at the potential MTF evacuation sites (r_{jksw}). Before diving into the calculation of this variable, the experiment makes a few assumptions about the number of litters available in each aircraft type (lit_k), the probability that at least one aircraft is available at the closest MTF evacuation site (*p_comp*), the operational fleet readiness of each aircraft type (o_k), and the actual number of each aircraft type that the model decides to emplace at the MTF evacuation sites(s). Therefore, aircraft K1 and K2 both have four litters where K3 has six litters. In addition, this experiment assumes the probability that at least one available aircraft equals a pre-determined probability of 95%, which we later examine in a sensitivity analysis, and the operational fleet readiness for all aircraft types equals 67.7%. From these data parameter values, the model computes the average maximum number of casualties per month that can be supported via MEDEVAC assets by taking the product of the number of patient litters available depending on aircraft type, the probability that at least one aircraft is available at the MTF evacuation site, the operational fleet readiness level, and the actual number of aircraft models positioned {2, 3, or 4}, for every combination of MTF evacuation sites, helicopter types, number of aircraft emplaced, and model scenarios.

3.2.4 MTF Site Vulnerability

As previously mentioned, the third criterion of the multi-criteria stochastic optimization model presented here is to minimize the value of the maximal MTF evacuation site total vulnerability. As a proxy, we assume in this model that the greater the total number of MEDEVAC helicopter dispatches from each MTF evacuation site, then the greater is its respective total vulnerability to enemy attack. Therefore, vulnerability calculations are subject to the amount of enemy activity (i.e., Taliban incidents) within each Afghan province affecting the MEDEVAC route in and out of each MTF evacuation site. Therefore, the first step was to develop an enemy capability lethality factor for each potential MTF evacuation site (en_attack_j), which is based on the 2008 data for the Taliban and other enemy incidents.[12] From this data, we determined an enemy capability lethality factor for each Afghan province by using the following equation: 1+ (number of Taliban incidents in the Afghan province divided by the total number of Taliban incidents in Afghanistan). Each MTF evacuation site is located in an Afghan province (where some share the same province) where MEDEVAC assets are dispatched from the MTF evacuation site to conduct missions. The lethality factor assigned to each MTF evacuation site is equivalent to the enemy capability lethality factor for the respective Afghan province in which it is located and where its operations are conducted. The second step involved the computation of the actual vulnerability value associated with each MEDEVAC route in and out of each MTF evacuation site (v_{jw}). This data was stochastically determined for each potential MTF helicopter emplacement site from the product of the enemy capability lethality factor per MTF evacuation site and a random uniform probability (0, 1) accounting for the uncertainty of enemy attack within that Afghan province; this was repeated for all modeling scenarios. In addition, U.S. Army medical planners must determine their desired total vulnerability threshold level for each potential MTF helicopter emplacement site (vc_{jw}), which is used for optimization purposes required in the model. Our solution methodology utilizes this total vulnerability threshold level as one of the scenario DOE factors, which is subject to the desired input of the decision maker.

3.3 Model Implementation and Solutions

Now that the theoretical methods have been established and the data parameters are quantified, our robust, scenario-based, stochastic optimization goal-programming model is ready for implementation.

3.3.1 Model Implementation Framework The General Algebraic Modeling System (GAMS), Microsoft Excel©, and Microsoft Visual Basic© platforms provided the model implementation framework for our robust, multi-criteria decision analysis methodology, particularly for the stochastic casualty generation, Monte Carlo simulation, optimization model solver, statistics generation and reports, and multi-use decision analysis tool. The GAMS is an appropriate framework to use when solving problems with multi-dimensional variables, constraints, and data parameters. In addition, the various stochastic calculations utilized the built-in GAMS seed assignment and random number generator, probability functions, and other programming controls necessary for our solution methodology. Lastly, the GAMS leveraged the CPLEX mixed integer programming solver to provide the model solutions with a given set of DOE scenarios.

3.3.2 Scenario Simulation Execution Based on the given set of DOE scenarios, our stochastic optimization goal-programming model emplaces the minimum number of helicopters at each MTF evacuation site necessary to maximize the aggregate coverage of the theatre-wide MEDEVAC casualty demand and the probability of meeting that casualty demand, while minimizing the value of the maximal MTF evacuation site total vulnerability to enemy attack. Our solution methodology uses a 2^3 factor design for the generation of eight different scenarios to better equip U.S. Army medical planners with a decision analysis tool useful for future strategic and tactical MEDEVAC asset planning. Moreover, the decision maker has full access to adjust each of these scenario DOE factors, as discussed in Section 2.2.6, to best use the model as an instrument for decision analysis. Also, each design scenario has a respective probability of occurrence assigned by the decision maker, which is part of the optimization model objective function. In this simulation experiment, we set arbitrary goal priority weights (P1, P2, and P3), casualty radii (*casrad*), total vulnerability threshold levels (*vuln*), and probabilities of occurrence (*occur*) for each scenario. Also, after running the model consecutively we noticed that the value of the goal priority weights clearly had a large influence on the resulting optimal solution. Therefore, we expanded the model to generate the pre-decided number of solutions (10 in our experimental study) necessary to conduct a sensitivity analysis on the goal priority weights, as well as the helicopter reliability percentage (see Section 3.4.3). Table 3 summarizes each of the design scenarios executed in this experiment.

Table 3. Scenario design factors for simulation

DOE scenario factors						
	occur	P1	P2	P3	casrad	vuln
1	0.125	500	0.2	0.5	50.0	1.010
2	0.125	500	0.2	0.5	50.0	1.005
3	0.150	500	0.2	0.5	100.0	1.010
4	0.100	500	0.2	0.5	100.0	1.005
5	0.125	600	0.6	0.3	50.0	1.010
6	0.125	600	0.6	0.3	50.0	1.005
7	0.100	600	0.6	0.3	100.0	1.010
8	0.150	600	0.6	0.3	100.0	1.005

3.3.3 Model Formulation Solutions For the following solutions representing the two different model formulations, the simulation and optimization was solved on a Dell Precision M60 laptop with a Pentium M 1.7 GHZ processor and 2 GB of random-access memory (RAM). Both model formulation solutions below were found using the CPLEX MIP solver embedded within the GAMS platform. The first model solution contained nine blocks of equations, seven blocks of variables, 39,919 non-zero elements, 806 single equations, and 2601 single variables. The second model solution contained 10 blocks of equations, eight blocks of

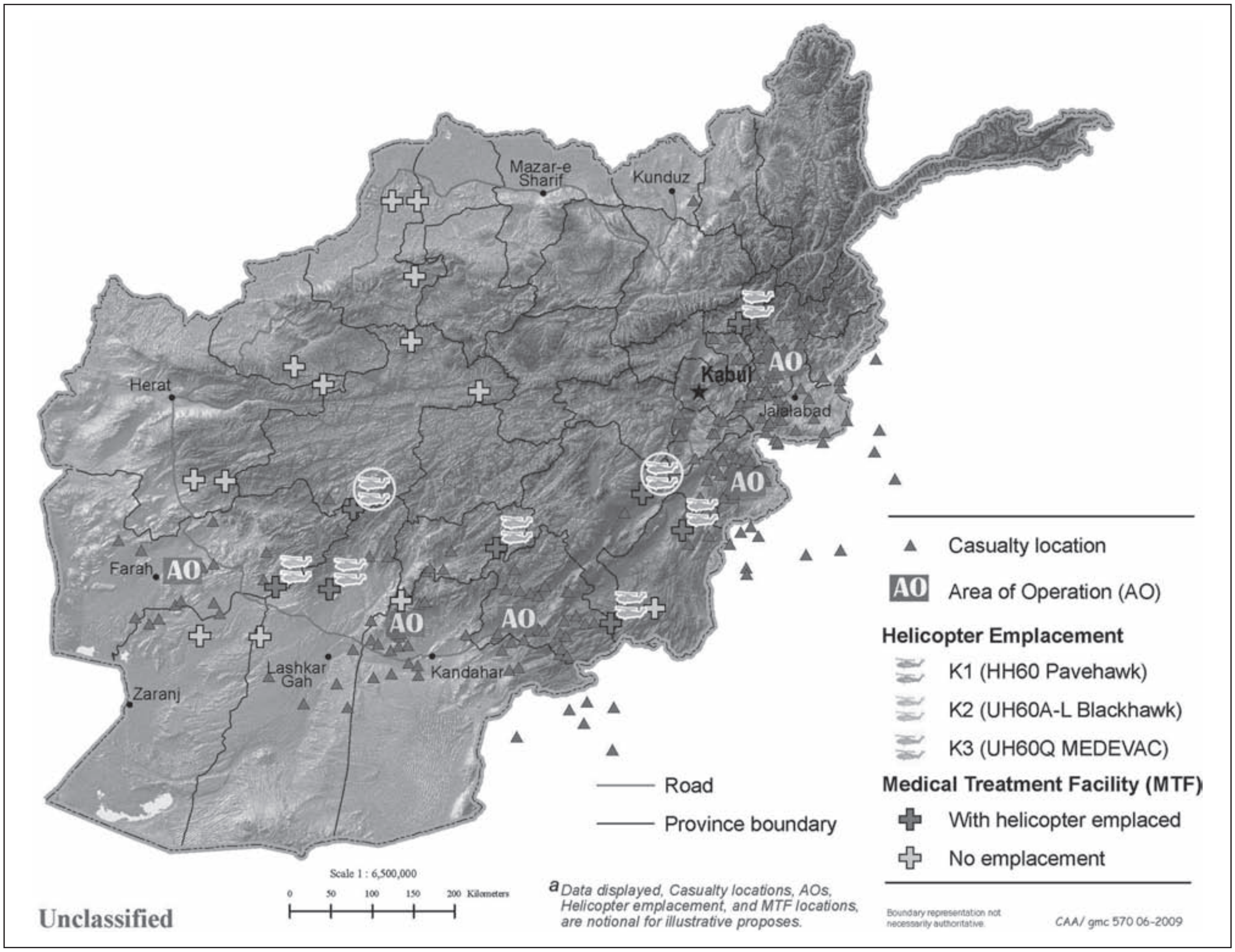

Figure 5. Model solution with helicopter emplacements

variables, 39,928 non-zero elements, 814 single equations, and 2602 single variables. In both model formulations, there were a total of 2079 binary variables representing the 1890 Y_{ijk} arcbirds and the 189 X_{jks} MEDEVAC helicopter emplacement location options (the 21 potential MEDEVAC emplacement sites times three aircraft model types times {2, 3, 4} helicopters positioned at each MTF evacuation site). The CPLEX MIP solver found an optimal solution for both model formulations in less than one minute each, which proves useful for tactical MEDEVAC asset planning. The solution for the second model formulation required nearly 10 times the number of iterations (10,355) and nearly 1000 times the number of branch-and-bound nodes. Both solutions, however, required a similar number of Gomory, clique, cover, and other valid inequalities.

3.4 Results and Analysis

This section presents the results and analysis of our robust, multi-criteria modeling approach for optimizing MEDEVAC asset emplacement. Specifically, this weighted goal-programming model optimizes over a given set of expected DOE scenarios to first stochastically generate the future casualty demand locations and actual monthly demand and then identify the optimal subset of MTF evacuation sites for the supporting MEDEVAC helicopters, and the type and number of aircraft to emplace at each MTF site. Although we calculated numerous descriptive statistics and performed sensitivity analyses for both model formulation solutions, this paper only displays the overall graphical results and the descriptive statistics/analyses of the first model formulation solution.

3.4.1 Graphical Results

The graphical results of both optimization model formulations have nearly equal solutions for the stochastic generation of casualty demand, and which type and where to optimally emplace MEDEVAC helicopters at a subset of the MTF evacuation sites. Figure 5 shows that both model formulations have identical results, except for the fact that

Table 4. Descriptive statistics for model formulation #1 solution

Descriptive Statistics Formulation #1	Design of Experiment Factor Scenarios								Average
	1	2	3	4	5	6	7	8	
Total number of casualities generated	35	32	35	38	38	36	37	33	36
Total number of casualities evacuated from casuaity sites to_from MEDEVAC Helicopters empiaced at a MTF									
E3	2	1	1	2	2	3	1	1	1
E4	1	1	1	1	2	1	3	1	1
E10	1	1	1	1	1	1	3	1	1
E11	1	1	3	1	1	1	1	1	2
E12	1	1	1	2	2	1	1	1	1
E14	1	1	1	1	2	1	1	1	1
E15	1	2	4	1	1	1	1	1	2
E16	1	2	1	1	1	1	1	2	1
Number of WIA evacuated	9	10	13	10	12	10	12	9	11
percent of total casualities evacuated	26%	31%	37%	26%	32%	28%	32%	27%	30%
Total distance traveied per month (NM) to_from MEDEVAC helicopters Empiaced at a MTF to evacuate WIAs									
E3	441.0	720.2	200.1	411.5	418.4	59.8	1001.1	148.7	425.1
E4	702.7	121.9	649.8	766.7	42.6	327.3	50.9	66.0	341.0
E10	589.5	598.4	143.1	36.7	685.4	201.2	37.4	210.0	312.7
E11	164.7	565.1	119.1	157.9	152.1	171.1	174.3	85.9	198.8
E12	149.8	302.4	704.6	54.9	137.4	352.8	126.8	420.4	281.1
E14	446.2	294.9	135.1	91.4	70.4	126.4	162.0	255.7	197.8
E15	456.7	39.1	29.8	44.3	140.4	576.9	111.2	36.7	179.4
E16	231.0	58.8	362.0	332.8	308.5	126.4	437.0	85.4	242.7
Mean MEDEVAC distance for all WIAs	452.8	349.8	333.9	295.3	328.0	257.7	284.7	174.3	309.6
Mean MEDEVAC velocity for all WIAs	157.3	157.3	155.9	155.5	156.3	156.7	156.3	156.7	156.5
Mean MEDEVAC time for all WIAs	2.88	2.22	2.14	1.90	2.10	1.64	1.82	1.11	2.0
E(X^2) for simulation average total MEDEVAC time	16.2	11.3	10.6	11.0	11.0	6.8	10.3	4.1	
(E(X))^2 for mean MEDEVAC time for all WIAs	8.3	4.9	4.6	3.6	4.4	2.7	3.3	1.2	
Standard deviation of MEDEVAC time	1.00	0.89	0.87	0.96	0.91	0.71	0.94	0.60	
Final standard error					8.7%				

the emplacement of aircraft types K1 and K3 are swapped at MTF sites E10 and E16 (depicted by circles).

3.4.2 Descriptive Statistics

Descriptive statistics for the modeling scenarios (see Table 4) are generated within our model implementation framework to capture the casualty generation, helicopter positioning, distance/speed/time, and scenario sampling statistics.

The total number of casualties generated was equivalent for both model formulation solutions with an average of 36 casualties generated per month, which is based on the probability mass function for the number of casualties evacuated from the same location used in our experiment. This amount slightly exceeds the historical, deterministic data of 30 WIA soldiers per month. From the descriptive statistics displayed in Table 4, it is interesting to note the actual number and percentage of casualties evacuated, where only an average of 30% of total casualties were evacuated each month. The reason for these low amounts and percentages of evacuated WIA soldiers directly correlates to the P_{ijkw} values, the probability of successfully evacuating patients from each of the casualty demand locations within two hours. Although most of the casualty locations have a maximum probability of successful casualty evacuation of 100% for each of the scenarios, the overall average probability of successfully evacuating casualties within two hours from all casualty demand locations over all scenarios equals 63%. These averages, however, do not account for the combinations of i, j, and k with success rates of 0% (if this were the case, then the average percentages would be much lower at around 10–20%). In fact, most of the combinations of i, j, and k have success probabilities of 0% because of the location we set for each AO hotbed, their distance away from the pre-determined feasible MTF evacuation sites, and our stochastic method for generating casualties up to 100 nautical miles away from an AO hotbed location. Regardless of these casualty statistics, nearly all of the WIA soldiers will be evacuated from the casualty demand locations in an actual combat environment despite the two-hour MEDEVAC time threshold. Also, Table 4 displays the mean MEDEVAC distance, velocity and time statistics, as well as the sampling statistics for each modeling scenario. These statistics consider all MEDEVAC times to evacuate casualties and not simply times under the two-hour threshold. Therefore, it is interesting to note that the average over all scenarios of mean MEDEVAC times was roughly two hours for the first (and second) model formulation solution. In addition, the final standard error between the Monte Carlo simulation average MEDEVAC time and the mean MEDEVAC time over all scenarios is less than 12% in both model formulation solutions (note: Euclidean distance is used for these time calculations).

3.4.3 Sensitivity Analyses

Our decision analysis methodology executes a preset number of times to better aid the decision maker with a range of solutions, as well as performing sensitivity analyses on two different model data parameters. In particular, we analyzed solution sensitivity for both model formulations by measuring the impact on the number of casualties evacuated per month when changing the probability that at least one helicopter is available to conduct an MEDEVAC mission, as well as each goal priority weight. Firstly, we tested the sensitivity of the helicopter availability reliability from 90% to 100% probability that at least one helicopter is available at a MTF evacuation site, but found no significant relationship. Next, we compared the average priority goal weight with the average number of casualties evacuated over 10 runs. We discovered that the priority weight of Goal #1 has the greatest impact on the optimal solution when compared to the other two goal priority weights. We conducted identical sensitivity analyses for the second model formulation solution, but we found no interesting difference. Nonetheless, Figure 6 illustrates the increasing linear relationship between the average priority weight for the first goal weight and the average number of casualties evacuated over the scenario set.

The results and analysis presented here clearly highlight the functionality of our scenario-based, stochastic optimization goal-programming model for determining the optimal emplacement (with respect to aircraft type and quantity) of MEDEVAC helicopters at a subset of feasible MTF evacuation sites, such that the aggregate expected casualty demand coverage is maximized while the MEDEVAC helicopter spare capacities and maximal MTF site total vulnerability are minimized. Furthermore, the solutions to our experiment concerning the Afghanistan MEDEVAC asset optimization problem are based on notional input data for U.S. Army security purposes, as well as numerous assumptions made for quantification of the model data parameters. Lastly, it is evident from the descriptive statistics and sensitivity analyses that our optimal solutions obtained from both model formulations are influenced by numerous factors as previously discussed.

4 Conclusions and Recommendations

4.1 Conclusions

Although more casualties survive compared to any other war due to the current HSS system, the U.S. Army can still greatly improve its systematic approach to treat and air evacuate casualties from combat zones in order to maintain a healthy force and to conserve the combat strength of deployed soldiers. In particular, military commanders have faced a significant combinatorial challenge since the beginning of OEF, integrating limited air evacuation assets into a comprehensive system for the entire combat theatre. Therefore, thorough modeling and analysis is crucial for military medical planners seeking the optimal emplacement of these MEDEVAC assets, which serve as the primary means for saving lives during steady-state combat operations. In addition, further investigation and development of improved analytical solutions concerning the optimization of casualty coverage, air ambulance helicopter utilization, and vulnerability to enemy attack measures directly supports the military medical mission.

This work described our robust, multi-criteria modeling approach for optimizing MEDEVAC asset emplacement, which U.S. Army medical planners can use as a strategic and tactical MEDEVAC asset-planning tool to help sustain and improve the MEDEVAC system in Afghanistan. Specifically, this model first generated casualty demand locations and then optimized over a set of expected scenarios based on these stochastically determined casualty locations in order to emplace the minimum number of helicopters at each MTF necessary to maximize the coverage of the theatre-wide casualty demand and the probability of meeting that demand, while minimizing the maximal MTF evacuation site total vulnerability to enemy attack.

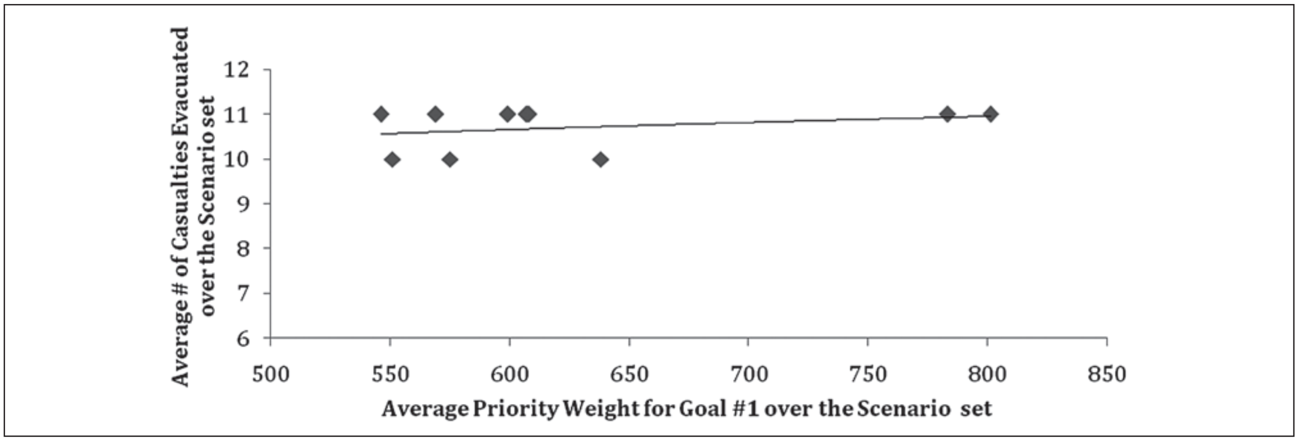

Figure 6. Model #1 sensitivity of average priority weight for Goal #1

Although our solution methodology used in the experiment focused on optimizing the U.S. Army's MEDEVAC system in Afghanistan, the results clearly demonstrate that our modeling approach can be employed as a useful analytical tool for decision makers seeking to optimize the emplacement of limited resources based on the probability of covering geographically variant demand requirements. Our decision analysis methodology utilizes multi-criteria, scenario planning, and stochastic optimization methods to help support tactical MEDEVAC asset planning for steady-state military operations. Endless opportunities exist to utilize our solution methodology within (and outside) the military medical community.

4.2 Limitations and Future Work

The results of our experiment are limited to the assumptions made and the data used during model development. Therefore, our experiment would improve with updated MEDEVAC data from in-theatre subject matter experts, particularly to fine tune the quantification of numerous model data parameters and the various probability distributions.

As seen from our results and analyses, optimal model solutions are heavily dependent on the DOE scenarios input by the decision maker, where the priority weight of the first optimization goal has the greatest sensitivity. In addition, our modeling approach is limited by the probability of successfully evacuating patients from each of the casualty demand locations within two hours. This data parameter greatly affects the number and percentage of actual monthly WIA casualty evacuations. Future work is needed to further develop and implement our three-dimensional shortest helicopter path algorithm to compute this essential model data parameter. Our algorithm implementation remains a work-in-progress due to the complexity associated with data collection for the feasibility conditions (as the real data is classified) and the algorithm inputs, yet proves useful as a future modeling add-in for more accurate three-dimensional helicopter flight times during combat operations.

Moreover, this experiment utilizes only a small sample of air ambulance and MTF attributes. The addition of attributes, however, increases problem complexity and slows the model computation time, which is a significant limitation for tactical MEDEVAC asset optimization. Also, our methodology only considers a monthly planning time horizon as opposed to multi-period analysis, because multi-period analysis is not particularly useful for geographically variant resource emplacement in military stability operations. Nonetheless, a multi-period extension to the model would be useful for strategic medical modeling in non-stability combat operations where the operation tempo varies over time and sufficient planning over multiple time periods is necessary.

Further expansion of the model is needed to account for ground casualty evacuation assets and not only MEDEVAC helicopter emplacement. This methodology can also be extended to account for MTF patient capacities, as well as inserting parameters that model the future capabilities of evacuation and hospital assets. The model, however, can be easily re-formulated to account for these changes, as well as different objective functions and constraints. Future areas of research concern dynamic approaches and techniques for military medical modeling to assist U.S. Army medical planners in both ground and air evacuation asset scheduling and routing decisions.

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References

1. Army Field Manual 4-02. *Force Health Protection in a Global Environment*. 2003.
2. Operation Enduring Freedom (OEF) U.S. Casualty Status Fatalities. http://www.defenselink.mil/news/casualty.pdf (accessed May 4, 2009).
3. Daskin M. What you should know about location modeling. *Naval Research Logistics* 2008; 55: 283–294.
4. Zeto J, Yamada W, and Collins G. *Optimizing the emplacement of scarce resources to maximize the expected coverage of a geographically variant demand function*. Study developed at the Center for Army Analysis (CAA), 2006.
5. Fulton L, Lasdon L, McDaniel R, and Wojcik B. *Two-stage stochastic optimization for the allocation of medical assets in steady state combat operations*. Study developed at the Center for AMEDD Strategic Studies (CASS), 2009.
6. Alsalloum O, Rand G. Extensions to emergency vehicle location models. *Computers & Operations Research* 2006; 33: 2725–2743.
7. Durbach I, Stewart T. Integrating scenario planning and goal programming. *Journal of Multi-Criteria Decision Analysis* 2003; 12: 261–271.
8. West P. Solution design. In Parnell G, Driscoll P, and Henderson D (eds) *Decision making in systems engineering and management*. 2008, pp.317–355.
9. Kleywegt A, Shapiro A. *Chapter 101: stochastic optimization*. Work done at the School of Industrial and Systems Engineering at Georgia Institute of Technology, 2000.
10. Basic Helicopter Handbook. http://www.geocities.com/flyingmouse1 (accessed June 26, 2009).
11. Dijkstra E. A note on two problems in connection with graphs. *Numerische Mathematik* 1959; 1: 269–271.
12. Campbell J, Shapiro J. *Afghanistan index: tracking variables of reconstruction and security in post-9/11Afghanistan*. http://www.brookings.edu/ afghanistanindex (2008, accessed May 9, 2009).
13. Operation Enduring Freedom aviation operations. *Combat aviation brigade in Afghanistan initial impressions report*, 2008.
14. Federal of American Scientists. *UH-60 Black Hawk, UH-60L Black Hawk, UH-60Q MEDEVAC, MH-60*. http://www.fas.org/programs/ssp/man/uswpns/air/rotary/sh60.html (accessed May 5, 2009).

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Nathaniel D. Bastian is a commissioned officer in the U.S. Army, where he serves as an Aeromedical Evacuation Officer in the Medical Service Corps branch. He earned his Bachelor of Science degree in Engineering Management with Honors from the U.S. Military Academy at West Point, and he earned his Master of Science degree in Econometrics and Operations Research from Maastricht University School of Business and Economics in The Netherlands. His work and research, which was conducted as a Fulbright U.S. Students Program Fellow through the Netherland–America Foundation, has application to medical evacuation and ambulatory asset optimization for systematic decision making. He is a certified engineer-in-training and engineering manager from the National Council of Examiners for Engineering and Surveying (NCEES) and Engineering Management Certification International (EMCI), respectively, and he serves as a co-editor for *The Internet Journal for Aeromedical Transportation*. In addition, he is a member of the American Society for Engineering Management (ASEM), the Military Operations Research Society (MORS), the Institute for Operations Research and Management Science (INFORMS), Phi Kappa Phi, and the Epsilon Mu Eta Engineering Management Honor Society.