

# Multi-criteria logistics modeling for military humanitarian assistance and disaster relief aerial delivery operations

Nathaniel D. Bastian<sup>1</sup> · Paul M. Griffin<sup>2</sup> ·  
Eric Spero<sup>3</sup> · Lawrence V. Fulton<sup>4</sup>

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**Abstract** Given that it is not always feasible to reach an affected area via land or sea within the first week following a natural disaster, aerial delivery provides the primary means to rapidly supply the affected population. Further, it is often the case that high density delivery of humanitarian aid supplies are taken over by non-friendly groups within the affected population. By using direct airdrop systems to deliver large quantities of individually wrapped food and water items, dispersion among the affected disaster relief population will occur more quickly. In this paper, we proffer a multiple criteria decision analysis (MCDA) framework to optimize the military humanitarian assistance/disaster relief (HA/DR) aerial delivery supply chain network. The model uses stochastic, mixed-integer, weighted goal programming to optimize network design, logistics costs, staging locations, procurement amounts, and inven-

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✉ Nathaniel D. Bastian  
ndbastian@psu.edu

Paul M. Griffin  
pgriffin@gatech.edu

Eric Spero  
eric.spero.civ@mail.mil

Lawrence V. Fulton  
larry.fulton@ttu.edu

- <sup>1</sup> Department of Industrial and Manufacturing Engineering, The Pennsylvania State University, 355 Leonhard Building, University Park, PA 16802, USA
- <sup>2</sup> School of Industrial and Systems Engineering, Georgia Institute of Technology, 755 Ferst Drive, Atlanta, GA 30332, USA
- <sup>3</sup> Vehicle Applied Research Division, U.S. Army Research Laboratory, 4603 Flare Loop, Aberdeen Proving Ground, Aberdeen, MD 21005, USA
- <sup>4</sup> Rawls College of Business Administration, Texas Tech University, 703 Flint Ave, Lubbock, TX 79410, USA

tory levels. The MCDA framework enables decision-makers to explore the trade-offs between military HA/DR aerial delivery supply chain efficiency and responsiveness, while optimizing across a wide range of real-world, probabilistic scenarios to account for the inherent uncertainty in the location of global humanitarian disasters as well as the amount of demand to be met.

**Keywords** Multiple criteria decision analysis · Stochastic optimization · Facility location · Humanitarian logistics · Supply chain engineering · Aerial delivery operations

## 1 Introduction

Upon the request of the U.S. Department of State (DOS) in conjunction with the U.S. Agency for International Development (USAID), the U.S. Department of Defense (DOD) may be called to respond to global disasters (hurricanes, earthquakes, tsunamis, flood, volcanic eruption, epidemic, fire, etc.) to conduct foreign humanitarian assistance and disaster relief (HA/DR) operations to relieve or reduce human suffering, disease, hunger, or privation [1]. HA/DR operations are often characterized by rapidly changing circumstances and asymmetric information, where there is substantial pressure to quickly provide relief supplies and material to an affected population overseas. If the DOD is called upon, the U.S. Transportation Command (USTRANSCOM) is typically responsible for planning and executing HA/DR aerial delivery operations by providing assistance within a few days in the form of food and water (consumable aid) [1]. In addition to the provision of consumable aid, the DOD is often tasked to assist with other humanitarian services such as sanitation, health-care, non-consumable aid (clothing, bedding, etc.), emergency shelter, and support to critical infrastructure [1]. Note that these latter HA/DR services are not required as quickly as consumable aid.

Within the 72-h immediate response authority [2] of a foreign humanitarian disaster, there lacks an effective, safe ability to provide food and water directly to individuals or small groups within the affected population via ground delivery operations. Normal HA/DR distribution channels are blocked or non-existent, and first responders from Non-Governmental Organization (NGOs) often cannot reach the affected population due to impassible roads, inoperable airports and seaports, and logistical bottlenecks. Since disasters can render normal ground lines of communication or transportation unusable for long periods of time, aerial delivery is the only mechanism for providing immediate aid. This method safely delivers and disperses food and water directly to the affected population, thereby reducing or possibly even eliminating the need for on-ground support in the disaster area. Further, aerial delivery allows USAID and the affected state to conduct needs assessments and establish the infrastructure required to provide sustained humanitarian assistance via land, air, or sea [1].

It should be noted that humanitarian aid distribution to the affected population by means of aerial delivery has some drawbacks. For example, aerial delivery does not ensure that the most vulnerable people will have access to this airdropped consumable aid (since nobody is necessarily coordinating the distribution on the ground). However, we emphasize that aerial delivery is the first means to reach the affected population, but

it should be not maintained for long periods of time. In other situations, humanitarian aid delivery to affected areas includes landing and giving it to people in charge of on-ground distribution. In this paper, we do not consider this latter situation but only aerial delivery operations (such as precision airdrop).

In order to support the strategic logistics planning and cost assessment of military HA/DR aerial delivery operations for the DOD, a decision support model is needed to facilitate both responsive and efficient logistics planning of the military HA/DR aerial delivery supply chain network. An optimal supply network design is a function of the humanitarian aid to be procured, transported, stored and delivered across the multi-stage supply chain.

## 1.1 Problem definition

The U.S. Army Natick Soldier Research, Development and Engineering Center (NSRDEC) has initiated development of the next generation HA/DR aerial delivery capability to enable airdrops to occur directly over the affected population. The direct aerial delivery of HA/DR consumable aid (food and water) through airdrop operations avoids the need for ground supply chain lines, which are often damaged as a result of the disaster, while providing HA/DR aid within days following a disaster [3].

In conjunction with the development of the next generation HA/DR airdrop capability, NSRDEC is further developing the food items, water items and airdrop containers, and they are investigating HA/DR aid distribution effectiveness and the dispersion of food items over the drop site (spread modeling). In addition to these efforts, NSRDEC seeks a strategic logistics planning model for military HA/DR aerial delivery operations in order to understand better the trade-offs of supply chain efficiency and responsiveness in the event of a disaster [3].

NSRDEC would like to identify the optimal number and location of pre-positioned facilities (distribution centers) for storing HA/DR consumable aid supplies. This entails analyzing current U.S. Air Force bases with consideration of the location of cargo aircraft capable of responding, proximity to high disaster risk areas, and storage space available. Further, the amount of consumable humanitarian aid (inventory) to be both procured and stored must be optimally determined to meet the estimated affected population size (consumer demand). Moreover, NSRDEC desires a cost assessment capability (i.e. an analysis of potential cost savings) of the entire military HA/DR supply network from the procurement of food and water items to the actual HA/DR aerial delivery mission execution [3].

## 1.2 Motivation and purpose

In this paper, we develop a multiple criteria decision analysis (MCDA) framework to optimize the military HA/DR aerial delivery supply chain network. The model uses stochastic, mixed-integer, weighted goal programming to optimize network design, logistics costs, staging locations, procurement amounts, and inventory levels. As a result, the optimization model provides strategic decision support to NSRDEC

and other HA/DR decision-makers for the aerial delivery of small HA/DR airdrop systems—airdrop of small food and water (consumable aid) packages directly onto affected disaster relief populations.

The MCDA framework enables decision-makers to explore the trade-offs between military HA/DR aerial delivery supply chain efficiency and responsiveness, while optimizing across a wide range of real-world, probabilistic scenarios to account for the inherent uncertainty in the location and severity of global humanitarian disasters as well as the amount of demand to be met. Moreover, the MCDA framework provides strategic decision support to help answer the following questions:

1. From a set of candidate staging facilities around the world, how many and which ones should be opened to pre-position and distribute consumable aid to disaster areas via several aerial delivery modes?
2. How much consumable aid should be procured from the suppliers as well as stored in inventory at both depots and staging facilities?
3. How many trips are necessary (between the different supply chain stages) for each of the different pre-positioned aerial delivery modes to achieve a best compromise solution, trading off supply chain efficiency and responsiveness?

## 2 Literature review

Supply Chain Management (SCM) for HA/DR delivery operations is the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people [4]. Logistics in the HA/DR sector encompasses several traditional activities such as the procurement, transportation and warehousing of goods and services, as well as other specific activities such as disaster preparedness and planning [4–6]. Network design emphasizes the optimal design of the HA/DR supply chain using mathematical models and methods to determine optimal strategies and policies for managing the supply chain [7]. Important performance criteria include supply chain efficiency, responsiveness, and risk [7].

Characteristics that bring additional complexity and unique challenges to HA/DR delivery supply chain design and management include: unpredictability of demand, in terms of timing, geographic location, type of commodity and quantity of commodity; suddenly-occurring demand in very large amounts and short lead times for a wide variety of supplies; high importance associated with response time; and lack of initial resources (supply, people, technology, transportation capacity and money) [8]. The flow of resources coincides with four main phases of disaster relief: assessment (minimal resources are required to identify what is needed), deployment (resource requirements ramp up to meet the needs), sustainment (operations are sustained for a period of time), and reconfiguration (operations are reduced, then terminated) [8].

Given that HA/DR delivery supply chains usually operate in highly uncertain environments, they must be engineered and executed in shorter periods of time as to provide relief to the affected population as soon as possible [9]. Further, inventory management in HA/DR delivery supply chains is affected by unreliable, incomplete or non-existent

information about lead times, demand levels, and locations [10]. In terms of distribution network configuration, the number and location of distribution centers is uncertain. This makes cost assessment difficult in terms of planning financial flows.

For the HA/DR supply chain network, there are three dominating costs: supply costs, distribution costs, and inventory holding costs. Unpredictable demand patterns increase the complexity of relief organization-supplier relationships, making them more difficult to foster than in the relatively stable demand environment of the commercial supply chain [11]. Further, supply procurement options generally cannot be evaluated before a disaster occurs. Thus, it may be difficult to control the cost of supplies. Distribution costs stem from the need to transport massive amounts of materials in a very short amount of time. Varied disaster locations lead to varied modes of transportation. The types of inventory costs include inventory investment, inventory obsolescence (and spoilage), order/setup costs, and holding (carrying) costs. Inventory control for supply warehouses in the relief chain is challenging due to the higher variations in lead times, demands, and demand locations [11]. Coordinating activities between various agencies for HA/DR is also a challenging issue [12–14].

Relatively few studies have been conducted to optimize HA/DR delivery operations in terms of distribution center pre-positioning and inventory staging. A survey of decision aid models for humanitarian logistics is provided in Ortuño et al. [15]. Akkihal [16] solves an array of mixed-integer linear program formulations to examine the strategic impact of inventory pre-positioning on delivery lead-time of HA/DR operations. The model determines optimal locations for warehousing non-consumable inventories required for initial deployment of aid. The objective of the model is to minimize the average global distance from the nearest warehouse to a forecasted homeless person. Demand patterns, along with correlated variables such as population and hazard frequency, offer views of regional vulnerability to natural disasters [16]. Similarly, Balcik and Beamon [8] consider facility location decisions for a humanitarian relief chain responding the quick-onset disasters, where they develop an optimization model that determines the number and locations of distribution centers in a relief network and the amount of relief supplies to be stocked at each distribution center to meet the needs of the affected population. The model integrates facility location and inventory decisions, while considering multiple item types and capturing budgetary constraints and capacity restrictions [8].

Duran et al. [17] develop a mixed-integer programming inventory location model to evaluate the effect that pre-positioning relief items would have on average relief-aid emergency response time. They find the optimal number and location of pre-positioning warehouses given that demand for relief supplies can be met from both pre-positioned warehouses and suppliers. They allow multiple HA/DR events to occur within a replenishment period, thus capturing the adverse effect of warehouse replenishment lead time. They also allowed the probability of need for each item to depend on both local conditions and natural hazard type [17]. Salmeron and Apte [18] developed a two-stage stochastic optimization model with the goal of minimizing casualties by determining location and expansion decisions of assets such as warehouses and shelters in the first stage and then determining the best supporting logistics decisions in the second stage. The second stage decisions classify the population into those that need emergency evacuation (critical) those that need commodities (stay-back), and those

that are displaced (transfer). The stochastic optimization formulation helps model the inherent uncertainty [18].

Mogilevsky [19] developed the Disaster Relief Airlift Planner (DRAP), which is an optimization-based decision-support tool that determines optimal routes to deliver material given certain data such as disaster location and available airports, aircraft, and supply stockpiles. DRAP is formulated to minimize disaster material shortages while preferring to choose routes that reduce transportation costs (and delivery times) based on decision-maker constraints and priorities. The model is also useful for helping determine the optimal aircraft allocation and positioning for HA/DR operations. DRAP can be used by logistics planners and decision-makers to conduct trade-off analysis among routes with respect to transportation costs and demand shortages in very short time horizon logistics planning [19]. The critical time window for resource allocation is the first 72 h after initial damage assessment has been made [20].

Even fewer studies have used multiple criteria optimization approaches for improving HA/DR delivery operations and logistics planning. As an exception, Park [21] develops a multi-objective decision-making model to incorporate the decision-maker(s) value trade-offs in the disaster relief resource allocation problem. The decision window for resource allocation is the critical first 72 h after the initial damage assessment has been made. Value-focused thinking was used to capture the value trade-offs, and the resulting value hierarchy is optimized via a mathematical programming model to solve the multi-objective resource allocation problem [21]. In another study, Vitoriano et al. [22] propose a goal programming model to provide decision-support to solve the multi-criteria humanitarian logistics aid distribution problem, attempting to minimize costs and time of response while maximizing equity of distribution or reliability and security of the operation routes [22].

In addition, Bozorgi-Amiri et al. [23] develop a multi-objective robust stochastic programming approach for HA/DR logistics under uncertain demand, supply and costs (procurement and transportation). Further, the model considers uncertainty for the locations where those demands might arise and the possibility that some of the pre-positioned supplies in the relief distribution center or supplier might be partially destroyed by the disaster. The multi-objective model attempts to minimize the sum of the expected value and the variance of the total cost of the relief chain while penalizing the solution's infeasibility due to parameter uncertainty. The model also aims to maximize the affected areas' satisfaction levels through minimizing the sum of the maximum shortages in the affected areas. To solve this bi-criteria problem, they formulated a compromise programming model and solve it to obtain a Pareto-efficient (non-dominated) compromise solution. The purpose of the model is to provide decision-support on both facility location and resource allocation in cases of HA/DR efforts [23].

Recent developments in social media have been useful to facilitate humanitarian relief. For example, emergency response times can be reduced through the use of Twitter data [20,24]. Further, web-based mapping services such as Ushahidi and Crisis Mapping have taken advantage of crowdsourcing to get information to relief agencies in a more timely way [25]. Geographic Information Systems (GIS) as a general framework has also been used in humanitarian relief, particularly as real time access becomes a reality [26,27]. For example, Jahre and Jensen [28] use GIS to help

to develop clusters to improve coordination activities. Tobler [29] discusses some of the challenges of spatial analysis on a global scale.

Despite these recent studies, a critical gap in the literature remains with assessing the trade-offs between supply chain efficiency (i.e. total logistics costs) and supply chain responsiveness (i.e. supply delivery time, demand fulfillment) for aerial delivery operations in the entire military HA/DR supply chain network. None of these previous studies considered the delivery of HA/DR consumable aid via aerial delivery mechanisms. Further, none of these previous studies considered the trade-offs of response time, total cost, and amount of demand satisfied. Therefore, we seek to fill the gap in the literature while providing military HA/DR decision-makers with strategic decision support using our MCDA framework.

### 3 Materials and methods

In this section, we first briefly describe the military HA/DR aerial delivery process flow for consumable aid distribution. We then briefly depict the military HA/DR aerial delivery supply chain network. Last, we discuss the MCDA framework and formulate the stochastic, mixed-integer, weighted goal programming model used for strategic military HA/DR logistics planning.

#### 3.1 Military HA/DR aerial delivery logistics network

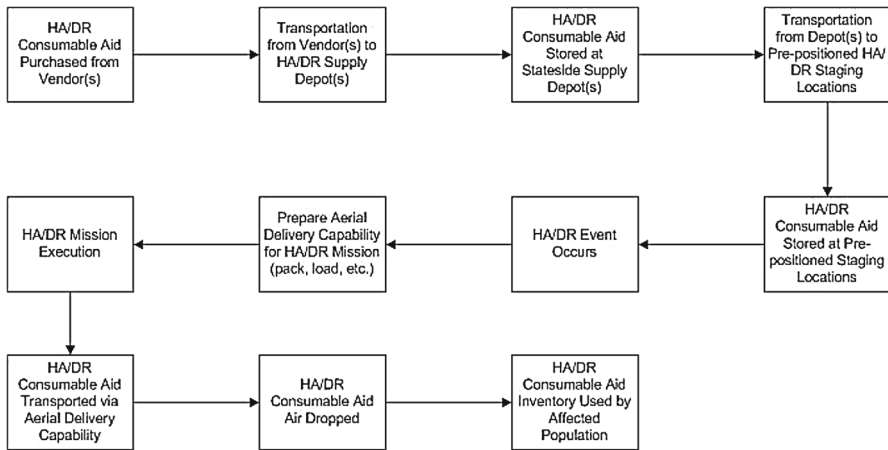
In the event of a natural disaster, military HA/DR aerial delivery planners and policy-makers must make a series of quick decisions in an effort to provide humanitarian aid to the affected population as soon as possible. In order to facilitate this tactical and operational-level decision-making, strategic planners must fully understand the process flow of consumable aid for military HA/DR aerial delivery operations. Figure 1 depicts the military HA/DR aerial delivery process flow.

In this aerial delivery process flow depicted in Fig. 1, HA/DR consumable aid is purchased from the vendor(s) and transported to (typically stateside) HA/DR supply depot(s). Next, the consumable aid is transported from the depot(s) to pre-positioned HA/DR staging locations around the world, where the consumable aid is stored. The consumable aid consists of food bars and water, both of which have an extremely long shelf lives and hence perishability is not a concern. In the event that a natural disaster occurs requiring HA/DR aerial delivery operations, the aerial delivery capability is immediately prepared for mission execution and the consumable aid is transported and air dropped to the affected population.

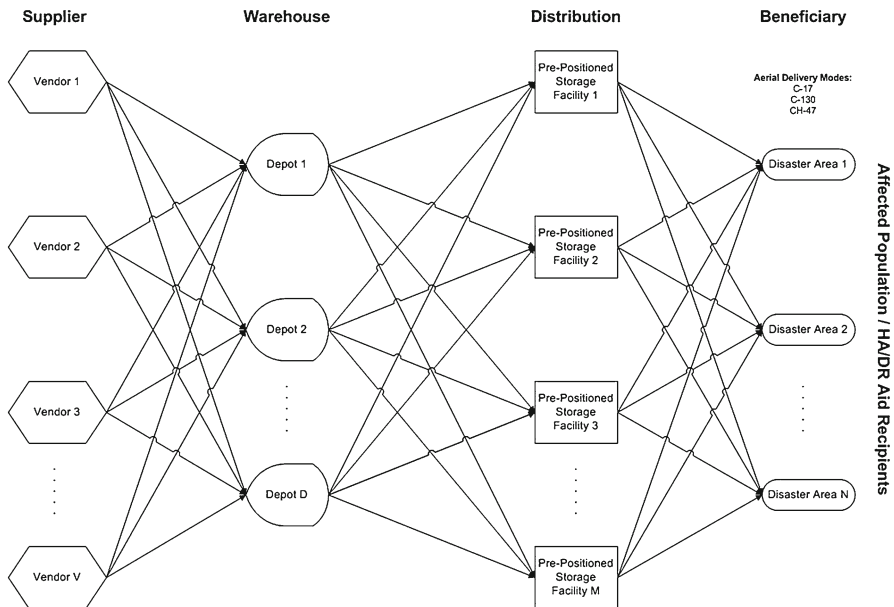
In addition to the process flow, Fig. 2 depicts the military HA/DR aerial delivery supply chain network.

The military HA/DR aerial delivery supply chain network in Fig. 2 matches the process flow illustrated in Fig. 1. Upon examining the four stages of the supply chain network, the vendors represent the suppliers, the depots represent the warehouses, the pre-positioned storage facilities represent the distribution centers, and the disaster areas represent the beneficiaries. We use this multi-stage supply chain network representation in Fig. 2 to develop the stochastic, mixed-integer, weighted goal pro-





**Fig. 1** Military HA/DR aerial delivery process flow



**Fig. 2** Military HA/DR aerial delivery supply chain network

gramming optimization model. This MCDA framework is used as a strategic planning tool for optimizing the military HA/DR aerial delivery supply chain network design.

### 3.2 Multiple criteria decision analysis framework

In our MCDA framework, we incorporate several modeling methodologies to provide a robust decision support tool. First, we use goal programming to allow decision-



makers to systematically explore and examine different optimization problem criteria. The decision-maker defines goals for each of the criteria considered and then evaluates the effects each of these criteria have on the global optimal solution. This methodology is particularly useful for strategic planning when incorporated with goal priority weights determined by the decision-maker(s) [30]. Second, we use Design of Experiments (DOE) to estimate the impact of the underlying factors causing uncertainty within the system. We use a  $2^3$  full-factorial DOE to model the interactive effects between experimental design factors; this approach helps identify robust alternatives over the set of probabilistic scenarios [30]. Third, we use stochastic optimization to incorporate random elements into the model objective function and data parameters; this method provides more robust solutions to aid decision-makers when optimizing under uncertainty [30]. In this model, we optimize the expected value of the objective function (due to the probabilistic scenarios) and calculate many of the data parameters stochastically.

Our MCDA framework uses stochastic, mixed-integer, weighted goal programming. We next describe the optimization model assumptions, sets, parameters, decision variables, objective, and constraints.

### 3.2.1 Optimization model assumptions

In this optimization model, we assume that each delivery mode transports its maximum allowable capacity each trip and that all consumable aid on-board is delivered. We assume that each aerial delivery mode is capable of traveling the full distance required each trip in terms of flight crew and fuel (i.e. fuel is available en route, if necessary). We also assume that there is no limit on the number of hours flown for each aerial delivery mode. Finally, we assume that all pre-positioned aerial delivery assets are available to be used (if necessary, but number of trips may vary) to deliver consumable aid to the disaster area (aircraft will fly in parallel, as opposed to each aircraft waiting for the prior vehicle to return before departing with aid).

In the model, there are three goals: (i) meet a target total aerial delivery response time (in trip-hours), (ii) spend no more on total supply chain cost than a target budget, and (iii) ensure that the amount of consumable aid demanded and the amount actually delivered (i.e., shortage) be no more than a specified target. The disaster planning scenarios (discussed in more detail later) generated from the DOE are related to the impact of disaster, which are represented by expected consumable aid demand, days of food required, and supply chain disruption. Further, the model iterations refer to the affected area hit by the disaster (i.e. one iteration per each disaster area).

### 3.2.2 Optimization model sets

$V$	set of consumable aid vendors (suppliers) with $v \in V$
$D$	set of consumable aid depots (warehouses) with $d \in D$
$M$	set of candidate storage facilities (distribution centers) with $j \in M$
$N$	set of high-risk disaster areas (beneficiaries) with $i \in N$
$K$	set of aerial delivery modes (aircraft types) with $k \in K$
$S$	set of disaster planning scenarios (based on impact factors) with $s \in S$

$B$	set of model iterations (mapped to disaster area affected) with $b \in B$
$G$	set of decision-maker goals with $g \in G$ .

### 3.2.3 Optimization model parameters

$p_{sb}$	probability of occurrence of disaster planning scenario $s$ in iteration $b$
$w_g$	decision-maker weight for goal $g$
$Disrupt_{sb}$	supply chain disruption effect on supply chain costs in scenario $s$ and iteration $b$
$Food_{sb}$	number of days worth of food to provide in scenario $s$ and iteration $b$
$Imp_{sb}$	disaster impact above or below estimated demand in scenario $s$ and iteration $b$
$Dem_{isb}$	expected consumable aid demand (pounds) per day at disaster area $i$ in scenario $s$ and iteration $b$
$ds_{ij}$	geodesic distance (nautical miles) from storage facility $j$ to disaster area $i$
$l_{dj}$	geodesic distance (nautical miles) from depot $d$ to storage facility $j$
$Spd_k$	average speed of aerial delivery mode $k$
$LoadDelay_k$	load time for aid (per trip) of aerial delivery mode $k$
$t_{ijk}$	travel time (per trip) from facility $j$ to disaster area $i$ via delivery mode $k$
$r_{dj}$	travel time (per trip) from depot $d$ to storage facility $j$
$OMF_k$	operation and maintenance and fuel cost (\$ per h) of aerial delivery mode $k$
$TDcost_{dj}$	transportation cost (per trip) from depot $d$ to storage facility $j$
$TScost_{ijk}$	transportation cost (per trip) from facility $j$ to disaster area $i$ via delivery mode $k$
$Atd$	amount of aid (lbs) transported (per trip) from depot $d$ to storage facility $j$
$Ats_k$	amount of aid (lbs) transported (per trip) from facility $j$ to area $i$ via mode $k$
$IHDcost_d$	inventory holding cost (per lb) at depot $d$
$IHScost_j$	inventory holding cost (per lb) at storage facility $j$
$Pcost_v$	procurement cost (per lb) of consumable aid from vendor $v$
$Cap_j$	inventory holding capacity (lbs) at storage facility $j$
$Cp_d$	inventory holding capacity (lbs) at depot $d$
$Fcost_j$	fixed cost of opening storage facility $j$
$Ntd_{dj}$	maximum number of trips with consumable aid from depot $d$ to storage facility $j$
$Nts_{ijk}$	maximum number of trips with consumable aid from storage facility $j$ to disaster area $i$ via aerial delivery mode $k$
$ADM_{jk}$	number of aerial delivery modes $k$ pre-positioned at storage facility $j$

$TG1_{sb}$	target goal for the total aerial delivery response time in scenario $s$ and iteration $b$
$TG2_{sb}$	target goal for for total supply chain cost in scenario $s$ and iteration $b$
$TG3_{sb}$	target goal for for unmet demand in scenario $s$ and iteration $b$ .

### 3.2.4 Optimization model decision and goal deviation variables

$X_j$	equals 1 if open storage facility $j$ , or 0 otherwise
$Y_{ij}$	equals 1 if disaster area $i$ is served by storage facility $j$ , or 0 otherwise
$Z_{ijk sb}$	number of trips with consumable aid from storage facility $j$ to disaster area $i$ via aerial delivery mode $k$ in scenario $s$ and iteration $b$
$H_{djsb}$	number of trips with consumable aid from depot $d$ to storage facility $j$ in scenario $s$ and iteration $b$
$Q_{dv}$	amount of aid (lbs) purchased from vendor $v$ for storage at depot $d$
$Inv_j$	amount of aid (lbs) to store in inventory at storage facility $j$
$In_d$	amount of aid (lbs) to store in inventory at depot $d$
$pos_{gsb}$	positive deviation for goal $g$ in scenario $s$ and iteration $b$
$neg_{gsb}$	negative deviation for goal $g$ in scenario $s$ and iteration $b$ .

### 3.2.5 Optimization model formulation

$$\min \sum_b \sum_s p_{sb} (w_{g=1} pos_{g=1, sb} + w_{g=2} pos_{g=2, sb} + w_{g=3} pos_{g=3, sb}) \quad (1)$$

$$\text{subject to } \sum_i \sum_j \sum_k t_{ijk} Z_{ijk sb} + \sum_d \sum_j r_{dj} H_{djsb} + neg_{g=1, sb} - pos_{g=1, sb} = TG1 \quad \forall s \in S, b \in B \quad (2)$$

$$\begin{aligned} & Disrupt_{sb} \left( \sum_d \sum_j T Dcost_{dj} H_{djsb} + \sum_i \sum_j \sum_k \sum_v T Scost_{ijk} Z_{ijk sb} \right. \\ & \quad + \sum_j (Fcost_j X_j + I H Scost_j Inv_j) \\ & \quad \left. + \sum_d I H Dcost_d In_d + \sum_v \sum_d Pcost_v Q_{dv} \right) + neg_{g=2, sb} - pos_{g=2, sb} \\ & = TG2 \quad \forall s \in S, b \in B \end{aligned} \quad (3)$$

$$\begin{aligned} & \sum_i Dem_{isb} Imp_{sb} Food_{sb} - \sum_i \sum_j \sum_k Ats_k Z_{ijk sb} ADM_{jk} + neg_{g=3, sb} \\ & - pos_{g=3, sb} = TG3 \quad \forall s \in S, b \in B \end{aligned} \quad (4)$$

$$\sum_j Y_{ij} = 1 \quad \forall i \in N \quad (5)$$

$$\sum_i Y_{ij} = X_j \quad \forall j \in M \quad (6)$$

$$\sum_i \sum_k Ats_k Z_{ijk sb} ADM_{jk} \leq Inv_j \quad \forall j \in M, s \in S, b \in B \quad (7)$$

$$Inv_j \leq Cap_j X_j \quad \forall j \in M \quad (8)$$

$$Inv_j \geq X_j \quad \forall j \in M \quad (9)$$

$$Atd \sum_j H_{djsb} \leq In_d \quad \forall d \in D, s \in S, b \in B \quad (10)$$

$$In_d \leq Cp_d \quad \forall d \in D \quad (11)$$

$$\sum_v Q_{dv} \leq In_d \quad \forall d \in D \quad (12)$$

$$H_{djsb} \leq Ntd_{dj} X_j \quad \forall d \in D, j \in M, s \in S, b \in B \quad (13)$$

$$Z_{ijk sb} \leq Nts_{ijk} Y_{ij} \quad \forall i \in N, j \in M, k \in K, s \in S, b \in B \quad (14)$$

$$Atd \sum_d H_{djsb} \geq \sum_i \sum_k Ats_k Z_{ijk sb} ADM_{jk} \quad \forall j \in M, s \in S, b \in B \quad (15)$$

$$\sum_d Q_{dv} \geq Atd \sum_d \sum_j H_{djsb} \quad \forall v \in V, s \in S, b \in B \quad (16)$$

$$X_j \in \{0, 1\} \quad \forall j \in M$$

$$Y_{ij} \in \{0, 1\} \quad \forall i \in N, j \in M$$

$$Z_{ijk sb} \geq 0, integer \quad \forall i \in N, j \in M, k \in K, s \in S, b \in B$$

$$H_{djsb} \geq 0, integer \quad \forall d \in D, j \in M, s \in S, b \in B$$

$$Inv_j \geq 0 \quad \forall j \in M$$

$$In_d \geq 0 \quad \forall d \in D$$

$$Q_{dv} \geq 0 \quad \forall d \in D, v \in V$$

$$pos_{gsb} \geq 0 \quad \forall g \in G, s \in S, b \in B$$

$$neg_{gsb} \geq 0 \quad \forall g \in G, s \in S, b \in B \quad (17)$$

The objective function in (1) seeks to minimize the sum of the three expected weighted goal deviations for target response time, target budget, and target demand met, across all probabilistic disaster planning scenarios  $s$  and iterations  $b$ . The weights allow the planner to prioritize the targets. Goal constraints (2) ensure target  $TG1$  is met for the total aerial delivery response time (in trip-hours) for each scenario  $s$  and iteration  $b$ . The amount by the target is not met, the  $pos_{g=1, sb} \geq 0$ , is minimized in (1). Note that  $TG1$  is set to 0 since the decision-maker wishes to minimize total aerial delivery time, which is a function of replenishment time between depots and storage facilities as well as the final disaster response time between storage facilities and affected areas.

Goal constraints (3) ensure the target for total supply chain cost ( $TG2$ ) with supply chain disruption factor is met for each scenario  $s$  and iteration  $b$ ; target deviation is captured in  $pos_{g=2, sb}$ . The amount by the target is not met, the  $pos_{g=2, sb} \geq 0$ , is minimized in (1). Note that  $TG2$  is set to 0 since the decision-maker wishes to minimize total supply chain cost. Goal constraints (4) ensure that the amount of delivered consumable aid shortage to the affected population including disaster impact and food factors for each scenario  $s$  and iteration  $b$  does not exceed the target  $TG3$ ; the amount of shortage above the target is captured in  $pos_{g=3, sb}$ . Again, the amount by the target is not met, the  $pos_{g=3, sb} \geq 0$ , is minimized in (1). Note that  $TG3$  is set to 0 since the decision-maker wishes for the estimated demand to be met.

The constraints in (5) ensure that each disaster area  $i$  is served by exactly one storage facility  $j$ . The constraints in (6) ensure that if disaster area  $i$  is served by storage facility  $j$ , then storage facility  $j$  must be opened for pre-positioning inventory and assets, and that each storage facility  $j$  can only serve one disaster area  $i$ . Note that (5) and (6) are set partitioning constraints. From (7), the amount of inventory to store at storage facility  $j$  must be greater than or equal to the sum of the product of the number of trips, the amount of consumable aid transported per trip and the number of assets pre-positioned for every scenario  $s$  and iteration  $b$ . From (8), the inventory is held only at opened storage facilities, and the amount of inventory kept at the storage facility  $j$  must not exceed its capacity. The constraints in (9) enforce that if a storage facility  $j$  is opened, then inventory must be stored there.

The constraints in (10) ensure that the amount of inventory to store at each depot  $d$  must be greater than or equal to the sum of the product of the number of trips (of a single C-17 aircraft) and the amount of consumable aid transported per trip for every scenario  $s$  and iteration  $b$ . In (11), all depots are assumed to be open, but the amount of inventory kept at depot  $d$  must not exceed its capacity. In (12), if consumable aid is purchased from the vendors for storage at depot  $d$ , then there is inventory for storage at depot  $d$ . The constraints in (13) ensure that the number of trips with consumable aid from each depot  $d$  to each storage facility  $j$  must not exceed its maximum; note that this maximum is a function of a target total flight time budget value set by the decision-maker.

In (14), the number of trips with consumable aid from each storage facility  $j$  to each disaster area  $i$  via each delivery mode  $k$  must not exceed its maximum; again, this maximum is a function of a target total flight time budget value by the decision-maker. The constraints in (15) ensure that the total amount of consumable aid shipped from the depots  $d$  to each storage facility  $j$  must appropriately backfill the total amount of aid delivered to the disaster areas  $i$  for each scenario  $s$  and iteration  $b$ . From (16), the amount procured from each of the vendors  $v$  for storage at all of the depots  $d$  must be greater than or equal to the total amount of aid shipped out of depot  $d$  for each scenario  $s$  and iteration  $b$ . In (17), we have the binary, integer and non-negativity decision variable constraints.

### 3.2.6 Optimization model scenarios and iterations

As part of the multiple criteria decision analysis framework, we incorporated a  $2^3$  full-factorial experimental design as a mechanism to help mitigate uncertainty associated

with consumable aid demand as well as the effects of supply chain disruption on total supply chain costs. By exploring three different design factors (each at two levels), we generate eight different disaster planning scenarios that are combinatorially applied to each of the disaster areas in the military HA/DR supply chain network. Note that each of these disaster areas represent a unique model iteration, making  $sb$  scenario-iteration pairs. These scenarios and iterations are discussed further in Sect. 4.2.

## 4 Computational experiment and results

In this section, we describe the computational experiments performed for NSRDEC using the MCDA framework for strategic-level military HA/DR supply chain network design optimization. The results of this computational experiment provided the decision-maker with the necessary decision support to assess the supply chain efficiency and responsiveness trade-offs for military HA/DR aerial delivery operations.

### 4.1 Data collection and analysis

The military HA/DR aerial delivery supply chain network consists of four separate stages. For the first stage, we consider  $v = 3$  consumable aid vendors (suppliers), where the supplier selection sub-problem consists of determining how much aid to purchase from each vendor  $v$  for storage at each depot  $d$ . This supply network design uses a multiple sourcing strategy [7]. Given the uncertainty associated with purchase prices, we model the procurement costs for each vendor  $v$  ( $PCost_v$ ) by randomly sampling from uniform distributions with minimum and maximum values determined by the decision-maker based on subject-matter expertise.

For the second stage, we consider  $d = 2$  consumable aid depots (warehouses) in the continental United States as a means of risk pooling—risk pooling is the practice of consolidating facilities into fewer locations by using a consolidated distribution strategy; note that risk pooling can help reduce supply chain costs as well as demand risk [7]. For this stage in the supply chain network, the two depots considered were U.S. Marine Corps Logistics Bases in Albany (Georgia, USA) and Barstow (California, USA). For this distribution and inventory planning sub-problem, the model determines the amount of aid to store in inventory at depot  $d$  as well as the average number of trips with consumable aid from depot  $d$  to storage facility  $j$ . We assume that there is one aerial delivery mode (C-17 aircraft) available at each depot for transportation, and that the amount of aid transported per trip from depot  $d$  to storage facility  $j$  ( $At_d$ ) equals its maximum loading capacity. The inventory holding costs at each depot ( $IHDcost_d$ ) and inventory holding capacity at each depot ( $Cp_d$ ) are modeled by randomly sampling from uniform distributions with minimum and maximum values again determined using subject-matter expertise.

For the third stage of the supply chain network, we consider  $m = 10$  candidate storage facilities (distribution centers) for pre-positioning  $k = 3$  different aerial delivery assets (C-17 Globemaster, C-130 Hercules, CH-47 Chinook) and consumable aid inventory. The ten storage facilities considered were U.S. Air Force Bases located in both the United States (North Carolina, Washington, Florida, and Hawaii) as well

as overseas in foreign countries (Germany, Japan, Turkey, South Korea, Kuwait, and Honduras). This stage of the supply chain network design uses a deconsolidated distribution strategy given that there are more facilities, each serving a smaller demand region; note that this supply chain strategy can help increase supply chain responsiveness, reduce the risk of supply chain disruption, and reduce outbound transportation costs [7]. For this facility location, inventory and distribution planning sub-problem, the model determines the candidate storage facilities  $j$  to open, the disaster areas  $i$  served by each facility  $j$ , the average number of trips with consumable aid from facility  $j$  to disaster area  $i$  using aerial delivery mode  $k$ , and the amount of aid to store in inventory at each storage facility  $j$ . Again, we assume that amount of aid transported per trip from facility  $j$  to disaster area  $i$  via each aerial delivery mode  $k$  ( $Ats_k$ ) equals the maximum loading capacity of each asset. The inventory holding costs at each facility ( $IHS_{cost_j}$ ), the inventory holding capacity at each facility ( $Cap_j$ ), and the fixed cost of opening each storage facility ( $Fcost_j$ ) are modeled by randomly sampling from uniform distributions with minimum and maximum values again determined by the decision-maker using subject-matter expertise. Also, note that the number of aerial delivery modes  $k$  available for pre-positioning at each storage facility  $j$  ( $ADM_{jk}$ ) is determined by the decision-maker.

To calculate the geodesic distance (in nautical miles) between each depot  $d$  and storage facility  $j$  ( $l_{dj}$ ), we used the Haversine formula [31]. This method estimates the great-circle distance between two points on a sphere using their longitudes and latitudes. Equation (18) shows the distance calculation:

$$l_{dj} = 2rc \arcsin \left( \sqrt{\sin^2 \left( \frac{\phi_2 - \phi_1}{2} \right) + \cos(\phi_1) \cos(\phi_2) \sin^2 \left( \frac{\lambda_2 - \lambda_1}{2} \right)} \right) \quad \forall d \in D, j \in M \quad (18)$$

where  $r$  is the radius of the sphere (6371 km for Earth),  $c$  is the kilometers to nautical miles conversion factor (0.539),  $\phi_1$  and  $\lambda_1$  are the latitude and longitude, respectively, of the first point, and  $\phi_2$  and  $\lambda_2$  are the latitude and longitude, respectively, of the second point.

In order to mitigate uncertainty in the transportation times and costs, we conducted a Monte Carlo simulation of 1000 trials to compute the average cruise speed (knots) of each aerial delivery mode  $k$  ( $Spd_k$ ) and the load delay time (hours) of each aerial delivery mode  $k$  ( $LoadDelay_k$ ). In each trial of the simulation, both the cruise speeds and load delay times were randomly sampled from uniform distributions using minimum and maximum values based on subject-matter expertise.  $Spd_k$  and  $LoadDelay_k$  were computed as the average values over all trials. The travel time (per one-way trip) from depot  $d$  to storage facility  $j$  ( $r_{dj}$ ) was calculated using Eq. (19):

$$r_{dj} = \frac{l_{dj}}{Spd_{k=C17}} + LoadDelay_{k=C17} \quad \forall d \in D, j \in M \quad (19)$$

As a component of the transportation costs, there is an operation, maintenance and fuel cost (in \$ per h) for each aerial delivery asset  $k$  ( $OFM_k$ ), which is computed by



randomly sampling from uniform distributions using minimum and maximum values determined by the decision-maker. Therefore, the transportation cost (per trip) from depot  $d$  to storage facility  $j$  ( $TDcost_{dj}$ ) is calculated using Eq. (20):

$$TDcost_{dj} = (f + OM F_{k=C17}) \times r_{dj} \quad \forall d \in D, j \in M \quad (20)$$

where  $f$  is the fixed aircrew cost per hour; we use  $f = 250$  as determined by the decision-maker. Also, we computed the maximum number of trips with consumable aid from depot  $d$  to storage facility  $j$  ( $Ntd_{dj}$ ) using Eq. (21):

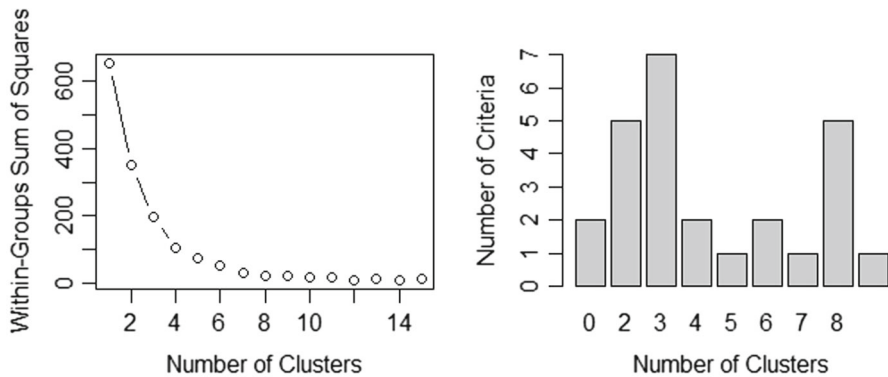
$$Ntd_{dj} = \left\lfloor \frac{T}{2 \times r_{dj}} \right\rfloor \quad \forall d \in D, j \in M \quad (21)$$

where  $T$  is the target total flight time budget value between the depots and facilities set by the decision-maker (an upper bound on total flight hours available from depot  $d$ ). This parameter is used to evaluate supply chain efficiency and responsiveness trade-offs in the model sensitivity analysis. For instance,  $T = 120$  infers a total flight time budget of 120 h (or 5 days).

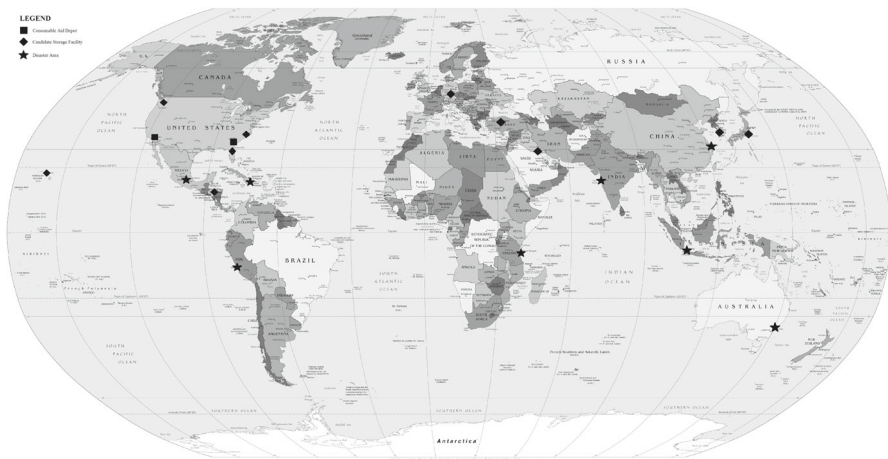
In the fourth stage of the supply chain network, we consider  $n = 8$  foreign disaster areas (beneficiaries) in separate high-risk geographic regions using the last 20 years of global disaster data from the Emergency Events Database (EM-DAT) maintained by the Centre for Research on Epidemiology of Disasters at Louvain University and supported by several organizations around the world, to include USAID; note the EM-DAT contains data on the occurrence and effects of over 18,000 mass disasters in the world from 1900 to present [32]. In order to determine the location of these foreign disaster areas representing the centroids of different high-risk geographic regions, we performed both k-means clustering and hierarchical clustering methods using several variables, to include disaster frequency, mortality, total number affected, and total economic damages.

Using complete linkage hierarchical clustering, we determined eight clusters was an appropriate number via a given cut of the associated dendrogram. For k-means clustering, we identified the appropriate number of clusters via a plot of the within-group sum of squares (WGSS) as well as using the results of 26 different criteria (from the NbClust function in R). The left plot of Fig. 3 displays the WGSS versus number of clusters, where we see the curve levels-off at eight clusters. The right plot of Fig. 3 shows a histogram of the number of clusters chosen by each of the criteria, which indicates a bimodal distribution. Although the highest frequency of criteria was three clusters, eight clusters was also significant as well as more pragmatic for the computational experiment.

Both clustering methods identified the following eight foreign disaster areas to serve as epicenters of various geographic regions: Haiti (Caribbean), Indonesia (South-Eastern Asia), Mexico (Central America), Tanzania (Eastern Africa), India (Southern Asia), China (Eastern Asia), Australia (Australia and New Zealand), and Peru (South America). Figure 4 [33] illustrates the locations of the two consumable aid depots (squares), ten candidate storage facilities (diamonds), and eight disaster areas (stars).



**Fig. 3** Determining appropriate number of cluster for k-means clustering



**Fig. 4** Location of depots, storage facilities and disaster areas

Further, we used the EM-DAT disaster data with a sample size of  $n = 2797$  disasters (from 1994 to 2014) to fit an ordinary least squares multiple regression model to estimate the total number of affected people per year. To satisfy the assumption of normally distributed residuals (error terms), we performed a Box–Cox transformation on the response variable, which suggested a natural log power transformation ( $\lambda = 0$ ). We then performed fivefold cross-validation (with best subset selection within each of the training sets) to select the best predictors for the model; this resulted in the following five variables: year, number of occurrences (occur), number of deaths (death), total monetary damages in \$000s (damage), and population (pop). There was no multicollinearity present in the model ( $VIFs < 5$ ), but the model diagnostics suggested non-constant variance of the residuals; the Modified Levene's test, Breusch Pagan test, and Special White's test all confirmed heteroscedasticity. Therefore, we calculated robust standard errors to compensate for the unknown pattern of non-constant error variance, giving more accurate p values for the predictors. Also, there was no temporal

**Table 1** Regression model results for estimated affected population per year

	Estimate	Robust standard error	<i>t</i> value	<i>p</i> value
Intercept	−90.316	29.362753	−3.08	0.002
Year	0.04854	0.0146549	3.31	0.001
Occur	0.29683	0.028824	10.3	0.000
Death	1.7E−05	8.331E−06	2.06	0.040
Damage	1.3E−08	9.36E−09	1.41	0.158
Pop	−3E−09	1.13E−09	−2.68	0.007

or spatial autocorrelation in the data used in the regression model. The final regression model results ( $R^2 = 0.21$ ,  $p$  value  $< 0.0001$ ) are displayed in Table 1:

From this regression model, we used Eq. (22) to compute the expected consumable aid demand per day at each high-risk disaster area  $i$  per each scenario  $s$  and iteration  $b$  ( $Dem_{isb}$ ). For each disaster planning scenario  $s$ , we assume in this computational experiment that demand emanates from only one high-risk disaster area that represents the epicenter of the geographic region (i.e. there is not simultaneous demand at multiple disasters areas). Thus, each disaster area  $i$  maps to each iteration  $b$ , and we ensure robustness in the supply chain network design by optimizing over  $sb = (8)(8) = 64$  scenario-iteration combinations.

$$Dem_{isb} = \frac{\exp\{Affect_i\}}{AvgOccur_i} (FoodConsume + WaterConsume) \quad \forall i \in N, s \in S, b \in B \quad (22)$$

where  $Affect_i$  is the log of the total number of affected per year for each disaster area  $i$  estimated using the regression model,  $AvgOccur_i$  is the average (over last 20 years) of the total number of disaster occurrences per year for each disaster area  $i$ ,  $FoodConsume$  is the expected amount (pounds) of food consumed per affected person per day (we used 0.8 pounds as determined by the decision-maker), and  $WaterConsume$  is the expected amount of water (pounds) consumed per affected person per day (we used 1.84 pounds as determined by the decision-maker).

Using the EM-DAT data, Table 2 depicts the HA/DR consumable aid demand calculations, where *Year* is the current year, *Occur* represents  $AvgOccur_i$ , *Death* is the average (over last 20 years) of the total number of deaths per year caused by disasters, *Damage* is the average (over last 20 years) of the total monetary damages (\$000s) per year caused by disasters, *Pop* is the current population for each of the disaster areas,  $\exp\{Affect\}$  is the average total number of affected people per year, and *Demand* is the estimated expected consumable aid demand (pounds per day) per disaster occurrence for each of the disaster areas representing the different worldwide high-risk geographic regions ( $Dem_{isb}$ ):

To calculate the geodesic distance (in nautical miles) between each storage facility  $j$  and disaster area  $i$  ( $ds_{ij}$ ), we used the Haversine formula again. Equation (23) shows the distance calculation:

**Table 2** Estimated expected consumable aid demand

Disaster area	Year	Occur	Death	Damage	Pop	$\exp\{Affect\}$	Demand
Australia	2014	6	57	1,426,790	23,558,900	7983	9231
China	2014	60	7107	18,010,076	1,365,590,000	1,398,028,739	36,418,118
Haiti	2014	5	11,951	429,331	10,413,211	6690	10,243
India	2014	36	5641	1,819,772	1,246,670,000	1,556,967	116,250
Indonesia	2014	20	9197	1,273,830	252,164,800	306,658	69,943
Mexico	2014	11	273	1,731,776	119,713,203	25,377	14,300
Peru	2014	9	340	48,764	30,814,175	16,427	12,413
Tanzania	2014	6	411	0	44,928,923	7028	8334

$$ds_{ij} = 2rc \arcsin \left( \sqrt{\sin^2 \left( \frac{\phi_2 - \phi_1}{2} \right) + \cos(\phi_1) \cos(\phi_2) \sin^2 \left( \frac{\lambda_2 - \lambda_1}{2} \right)} \right) \quad \forall i \in N, j \in M \quad (23)$$

The travel time (per one-way trip) from storage facility  $j$  to disaster area  $i$  via aerial delivery mode  $k$  ( $t_{ijk}$ ) was calculated using Eq. (24):

$$t_{ijk} = \frac{ds_{ij}}{Spd_k} + LoadDelay_k \quad \forall i \in N, j \in M, k \in K \quad (24)$$

Further, the transportation cost (per trip) from storage facility  $j$  to disaster area  $i$  via aerial delivery mode  $k$  ( $TScosti_{jk}$ ) is calculated using Eq. (25):

$$TScosti_{jk} = (f + OMF_k) \times t_{ijk} \quad \forall i \in N, j \in M, k \in K \quad (25)$$

In addition, we computed the maximum number of trips with consumable aid from storage facility  $j$  to disaster area  $i$  via aerial delivery mode  $k$  ( $Nts_{ijk}$ ) using Eq. (26):

$$Nts_{ijk} = \left\lfloor \frac{R}{2 \times t_{ijk}} \right\rfloor \quad \forall i \in N, j \in M, k \in K \quad (26)$$

where  $R$  is the target total flight time budget value between the facilities and the disaster areas set by the decision-maker. Again, this parameter is used to evaluate supply chain efficiency and responsiveness trade-offs in the model sensitivity analysis. For instance,  $R = 72$  infers a total flight time budget of 72 h (or 3 days).

## 4.2 Disaster planning scenarios

As previously noted, we incorporated a  $2^3$  full-factorial DOE as a mechanism to develop disaster planning scenarios to better account for the uncertainty within the military HA/DR aerial delivery supply chain network. The three experimental design

factors included  $Imp_{sb}$ ,  $Food_{sb}$ , and  $Disrupt_{sb}$ .  $Imp_{sb}$  represents a disaster impact factor that adjusts the estimated expected consumable aid demand in each scenario  $s$  and iteration  $b$  up or down by 25 % to account for the deviation from expected impact.  $Food_{sb}$  represents a days of food factor that adjusts the estimated expected consumable aid demand in scenario  $s$  and iteration  $b$  by the number of days worth of food to provide for each affected person; this factor is also varied at two levels (7 or 14 days worth of food). Note that these first two DOE factors address uncertainty involving the amount of beneficiary demand, affecting both supply chain efficiency and responsiveness.  $Disrupt_{sb}$  represents a supply chain disruption impact factor to better account for uncertainty in supply chain costs for each scenario  $s$  and iteration  $b$ , while also increasing the robustness of the supply chain network design. We assume that supply chain disruptions (such as aerial delivery weather delays and maintenance issues) will affect supply chain processes associated with transportation and storage of consumable aid, which is reflected in the overall supply chain costs. Therefore, this factor increases the total supply chain costs by 0 % (low risk) and 11 % (high risk); note that the average effect of disruptions is an 11 % growth in cost [35].

From the eight disaster planning scenarios coupled with the eight model iterations (one iteration per each disaster area), the model optimizes over 64 total scenario-iteration combinations to determine the best compromise solution that balances supply chain efficiency and responsiveness. Note that we calculated the probability of occurrence of scenario  $s$  in iteration  $b$  ( $p_{sb}$ ) using Eq. (27):

$$p_{sb} = \frac{1}{s} DisProp_b \quad \forall s \in S, b \in B \quad (27)$$

where  $DisProp_b$  represents the proportion of historical (over last 20 years) disaster frequency for each iteration  $b$ , which equals the quotient of the average number of disaster occurrences per year for each disaster area (mapping to a unique iteration) divided by the sum of the average number of disaster occurrences per year over all disaster areas.

In Table 3, we highlight the  $2^3$  full-factorial experimental design factors (and levels) used to generate the eight disaster planning scenarios for the computational experiment:

**Table 3**  $2^3$  Full-factorial DOE factors for disaster planning scenarios

Scenario	Disaster impact	Days of food	Supply chain disruption
1	0.75	7	1
2	1.25	7	1
3	0.75	14	1
4	1.25	14	1
5	0.75	7	1.11
6	1.25	7	1.11
7	0.75	14	1.11
8	1.25	14	1.11

Again, these eight disaster planning scenarios shown in Table 3 are applied to each of the eight model iterations, representing a total of 64 different scenario-iteration combinations employed in the optimization model as a means to help mitigate uncertainty in the system. This method helps provide a robust, best compromise solution to the stochastic, mixed-integer weighted goal programming problem.

### 4.3 Model implementation and solutions

To implement the MCDA framework for solving the multi-criteria military HA/DR aerial delivery supply chain network design optimization problem under uncertainty and provide decision support to NSRDEC, we leveraged the General Algebraic Modeling System (GAMS) [34], Microsoft Excel, and Microsoft Visual Basic for Applications (VBA) platforms. In particular, we used GAMS v.23.9.3 with IBM ILOG Cplex 12.4.0.1 to solve the stochastic, mixed-integer weighted goal programming model, and we used Excel/VBA to create an automatic, user-friendly interface with the decision-maker for model input and analysis of model output. The following best compromise solution to the computational experiment was solved in 0.499 s on a Lenovo Thinkpad W510 laptop with an Intel i7 CPU (1.6 GHz) and 8.00 GB of RAM.

In the following solution, the decision-maker heavily weighted the third goal to place significant priority on meeting the estimated expected consumable aid demand across all high-risk disaster areas. Note that the solution depends upon the pseudo-random number generator seed in GAMS. For this instance of the experiment, Table 4 highlights which storage facilities were opened, the amount of pre-positioned inventory to store, and the number of required trips by each aerial delivery model:

Given that each storage facility must serve exactly one disaster area, the results in Table 4 indicate that eight of the ten candidate storage facilities are opened for pre-positioning both aerial assets and consumable aid inventory; note that the U.S. Air Force Bases in Kuwait and Honduras should not be opened as part of the optimal supply chain network design.

In addition, Table 5 highlights the amount of inventory to store at each of stateside Marine Corps Logistics Bases as well as the breakdown of the amount procured from each of the three consumable aid vendors:

These results in Table 5 indicate that both depots in the supply chain network are used to store inventory stateside, but it is clear that the depot in Albany is utilized more heavily. Further, only one of the three vendors supplies consumable aid to both depots. Figure 5 shows the average number of trips via C-17 from each of the stateside depots to the opened storage facilities; note that this is the average over all scenario-iteration combinations. As anticipated, there are no trips from either depots to the U.S. Air Forces Bases in Kuwait (Ali Al Salem) and Honduras (Soto Cano) because those facilities were not opened.

Figure 5 also indicates that the distribution of average number of trips from the depot in Barstow, California (USA) to all of the opened storage facilities are relatively uniform. Further, the greatest average number of trips are from the depot in Albany, Georgia (USA) to the storage facility at Charlotte Air National Guard Base in Charlotte,

**Table 4** Results for storage facility locations, inventory and trips

Storage facility name	Opened	Inventory	Number of trips		
Ramstein Air Base (Germany)	1	665,600	4	2	0
Charlotte Air National Guard Base (North Carolina, USA)	1	832,000	3	5	0
McChord Air Force Base (Washington, USA)	1	896,000	4	5	0
Hickam Air Force Base (Hawaii, USA)	1	769,600	3	2	1
Yokota Air Base (Japan)	1	640,000	3	5	0
Incirlik Air Base (Turkey)	1	588,800	3	4	0
Osan Air Base (South Korea)	1	563,200	2	4	0
Ali Al Salem Air Base (Kuwait)	0	0	0	0	0
Soto Cano Air Base (Honduras)	0	0	0	0	0
MacDill Air Force Base (Florida, USA)	1	435,200	4	7	0
			C-17	C-130	CH-47

**Table 5** Results for depot inventory and vendor procurement

Depot name	Inventory	Amount procured from vendors		
Marine Corps Logistics Base Albany (Georgia, USA)	14,208,000	3,072,000	5,568,000	5,568,000
Marine Corps Logistics Base Barstow (California, USA)	2,496,000	2,496,000	0	0
		V1	V2	V3

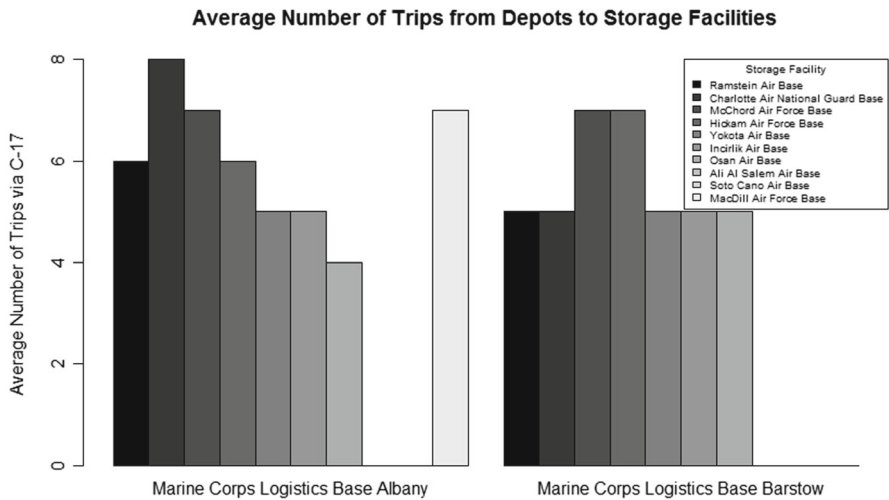
North Carolina (USA); this makes sense because these two locations are relatively close in terms of geodesic distance.

In addition, Table 6 depicts which global disaster areas (representing high-risk geographic regions) are served by which opened storage facilities:

From these best compromise solution results, Fig. 6 [33] provides a visual illustration of the optimal military HA/DR aerial delivery supply chain network design.

Upon investigating the trade-offs of supply chain efficiency versus responsiveness for this best compromise solution to the multiple criteria problem, the goal deviation variables provided critical information about response time, cost, and demand unmet





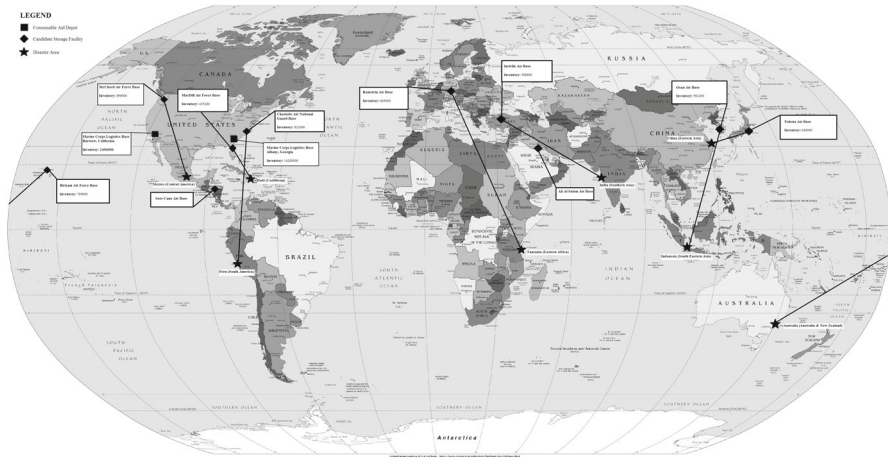
**Fig. 5** Results for average number of trips from depots to storage facilities

**Table 6** Results for disaster area and storage facility assignments

Disaster area (geographic region)	Servicing storage facility
Haiti (Caribbean)	MacDill Air Force Base (Florida, USA)
Indonesia (South-Eastern Asia)	Osan Air Base (South Korea)
Mexico (Central America)	McChord Air Force Base (Washington, USA)
Tanzania (Eastern Africa)	Ramstein Air Base (Germany)
India (Southern Asia)	Incirlik Air Base (Turkey)
China (Eastern Asia)	Yokota Air Base (Japan)
Australia (Australia and New Zealand)	Hickam Air Force Base (Hawaii, USA)
Peru (South America)	Charlotte Air National Guard Base (North Carolina, USA)

for every scenario  $s$  and iteration  $b$ . In particular, this supply chain network design provided an average total aerial delivery response time (across all disaster areas) of roughly 6 days, an average total supply chain cost (across all stages of the supply chain network) of roughly \$153 billion, and an average total demand shortage (across all disaster areas) of roughly 47 million pounds. Moreover, this supply chain network design provided identical median values for the response time and cost, but the median total demand shortage equaled 0; in fact, there were only eight of the 64 scenario-iteration combinations (13 %) where the demand was unmet.

In addition to this solution determined by incorporating the  $sb$  probabilistic scenario-iteration combinations, we leveraged the sample average approximation



**Fig. 6** Optimal military HA/DR aerial delivery supply chain network design

(SAA) method [36] within the MCDA framework to better estimate the optimal solution to the stochastic goal program, given that many of the parameters were computed by randomly sampling from a prior probability distribution. In particular, the decision-maker used the MCDA framework to run the optimization model for 30 separate instances to obtain 30 optimal solutions; in theory, the average of these solutions provides an unbiased estimate of the true optimal solution. Given that each of the 30 optimal solutions provided different results (in terms of which storage facilities to open, the amount of inventory to store at each depot and facility, the average number of trips for each of the aerial delivery assets pre-positioned, and the amount of consumable aid to procure from vendors), it did not make practical sense to provide the decision-maker with mere averages of the decision variable values. Instead, the MCDA framework uses the results of the SAA method to construct statistical lower and upper bounds [37]. This approach served as strategic decision support by helping the decision-maker to better understand the range of possible best compromise solutions to the multi-criteria military HA/DR aerial delivery supply chain network design problem. ,bounds (LBs) and upper bounds (UBs) by constructing 95 % confidence intervals (CIs) on the amount of consumable aid inventory to store at each of the depots and storage facilities. Table 7 shows these results:

The decision-maker used the results in Table 7 to conduct post-hoc analyses based on the ranges of inventory storage amounts. For example, the 95 % CI for the inventory to store at the Soto Cano Air Base (Honduras), included negative values, which suggests that this storage facility should probably never be opened for pre-positioning of assets and inventory. This indicated to the decision-maker that it should be removed from the list of potential candidate storage facilities.

We also computed the statistical LBs and UBs on the amount of consumable aid procured from the vendors for storage at each of the depots. Table 8 provides these results:

**Table 7** Statistical upper and lower bounds for amount of inventory to store

Storage facility/depot name	95 % UB inventory	95 % LB inventory
Ramstein Air Base (Germany)	634,227	512,279
Charlotte Air National Guard Base (North Carolina, USA)	906,438	801,936
McChord Air Force Base (Washington, USA)	905,340	777,940
Hickam Air Force Base (Hawaii, USA)	770,074	713,660
Yokota Air Base (Japan)	588,970	504,684
Incirlik Air Base (Turkey)	642,841	541,585
Osan Air Base (South Korea)	596,881	506,079
Ali Al Salem Air Base (Kuwait)	213,674	71,340
Soto Cano Air Base (Honduras)	5076	−1742
MacDill Air Force Base (Florida, USA)	336,653	177,053
Marine Corps Logistics Base Albany (Georgia, USA)	7,419,858	3,750,276
Marine Corps Logistics Base Barstow (California, USA)	12,184,000	8,210,666

The decision-maker used the results in Table 8 to conduct post-hoc analyses based on the ranges of the inventory procurement amounts. For example, the inventory procurement LBs for vendors *V1* and *V2* were significantly lower than the LB for vendor *V3* for inventory storage at Marine Corps Logistics Base Albany (Georgia, USA). Also, the inventory procurement LB for vendor *V3* was significantly lower than the LBs for vendors *V1* and *V2* for inventory storage Marine Corps Logistics Base Barstow (California, USA). This suggests to the decision-maker that Albany (Georgia, USA) may want to consider a single sourcing supplier strategy with vendor *V3*, while Barstow (California, USA) may want to consider a multiple sourcing supplier strategy with vendors *V1* and *V2*.

We also computed the statistical bounds of the response time, cost and demand unmet to further explore the trade-offs of supply chain efficiency versus responsiveness (note that these results are based on the given inputs to the optimization model). In particular, the 95 % CI of the average total aerial delivery response time (across all disaster areas) was [6, 7.21] days, the average total supply chain cost (across all stages of the supply chain network) was [\$110, \$166] billion, and the average total demand shortage (across all disaster areas) was [47.1, 47.2] million pounds. These results provided a baseline for “what if” sensitivity analyses conducted for the decision-maker.

**Table 8** Statistical upper and lower bounds for amount of inventory to procure

Depot name	Vendor	95 % UB procure	95 % LB procure
Marine Corps Logistics Base Albany (Georgia, USA)	V1	1, 281, 224	314, 510
Marine Corps Logistics Base Albany (Georgia, USA)	V2	2, 376, 233	593, 367
Marine Corps Logistics Base Albany (Georgia, USA)	V3	3, 775, 165	2, 829, 635
Marine Corps Logistics Base Barstow (California, USA)	V1	5, 020, 958	3, 904, 908
Marine Corps Logistics Base Barstow (California, USA)	V2	4, 720, 729	2, 831, 271
Marine Corps Logistics Base Barstow (California, USA)	V3	2, 449, 673	1, 467, 127

#### 4.4 Sensitivity analyses

As the final component of the computational experiment, we conducted sensitivity analysis to investigate how changes in certain model parameters affected the optimal solution as a means to provide strategic decision support of the supply chain network trade-offs.

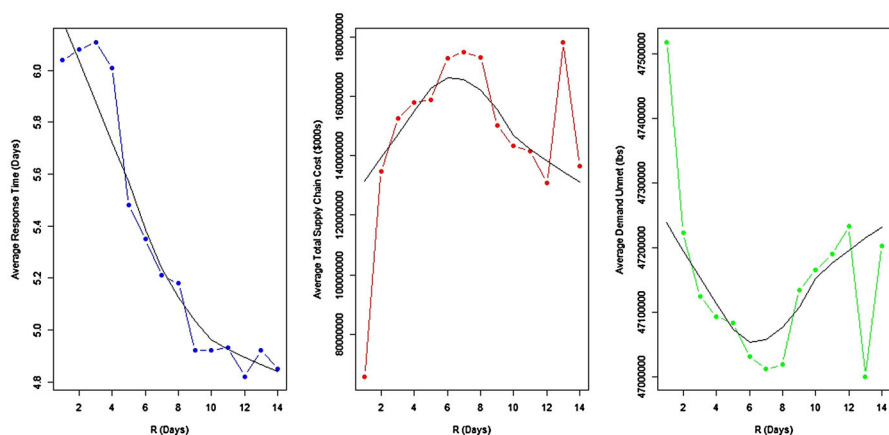
We first adjusted the data parameter  $R$ , which is the decision-maker's target total flight time budget that directly affects the maximum number of trips with consumable aid from storage facility  $j$  to disaster area  $i$  via aerial delivery mode  $k$ ; note that the maximum number of trips increases as  $R$  increases. Here, all other model parameters were fixed as previously described, but we evaluated the changes in the average response time, supply chain cost, and demand shortage as  $R$  was varied from 1 day (24 h) to 14 days (336 h). We first noted that the optimal subset of storage facilities to open changed at  $R = 4$  days (96 h), where the optimization model decided to open the Soto Cano Air Base (Honduras) for pre-positioning while closing the Osan Air Base (South Korea).

In addition, we found that as the value  $R$  increased, the average total aerial delivery response time (across all disaster areas) tended to decrease. The average total supply chain cost, however, tended to increase through  $R = 7$  days but then decreased slightly. Moreover, the average total demand shortage tended to decrease through  $R = 7$  days but then increased slightly; a relationship inverse to that of total cost. Table 9 displays these results:

The scatter plots in Fig. 7 also depicts these supply chain network design trade-offs of average response time, cost and demand unmet. In each of the plots, we also show

**Table 9** Supply chain network design trade-offs from adjusting  $R$

$R$ (days)	$R$ (h)	Time (days)	Total cost (000s)	Demand unmet (lbs)
1	24	6.04	\$65,699,925	47,518,280
2	48	6.08	\$134,834,650	47,223,830
3	72	6.11	\$152,475,550	47,124,980
4	96	6.01	\$157,934,050	47,093,180
5	120	5.48	\$158,980,950	47,083,630
6	144	5.35	\$172,945,300	47,031,580
7	168	5.21	\$174,846,850	47,012,530
8	192	5.18	\$173,146,700	47,018,930
9	216	4.92	\$150,118,800	47,134,130
10	240	4.92	\$143,208,850	47,166,130
11	264	4.93	\$141,531,750	47,190,130
12	288	4.82	\$130,832,750	47,233,180
13	312	4.92	\$178,315,600	47,000,730
14	336	4.85	\$136,600,800	47,202,780

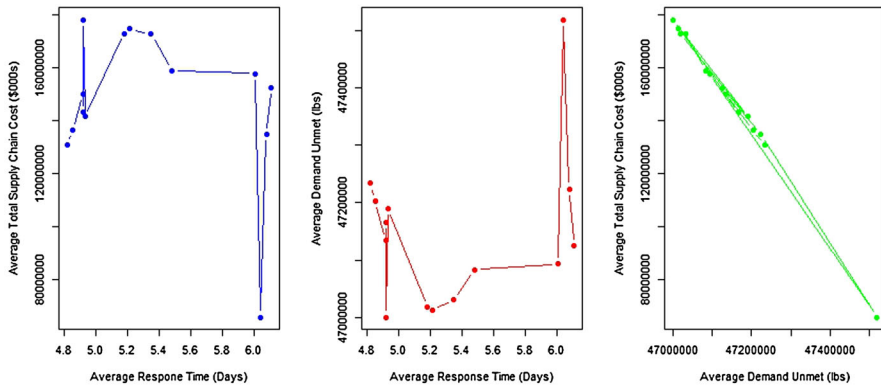


**Fig. 7** Scatter plots of supply chain network design trade-offs from adjusting  $R$

the *LOWESS* smoother that uses locally-weighted polynomial regression to see the overall trend.

The scatter plots indicate the direct trade-off between cost and demand unmet. For example, when  $R = 7$  days the average total cost reached its maximum while the average amount of demand unmet reached its minimum. These plots reveal an inverse relationship between supply chain efficiency and responsiveness. Note that at  $R = 7$  days, the average total aerial delivery response time is not at its minimum or maximum point.

To further illustrate the supply chain network design trade-offs, Fig. 8 depicts the bi-criteria objective spaces between time and cost, time and demand, and cost and demand; these plots highlight the non-dominated solution sets.



**Fig. 8** Supply chain network design bi-criteria solution sets from adjusting  $R$

For example, in the left plot of Fig. 8 there are two non-dominated solutions (4.82 days, \$130,832,750,000) at  $R = 12$  days and (6.04 days, \$65,699,925,000) at  $R = 1$  day. The non-dominated solutions are also evident in the middle plot. In the right plot, there appears to be a linear trade-off between average demand unmet and average total supply chain cost; this confirms our previous finding that these supply chain network design objectives are inversely related.

Next, we adjusted the data parameter  $T$ , which is the decision-maker's target total flight time budget that directly affects the maximum number of trips with consumable aid from depot  $d$  to storage facility  $j$  via the C-17 aerial delivery platform; again, note that the maximum number of trips increases as  $T$  increases. Here, all other model parameters were fixed as previously described in the setup of the computational experiment, but we evaluated the changes in the average total aerial delivery response time, supply chain cost, and demand shortage as  $T$  was varied from 2 days (48 h) to 14 days (336 h). We first noted that the optimal subset of storage facilities to open changed several times at  $T = 2, 3, 4$  days; the storage facilities that changed included Soto Cano (Honduras), Osan (South Korea) and Ali Al Salem (Kuwait) Air Bases.

Moreover, we found that as the value  $T$  increased, both the average total aerial delivery response time and the average total supply chain cost tended to increase; however, the amount of demand unmet tended to decrease. Again, there appears to be an inverse relationship between cost and demand unmet. Table 10 displays these results:

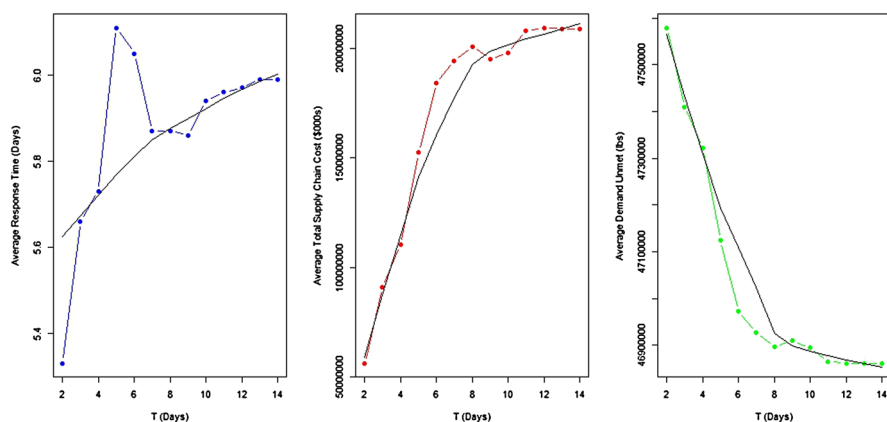
The scatter plots with *LOWESS* smoothers in Fig. 9 further illustrate these supply chain network design trade-offs.

In the left plot, the average total aerial delivery response time peaks at  $T = 5$  days, indicating to the decision-maker that the target total flight time budget should be somewhere between 2 and 4 days or between 7 and 14 days (depending on the desired trade-offs). Upon examining the middle and right plots, the distinct trade-off between cost and demand unmet is again clearly illustrated. Figure 10 depicts the objective spaces between these criterion.

The left plot in Fig. 10 illustrates that average total aerial delivery response time and total cost are not conflicting, as there is only one non-dominated solution (5.33 days, \$56,041,825,000) at  $T = 2$  days. On the other hand, the middle plot contains numerous

**Table 10** Supply chain network design trade-offs from adjusting  $T$

$T$ (days)	$T$ (h)	Time (days)	Total cost (000s)	Demand unmet (lbs)
2	48	5.33	\$56,041,825	47,579,104
3	72	5.66	\$91,068,740	47,409,980
4	96	5.73	\$110,316,950	47,321,980
5	120	6.11	\$152,475,550	47,124,980
6	144	6.05	\$184,322,650	46,973,430
7	168	5.87	\$194,610,500	46,927,180
8	192	5.87	\$201,143,350	46,896,180
9	216	5.86	\$195,205,400	46,909,530
10	240	5.94	\$198,269,300	46,894,230
11	264	5.96	\$208,352,800	46,865,030
12	288	5.97	\$209,670,200	46,861,280
13	312	5.99	\$209,277,500	46,861,280
14	336	5.99	\$209,041,400	46,861,280

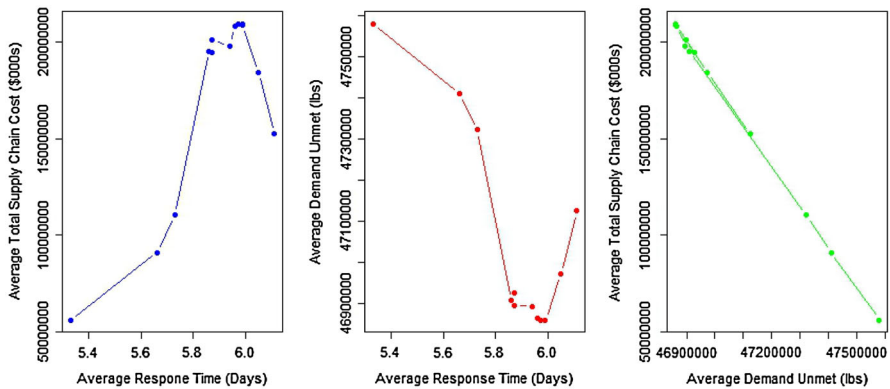


**Fig. 9** Scatter plots of supply chain network design trade-offs from adjusting  $T$

non-dominated and dominated solutions between the time and demand unmet criteria; for example, the bi-criteria solution (5.33 days, 47,579,104 lbs) at  $T = 2$  days is non-dominated while (6.11 days, 47,124,980 lbs) at  $T = 5$  days is dominated. The right plot again shows the almost perfectly linear trade-off between average demand unmet and average total supply chain cost.

Given that the MCDA framework employed *weighted* goal programming, it is sensitive to the assignment of decision-maker weights for each goal; this is especially important since the goals are measured in very different units (time, money, pounds). Thus, giving equal weights will give more importance to goals measured in large quantities. Since the magnitude of dollars in the framework is much higher than either response time or units of demand,  $W_2$  should be smaller than the other weights. For





**Fig. 10** Supply chain network design bi-criteria solution sets from adjusting  $T$

**Table 11** Supply chain network design trade-offs from varying decision-maker weights

W1	W2	W3	Time (days)	Total cost (000s)	Demand unmet (lbs)
1	1	100	6.11	\$152,475,550	47,124,980
1	2	100	6.30	\$89,833,355	47,406,130
1000	1	1	6.06	\$145,540,950	47,161,780
100	1	100,000	6.04	\$148,996,700	47,133,330

example, if  $W3$  is not much greater than  $W2$ , then storage facilities will likely not be opened since the third goal is to maximize the amount of demand met. We illustrate this in Table 11, which shows the supply chain network design trade-offs (response time, supply chain cost, and demand unmet) given different combinations of decision-maker weights. It should be noted that these combinations of weights were chosen in an interactive fashion with the decision-maker, who wanted an understanding of the impact of changing the importance of each goal. Again, the reason for the large difference in weight values (e.g., 1000 compared to 1) is to account for the differences in the goal units.

From Table 11, we found that the third goal required significantly greater weight than the first and second goals to achieve a pragmatic best compromise solution. However, the weight of the second goal was the most significant in its effect on the solution. For example, when increasing the weight of the second goal by merely one, the average total aerial delivery response time increased by 0.19 days, total cost decreased by over \$62 billion, and amount of demand unmet increased by over 28,000 pounds. As another instance, when increasing the weight of the first goal by 999 (and decreasing the weight of the third goal by 99), the average total aerial delivery response time decreased by 0.05 days, total cost decreased by nearly \$7 billion, and demand unmet increased by over 36,000 pounds. As a result of these findings, the selection of appropriate goal weights by the decision-maker requires significant attention.

## 5 Concluding remarks

In this paper, we developed a multiple criteria decision analysis framework to support the strategic logistics planning and cost assessment of military HA/DR aerial delivery operations. The decision support tool facilitated both responsive and efficient logistics planning under uncertainty by optimizing the military HA/DR aerial delivery supply chain network.

In particular, the framework employed stochastic, mixed-integer, weighted goal programming to optimize supply chain network design, logistics costs, staging locations, procurement amounts, and inventory levels. Moreover, the framework incorporated several methodologies to provide robustness and mitigate uncertainty in the system. Finally, the framework enabled the decision-maker to explore the supply chain network design trade-offs of average total aerial delivery response time, total supply chain cost, and amount of demand unmet.

We determined a recommended network design based on the criteria and data provided by U.S. Army Natick Soldier Research Development and Engineering Center, which provided an average response within 6 days and a supply chain cost of \$153 billion. Sensitivity analysis on the solution showed a direct tradeoff between cost and unmet demand. Further, as the flight time budget increased, the average response time and supply chain cost increased while unmet demand decreased. The use of goal programming, however, gave significant flexibility for the decision-maker. Although we applied the modeling framework to a particular application, it can easily be adopted to other HA/DR aerial delivery applications.

There are several limitations to the work that should be mentioned. First, parameter estimation for rare events is difficult since the historical data tends to be sparse. In addition, we lacked information to be able to define detailed distributions on several factors including vendor procurement costs, and cruise speed, and instead modeled a range of values using the uniform distribution. We used average values derived by the regression model as the basis for demand the scenarios. The results might change if we had data to better model potential extremes. In addition, the regression model used to estimate the affected population per year only explained 21 % of the variation, in part due to the limited number of factors in the EM-DAT data set. Further, the commodities modeled here are simple in that they are not perishable and may be characterized purely by their weight. Other applications may require more sophisticated models of capacity that take into account volume, weight, and perishability. Finally, we minimized the sum of the expected goal deviations in the optimization model. Although this is a very common form in practice and in previous literature, using expectations has limitations when the variance is quite high [38]. It also assumes that the decision-makers are risk neutral.

In future work, we plan to conduct additional sensitivity analyses by adjusting the levels of the experimental design factors. We also intend to evaluate the effects of procurement cost variability, as the range set by the decision maker for this study may have been artificially tight. Further, we aim to re-configure the optimization model formulation by incorporating a fourth decision-maker goal that accounts for the conflicting criterion of supply chain disruption/risk as well as altering some of the model constraints (such as allowing storage facilities to serve more than one disaster area).

Finally, we plan on tying the strategic model developed here to operational/tactical planning models.

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