Journal of the Operational Research Society

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tjor20

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JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY
https://doi.org/10.1080/01605682.2021.1877576

ORIGINAL ARTICLE

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ABSTRACT
The United States Coast Guard is charged with coordinating all search and rescue missions in maritime regions within the United States' purview. Given the size of the Pacific Ocean and limited available resources, the service seeks to posture its fleet of organic assets to reduce the expected response time for such missions. Leveraging 7.5 years of historic event records for the region of interest, we demonstrate a two-stage solution approach. In the first stage, we develop a stochastic zonal distribution model to evaluate spatiotemporal trends for emergency event rates and response strategies. In the second stage, results from the aforementioned analysis enable parameterization of a bi-objective MILP to identify the best locations to station limited heterogeneous search and rescue assets. This research models both 50th and 75th percentile forecast demands across both the set of current homeports, and a larger set of feasible basing locations. Results provide a minimum 9.6% decrease in expected response time over current asset basing. Our analysis also reveals that positioning assets to respond to 75th percentile demands sacrifices, at most, 2.5% in response time during median demand months, whereas positioning for median demand results in operationally inadequate response capability when 75th percentile demands are encountered.

ARTICLE HISTORY
Received 9 April 2020
Accepted 11 January 2021

KEYWORDS
Search and rescue; spatiotemporal forecasting; location-allocation modeling; p-median location problem; multi-objective optimization

1. Introduction

The United States Coast Guard (USCG) is charged with coordinating search and rescue (SAR) missions in maritime regions within the United States' purview (National Search & Rescue Committee, 2018). As the federal SAR coordinator for these emergencies, the USCG responds to SAR events with its own maritime and aeronautical assets, and coordinates as necessary with private, commercial, and Department of Defense assets in the vicinity of SAR events to provide supplementary support. The time required for the USCG to receive an emergency notification, dispatch an asset, locate the individual(s) in distress, and provide aid can be the difference between life and death, so it is important to ensure response assets are well positioned to service expected demands.

Organizationally, the command and control of USCG operations is divided among administrative districts, and each district is assigned to direct operations for a geographic area of responsibility (AOR). Headquartered in Honolulu on the island of O'ahu, USCG District 14 is responsible for missions across most of the Pacific Ocean, a region over 12 million square nautical miles in size which the district supports with assets stationed among the Hawaiian Islands and Guam. Despite having the largest geographic AOR, District 14 is allocated relatively few resources, a result of both resource priorities across USCG districts, and a historically lean budget authorization for a service responding to very high levels of demand (United States Coast Guard, 2019a, 2019b). Moreover, every USCG district must service multiple missions (e.g. search and rescue, drug interdiction, migrant interdiction, marine safety); although every search and rescue mission relates to saving lives and is of paramount importance, the assets within District 14 are needed to support a myriad of activities.

Given its limited available resources, District 14 seeks to posture its fleet strategically to minimize the expected response time to respond to emerging SAR missions. The strategic posturing of the District 14 fleet is complicated by the size of the AOR, the need to consider a heterogeneous fleet of maritime and aeronautical assets, and the inherent uncertainty of both the emergency event locations and frequencies for SAR events. Thus, it is first necessary to predict expected SAR demands and subsequently optimize both the locations of assets and allocation of expected demands among such assets within the District 14 fleet.

This research makes three contributions to the field of maritime resource location-and-allocation problems. First, it introduces the Stochastic Zonal

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Distribution Model (SZDM), a stochastic extension to the works of Azofra et al. (2007) and Razi and Karatas (2016) to develop spatiotemporal maritime incident forecasts using historic demand data. Second, it sets forth a multi-objective mathematical programming model, leveraging the output of the SZDM, to optimize the placement of a fleet of heterogeneous response assets to address the competing objectives of minimizing the expected response time for future SAR events and minimizing the cost of moving assets from their current locations. Third, it demonstrates the use of the SZDM and math programming in combination, applying them to search and rescue data and organizational asset information for the US Coast Guard in a subregion of the Pacific Ocean to examine both median and higher (i.e. 75th percentile) realizations of expected demands, from which practical recommendations are derived.

The remainder of this paper is organized as follows. Section 2 reviews the relevant research literature that informs the modeling and analysis described herein. Section 3 discusses the respective stochastic zonal distribution and the asset location-and-allocation models and their implementations. Section 4 presents and discusses the results of applying these models to District 14's problem using seven years of recent historic SAR event data, and Section 5 summarizes major insights and provides recommendations for future research.

2. Literature review

The research presented in Sections 3 and 4 is informed by two subdisciplines from the technical literature: spatiotemporal forecasting and location theory.

The two major threads of published spatiotemporal forecasting research relate to predicting either natural or man-made incidents. The potential to leverage wind power via spatiotemporal forecasting is examined by Xie et al. (2014) and Tastu et al. (2011), whereas Tascikaraoglu et al. (2016) sought to predict meteorological qualities suitable to generate solar power. In contrast, Madadgar and Moradkhani (2014) sought to predict droughts with Bayesian networks to mitigate agricultural impacts. With a more somber view towards hazards, research by Hashimoto et al. (2013) developed spatiotemporal predictions of nucleotide deposits in the forests in the vicinity of the Fukushima nuclear accident in Japan. By comparison, most work related to man-made incidents pertains to predicting traffic congestion, whether vehicular (Frihida et al., 2002; Sirvio & Hollmén, 2008) or pedestrian (Zhang et al., 2017). Other research seeks to predict the times and locations of deliberate, malicious behavior by humans, such as wildlife poaching (Gholami et al., 2017), internet system attacks (Soldo et al., 2011), and crime (Wang et al., 2012; Wang & Brown, 2011, 2012). Benigni and Furrer (2012) sought to develop effective spatiotemporal predictions for insurgents using improvised explosive devices on a subset of roads in Baghdad, Iraq. More closely related to the current study is work by Prasannakumar et al. (2011) to predict the times and locations of road accidents, albeit for incidents relatively restricted in their geography. Marchione and Johnson (2013) sought to predict maritime piracy incidents, but their consideration of events resulting from deliberate human behavior renders it ill-suited for the problem considered herein. Instead, we seek to predict accidents (i.e. SAR events) resulting from maritime human activity across an expansive region, and which may or not be related to natural phenomena such as rough seas and inclement weather.

Setting aside the question of weather as a strictly causal factor for SAR events, there do exist studies that forecast SAR demands that relate to the movement of people by maritime assets across an expansive region. Most such works (e.g. (Afshartous et al., 2009; Akbari et al., 2018; Karatas et al., 2017)) address the uncertainty of SAR demands by decomposing a maritime region of study into a rectangular mesh of zones and subsequently modeling the temporal nature of the aggregated, zonal demand volumes via a simulation-based approach using either Poisson or uniform distributions, with the spatial identification of SAR events occurring at the center of each zone. Related studies consider a more customized decomposition of a region using the zonal distribution model set forth by Azofra et al. (2007). Ai et al. (2015) and Razi and Karatas (2016) implemented variations of the zonal distribution model using static average historical demands as a deterministic demand volume for each zone, while considering zonal demands to occur at fixed points (i.e. the centroids) within the respective zones. Given the size of the District 14 AOR, the disparity of demand volume across its geographic expanse, and the uncertainty inherent in SAR demand, we develop and implement a *stochastic zonal distribution model* that leverages both the stochastic components of simulation-based methods and the customized zoning approach used by the aforementioned deterministic models.

Given the need to locate the District 14 fleet of maritime and aeronautical assets to service expected SAR demands, the second stage of our research is informed by the field of location theory. Early works in location theory focused on where a decision maker should locate facilities (Church & ReVelle, 1974; Daskin & Stern, 1981; Toregas et al., 1971) and how many facilities to emplace at each possible location (Baker et al., 1989; Berlin & Liebman, 1974; Hall, 1972). Among these works are models fundamental to the discipline, including the set covering location problem (SCLP), maximal covering location problem (MCLP), p-center problem, and p-median problem. Given a limit on the range of a facility to cover demands, the SCLP identifies the minimal number (or cost) of facilities required to cover all demands, whereas the MCLP maximizes the number of demands covered by a bounded number (or cost) of facilities. Setting aside the restriction of a fixed covering range (radius in Cartesian space) and adopting a location-allocation framework, the p-center problem locates p facilities among a set of possible sites and allocates a set of demands to the located facilities, seeking to minimize the maximum facility-to-assigned-demand distance. Alternatively, the p-median problem likewise locates facilities and allocates demands to them, but it minimizes the total (or equivalently, the average) facility-to-assigned-demand distance. Extensions to these early models consider facilities having capacities (Berman et al., 2007), deterministic and stochastic demands (Snyder et al., 2007; Wang et al., 2002), multiple covering of demands (Batta & Mannur, 1990; Daskin et al., 1988), hierarchical facility structures (Teixeira & Antunes, 2008), and other variants (McLay, 2009; Snyder, 2006); an interested reader is referred to recent reviews by Jia et al. (2007), Simpson and Hancock (2009), and Farahani et al. (2012), or to any of four excellent books by Drezner and Hamacher (2001), Daskin (2011), Laporte et al. (2015), or Church and Murray (2018), each of which provides a thorough treatment of the subject. Most closely related to our problem is the p-median location problem, which we adapt for the heterogeneous District 14 fleet of assets, as well as the multiple objectives entailed by locating assets effectively yet minimizing changes to the existing enterprise.

Although it does not directly inform our work, it is appropriate to mention the related work in locating emergency response assets, pre-positioning assets for humanitarian operations, and in a more limited stream of literature, locating assets that respond specifically to maritime emergencies. A rich body of literature also exists for the location of emergency management system (EMS) assets. Each of the recent surveys by Aringhieri et al. (2017), Gholami-Zanjani et al. (2018), and Bélanger et al. (2019) is quite thorough. Although EMS missions are conceptually related to the Coast Guard's SAR mission, both the distance metric (i.e. road distance) and the oft heterogeneous assets located for EMS modeling make it sufficiently different to preclude the adoption of existing models from the ground-based EMS literature to address the District 14 problem. Extensive literature examines the optimal location of 'assets' (e.g. emergency supplies, or search and rescue teams) for humanitarian operations; however, research within this field does not, in general, account for the limitations of asset locations specific to *maritime* search and rescue. A reader interested in humanitarian asset prepositioning research is referred to a recent survey by Sabbaghtorkan et al. (Sabbaghtorkan et al., 2020).

Previous studies regarding the placement of resources to respond to maritime emergencies are more limited, and they typically restrict their examination to a single asset type or the operational range of a station. Wagner and Radovilsky (2012) and Razi and Karatas (2016) both developed allocation tools limited to the assignment of USCG boats, and Akbari et al. (2018) and Azofra et al. (2007) developed models to locate maritime vessels. In contrast, Karatas et al. (2017) scoped their allocation plan to Turkish Coast Guard helicopters, whereas Afshartous et al. (2009) constructed a statistical model to locate air stations and concluded by suggesting their methodology could be applied to consider the allocation of resources at those stations. For a unique application to decide where to *build* man-made islands for basing search and rescue assets, Zhou et al. (2019) created a set of potential locations, estimated demand density, and leveraged a mathematical program model to select the bases to utilize (i.e. build). However, their research relied on kernel density for estimation of demand and assumes a homogeneous set of response assets. In a subsequent work, Zhou et al. (2020) examined the performance of existing search and rescue assets over three assessment criteria to three scenarios, identifying enterprise shortfalls and arguing for increased capacity. Recent research conducted by Ferrari and Chen (2020) examines the ad hoc basing of aerial assets and their allocation to search zones in response to a search and rescue incident. Although these studies tend to include detailed operational requirements for their specific asset types within the models, they lack the general applicability to the location of heterogeneous assets using different transportation modes necessary to address the problem examined herein. Most closely related to our problem is recent research conducted by Karatas (2021); the author applied a goal programming approach to locate helicopters and boats to support search and rescue incidents in the Aegean Sea, relocating vessels seasonally to address response time, workload balance, and budget.

Asset relocation problems are intrinsically multi-objective; at a minimum, a decision maker must balance asset relocation costs against increases in efficacy. Numerous, excellent publications summarize the field of multi-objective optimization (e.g. (Deb & Deb, 2014; Ehrgott, 2005; Mandal et al., 2018)). However, a few techniques merit highlighting. The Weighted Sum Method (Zadeh, 1963) is an easily applied technique which uses convex combinations of weights on the respective objective functions to search for Pareto efficient solutions to – most typically – bi-objective optimization problems. However, this method requires well-scaled objective functions, and it is well known this method will fail to identify efficient solutions on a non-convex objective space. The ε-constraint Method (Haimes, 1971) iteratively optimizes one objective while bounding the other(s). Unlike the Weighted Sum Method, this technique can find all the Pareto efficient solutions, given sufficient granularity in the iterative applications of objective function bounds, and it does not require objective functions be well-scaled because the objective functions are addressed disparately. The ε-constraint Method is most readily applicable when either the constrained objective functions have a countable number of solutions (e.g. when they are integer-valued), or when the range of potential solutions is sufficiently small that it can be explored in a tractable manner. Of note, the ε-constraint Method is more practical for problems having few (e.g. two or three) objective functions; utilizing this technique with a larger number of objective functions provides challenges to imposing bounds that yield an evenly distributed set of non-dominated solutions. Moreover, a subset of bound combinations will correspond to infeasible solutions, a relatively trivial issue with two or three objective functions that will unproductively consume greater computational effort for problems having many objective functions. Advances in metaheuristic search techniques offer additional techniques to explore the Pareto frontier of non-dominated solutions. Among the widely embraced techniques is NGSA-II (Deb et al., 2002), a state of the art multi-objective genetic optimization algorithm that seeks a diverse (i.e. not crowded) set of non-dominated solutions across the Pareto frontier. Although such algorithms have the potential to find a large set of non-dominated solutions relatively quickly, they are not guaranteed to return globally optimal solutions on the actual Pareto frontier. However, they do provide an excellent alternative when the computational complexity of the problem renders the identification of an optimal solution to even a single instance of the problem practically intractable.

Additional probabilistic methods were examined for applicability before determinations were made that they did not impact this study. These include capacitated facility location problems, queuing theory, Markov Decision Processes, and Approximate Dynamic Programming. While these topics are used to excellent result in several humanitarian operations studies (e.g. (Bertsimas & Ng, 2019; Jenkins et al., 2020)) the default assumption for such probabilistic methods is that 'servers'can be busy. Given the relatively lower density of maritime search and rescue efforts a deterministic assumption of server availability was deemed sufficient for this study.

3. Models and solution methodologies

Our hybrid methodology can be summarized as follows: First, in Section 3.1 we develop SAR emergency demand zones using historic demand data and, utilizing stochastic techniques, estimate demand by zone. The results of this analysis allow us to fully parameterize a mathematical programming model. Second, in Section 3.2 we define our notation (i.e. sets, parameters, and decision variables) and set forth the corresponding mathematical programming formulation to locate USCG District 14 heterogeneous response assets in order to balance minimal expected response time with minimal relocation costs.

3.1. Model parameterization for stochastic demand

In SAR operations, future emergencies are inherently uncertain with respect to both time and location. This uncertainty presents a challenge to applying a prescriptive optimization model because the stochastic demands are typically decimal-valued, whereas the different assets to be located are, of course, integer-valued. Moreover, the challenge of determining uncertain demand levels is amplified by the size of the AOR, the variability in demand across the AOR, and the variability of demand for different asset types. To address these challenges, we extend the work of Razi and Karatas (2016) by developing the stochastic zonal distribution model. This model addresses the spatiotemporal forecasting problem in three steps: construction of SAR demand zones, stochastic characterization of zonal demand frequencies, and identification of the levels (i.e. type and numbers of each asset) of such SAR demands.

3.1. Step 1. Hierarchical clustering of historical SAR data

First, the region of study is decomposed into zones using a hierarchical k-means clustering algorithm. This algorithm first sorts historical SAR data into mutually exclusive groups based upon the organizational unit which coordinated the emergency response, and the assets operationally capable of responding. For this study, SAR events were categorically classified as either *boat/helicopter events* or *cutter/airplane events*, where the former classification entails an event to which shorter range assets can adequately respond. The islands with USCG boat stations are the Hawaiian islands of Kaua'i, O'ahu, and Maui as well as the island of Guam. Due to the operational constraints of USCG boats and the tendency to combine boats and helicopters together in operations, SAR events within 50 nautical miles of these islands were classified as boat/helicopter events whereas emergencies beyond these boundaries were classified as cutter/airplane events. Each group is then geographically clustered using a *k*-means technique. The implementation of a *k*-means algorithm for determining zones within a region of study was inspired by the work of Razi and Karatas (2016).

3.1. Step 2. Probabilistic representation of SAR demand for each zone

Second, probabilistic representations of monthly SAR demands are constructed for each zone. Given the stochastic nature of SAR emergencies, we identify probability distributions that accurately represent the emergence of SAR events over time. Afshartous et al. (2009) and Akbari et al. (2018) identified SAR events as likely being Poisson-distributed within their simulation-based approach to locate SAR assets. We hypothesize the historical SAR data for this study is likewise represented appropriately via Poisson processes, although the assumptions of independence and stationarity are evaluated.

3.1. Step 3. Probabilistic representation of SAR event asset response requirements

Third, based upon the probabilistic representation of SAR demand for each zone, the corresponding response is modeled. When the Coast Guard receives notification of an emerging crisis, a SAR team uses an operational dispatching system known as SAROPS to determine the appropriate assets to respond, given the weather, asset availability, and case details. Although the asset location modeling herein is tactical in nature (i.e. it does not address the SAROPS problem), effective staging of SAR assets depends on understanding localized response trends; accordingly, we classify response strategies in each zone and determine their respective frequencies of occurrence. We bounded the response requirement to be no more than four maritime assets and two aeronautical assets due to the number of current assets belonging to the district. For notational purposes, a response strategy in this study is represented as (# of Maritime Assets, # of Aeronautical Assets). For zones of boat/helicopter events, these are assumed to be (Boats, Helicopters) whereas, for zones of cutter/airplane events, they are assumed to be (Cutters, Airplanes). The respective frequencies of occurrence for each response strategy was modeled by empirically-constructed probability mass functions, developed for each zone.

3.2. Location model for heterogeneous assets

Using forecast demands developed from the stochastic zonal distribution model, a prescriptive approach is necessary to locate District 14's boats, cutters, airplanes, and helicopters to reduce the expected response time for future SAR events. As such, it is appropriate to solve (or resolve) this model under any of three conditions: (1) when the spatiotemporal trends in SAR incidents change notably; (2) when there is a change in the numbers and types of assets available for locating; or (3) when there is a change to the available basing options for asset types. To formulate the mathematical programming model for this problem, we first define the following sets, parameters, and decision variables.

Sets:

- $n \in N$: Set of asset categories, where N = {Boat, Cutter, Airplanes, Helicopters} for the District 14 asset location problem.
- $m \in M$: Set of location categories, where M = {Harbor, Airport} for the District 14 asset location problem.
- $(n, m) \in P$: Set of *infeasible* asset-location combinations. As would be expected, P = {(Cutter, Airport), (Boat, Airport), (Airplane, Harbor), (Helicopter, Harbor)}.
- $h \in H_n$: Set of all individual assets within asset category n. For the problem considered herein, this set is informed by current District 14 operational capabilities.
- $i \in I_m$: Set of candidate homeports. This set is informed by airports and ports identified in coordination with District 14 operational staff.
- $j \in J$: Set of demand nodes. This set is informed via the historical data and the process described in Section 3.1.

Parameters:

- c_{hi}: Time (hours) to (re)assign asset $h \in H_n$ to candidate homeport $i \in I_m$. Each c_{hi}-value is computed by dividing the distance (nmi) between the current homeport of asset $h \in H_n$ and candidate homeport $i \in I_m$ by the cruise speed (knots) of asset

$h \in H_n$. Note that assigning an asset to its current homeport yields $c_{hi} = 0$.

- d_{hij}: Time (hours) to deploy asset $h \in H_n$ from candidate homeport $i \in I_m$ to demand node $j \in J$. The time to deploy assets is computed by dividing the distance (nmi) between the candidate homeport $i \in I_m$ and the demand node $j \in J$ by the maximum speed (knots) of asset $h \in H_n$.
- l_{nj}: Level of demand (number of assets required) for asset type $n \in N$ at site $j \in J$.
- u_h: Monthly hours allocated for SAR operations by asset $h \in H_n$. This allocation is user-determined and depends on organizational staffing, training, maintenance, and budget limitations.
- t: Time (hours) required on-site to complete a SAR mission. We assume a constant value of $t = 1.5$ for all SAR missions, but a practitioner can readily alter the model to accommodate alternative assumptions.
- Q: An arbitrarily large number used within a logical constraint to relate location and allocation decisions.

Decision Variables:

- x_{hi}: Binary variable equal to 1 if asset $h \in H_n$ is assigned to candidate homeport $i \in I_m$, and 0 otherwise.
- y_{hij}: Integer-valued number of SAR events to which asset $h \in H_n$, assigned to candidate homeport $i \in I_m$, is poised to respond at demand nodes $j \in J$.

Given this framework, we propose the following formulation for the Optimal Location Model for Heterogeneous Search and Rescue Assets:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \left(f_1(\boldsymbol{x}), f_2(\boldsymbol{y})\right) \tag{1}$$

$$\text{s.t.} \quad f_1(\boldsymbol{x}) = \sum_{(m,n)\in\{M\times N\}\setminus P} \left(\sum_{h\in H_n}\sum_{i\in I_m} c_{hi}x_{hi}\right), \tag{2}$$

$$f_2(\boldsymbol{y}) = \sum_{(n,m)\in\{N\times M\}\setminus P} \left(\sum_{h\in H_n}\sum_{i\in I_m}\sum_{j\in J} d_{hij}y_{hij}\right), \tag{3}$$

$$\sum_{m\in M}\sum_{i\in I_m} x_{hi} = 1, \forall h \in H_n, n \in N, \tag{4}$$

$$\sum_{h\in H_n}\sum_{i\in I_m} x_{hi} = 0, \forall (m,n) \in P, \tag{5}$$

$$\sum_{h\in H_n}\sum_{m\in M}\sum_{i\in I_m} y_{hij} \geq l_{nj}, \forall n \in N, j \in J, \tag{6}$$

$$\sum_{j\in J} y_{hij} \leq Qx_{hi}, \forall h \in H_n, n \in N, i \in I_m, m \in M, \tag{7}$$

$$\sum_{m\in M}\sum_{i\in I_m}\sum_{j\in J} (2d_{hij} + t)y_{hij} \leq u_h, \forall h \in H_n, n \in N, \tag{8}$$

$$x_{hi} \in \{0,1\}, \forall h \in H_n, n \in N, i \in I_m, m \in M, \tag{9}$$

$$y_{hij} \in \mathbb{Z}_+, \forall h \in H_n, n \in N, i \in I_m, m \in M, j \in J. \tag{10}$$

The multiobjective formulation seeks to minimize two objectives. The first objective (2) calculates the total time (in hours) required to reassign assets to new homeports, and the second objective (3) computes the expected total time (in hours) to deploy assets from their homeports to assigned demand nodes. Although the two objectives share the same units of measure, this characteristic of the formulation is merely a coincidence resulting from the decision to model asset relocation costs in units of time to physically move the assets between locations. The first objective to minimize the number of assets moved from current locations is a proxy for minimizing the cost of moving assets, a measure that is more elusive to compute due to the imposition of both tangible costs (e.g. purchasing real estate, leasing warehousing for aircraft or berthing for seagoing vessels, building support infrastructure) and intangible costs (e.g. political negotiation, military appropriations testimony) when relocating assets. However, the first objective is of fundamental importance because assets cannot be freely relocated from their current berths without notable coordination, funding, and approval from higher echelons of decision-making authority. Although the calculation in (2) is a coarse approximation to the actual costs of moving assets, it provides a relevant proxy. USCG decision makers found it to be an appropriate substitute for calculations that cannot be attained *a priori*; the distances are proportional to the asset relocations costs, and the resulting calculation is relatively well-scaled with the second objective function (3) (as will be evidenced via testing results reported in Section 4 and, specifically, Figure 3), thereby enabling easy understanding by decision makers of the trade-space between the two objectives. The second objective seeks to minimize response time and is of natural importance because it directly relates to the number of lives saved. Moreover, the two objectives are not necessarily well-scaled, although we find them to be well-scaled for the District 14 problem instances during testing in Section 4.

Constraint (4) ensures that every asset is assigned to exactly one homeport, whereas Constraint (5) prevents erroneous assignments, such as homeporting a maritime asset at an airport. Constraint (6) requires the demand requirement for each asset type to be met. Constraint (7) only allows assets to be deployed from a homeport if they are assigned to that homeport. An arbitrarily large value is used for Q (e.g. $Q = 100|J|$), indicating that assigned assets can respond to at most $100|J|$ SAR events. Constraint (8) enforces the monthly utilization rates for individual assets, where each SAR event imposes the time to travel to and from the demand node as well as the duration of the mission. Constraints (9) and (10) respectively enforce binary and nonnegative integer constraints on the location- and assignment-related decision variables.

Among the methods available to address the multi-objective nature of the formulation (Ehrgott, 2005), we utilize the ε-constraint Method for testing. We impose the constraint $f_2(y) \leq \varepsilon$ and minimize $f_1(x)$, iteratively solving the problem over an appropriate range of ε-values. Based upon discussions with subject matter experts for the motivating problem, we examine increments of $\varepsilon = 0.25$, equivalently 15-minute increments in expected response time.

This formulation can be used to consider a number of scenarios. Within this study, we consider how District 14 should posture its organic assets such that the total response is minimized across a taxonomy of scenarios: with District 14 vessels being either restricted to operate only out of its currently owned stations or allowed to position its assets at any operational airport or harbor across the AOR and, for each such case, considering the simultaneous minimization of the cost associated with reassigning assets to new homeports in addition to the expected cost of operating from those homeports.

Alterations can be made to the sets and parameters to consider each of these scenarios. The homeports $i \in I_m$ are adjusted to model, alternatively, only locations currently operated by District 14 or a large collection of airports and harbors across the region. Similarly, the objective function weights (w_1, w_2) are adjusted based on the relative priorities for the two objective functions.

To identify an optimal solution to this integer linear programming formulation, there exist a plethora of readily available, commercial solvers (e.g. CbC, CPLEX, FICO-Xpress, gurobi, MOSEK). To encode the formulation, many algebraic modeling languages (e.g. AMPL, GAMS, LINGO, OPL) and general programming languages (e.g. C++, Java, Python, R) likewise abound. However, we also required a modeling environment within which we could automate the computation of several complex parameters to calculate instance parameters. Among the various parametric calculations, we needed to quickly compute the haversine distances between all considered locations, and the corresponding travel times for each asset based on vehicle specifications. Based on the simplicity of coding environment and readily available trigonometric functions, we modeled the formulation using General Algebraic Modeling Software (GAMS) version 25.1.3 and invoked CPLEX version 12.7 to identify solutions to specific instances.

4. Testing, results, and analysis

Within this section, we provide in Section 4.1 an overview of the historical SAR event data set and data cleaning requirements, present in Section 4.2 the results of the stochastic zonal distribution model, and report and discuss in Section 4.3 the results of solving the prescriptive location model for District 14. In subsequent examinations in the final subsection, we also apply the ε-constraint Method to identify non-dominated (i.e. Pareto optimal) solutions for both variants of allowable sets of homeports for basing, under both the 50th and 75th percentile realizations of expected demand levels, followed by an examination of the relative sensitivity of the enterprise performance to this assumption.

4.1. Historical demand data

For this study, the historical SAR data was provided from the USCG Marine Information for Safety and Law Enforcement (MISLE) database by the USCG Research and Development Center. The event data consisted of a list of SAR events spanning from December 2010 through May 2018.

Not every event within the data was applicable to this study, for which the scope is limited to SAR events within District 14's AOR that require the response of USCG assets. Figure 1 depicts the Honolulu Maritime Search and Rescue Region, as stipulated in the district's search and rescue plan (United States Coast Guard District 14, 2014) and used as a SAR-specific proxy for the (larger) District 14 AOR for this analysis. Thus, this analysis supports asset location planning for response to events within the SAR region supported by deliberate district plans.

Three categorical subsets of data were removed from the data set. First, SAR event records having the subtype 'MEDICO' were removed because they consist of medical consultation only via phone or radio communication and do not require the response of USCG assets. The second and third categories of event records removed from the data set were SAR events for which, respectively, either no GPS location was provided with the SAR event record or the event occurred outside the region depicted in Figure 1.

There did exist SAR event records within the MISLE data that occurred within the Honolulu Maritime SAR Region but for which no assets were dispatched in response. These records did not exhibit any geographic or subtype commonality, and it is assumed the records were correct and the decision not to dispatch assets in response to these events was deliberate (e.g. support was provided by an non-USCG asset). As such, these SAR event records were retained within the data set. Table 1 summarizes the results of the data cleaning; 91.52%

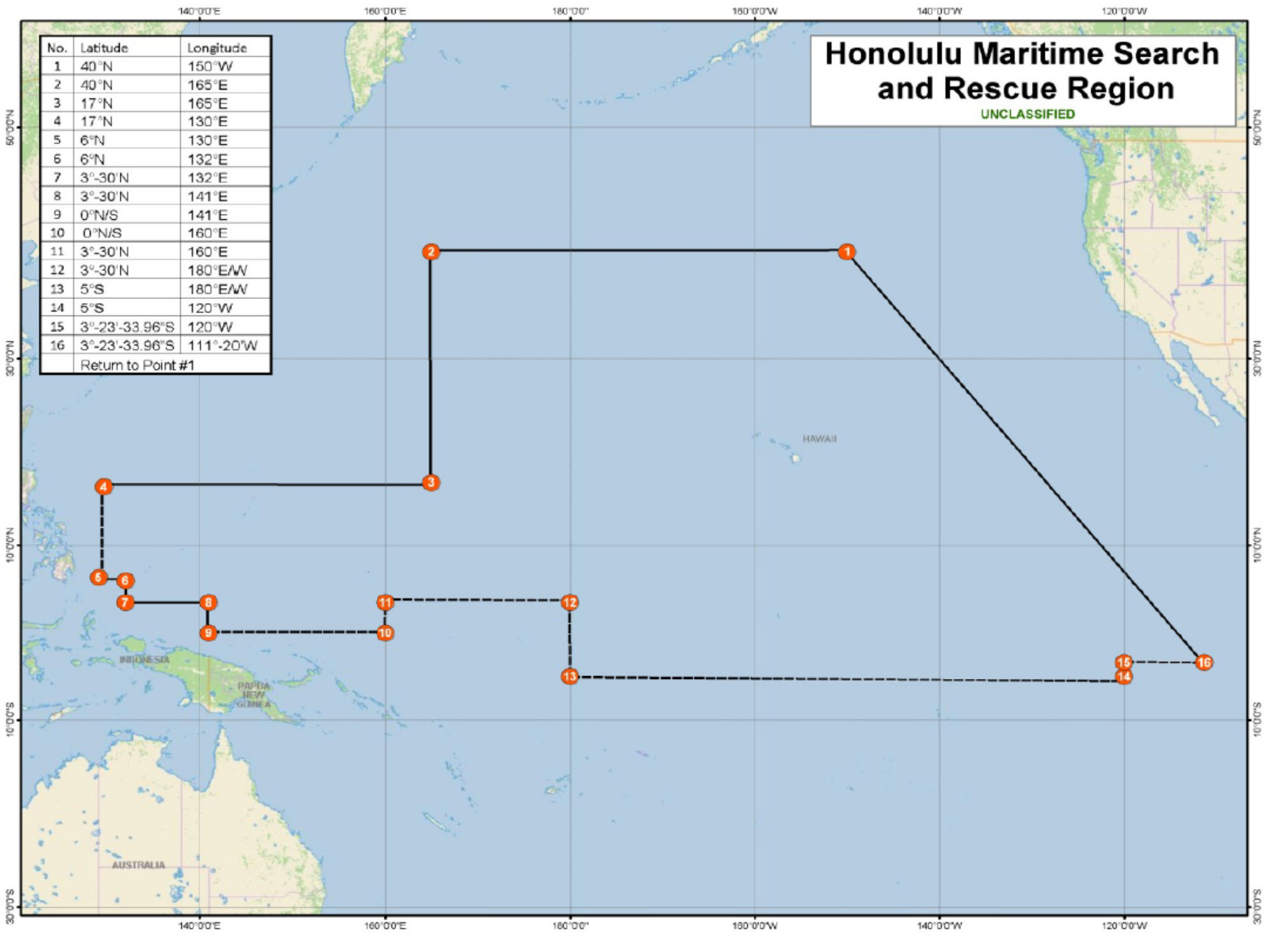

Figure 1. Honolulu Maritime SAR Region (United States Coast Guard District 14, 2014).

of the historical record data was retained to inform the stochastic zonal distribution model.

Providing response to forecast events are District 14's fleet of 21 assets: eight boats, nine cutters, two helicopters, and two airplanes. The district operates out of six locations: four harbors and two air stations. Expanding consideration for possible asset locations across the Pacific region yields 50 civilian locations (i.e. 28 harbors and 22 airports) identified for this study.

Several assumptions were necessary to leverage the MISLE data in both the forecasting and optimization models. First, the historical SAR data is assumed to be indicative of future trends in USCG District 14's SAR region. Second, the 3949 records in the cleaned data set are assumed to accurately represent the SAR missions within the District 14 SAR region and the corresponding demands upon District 14 assets from December 2010 through May 2018. The last assumption relates to the distance measurements used in the location problem formulation. This study uses the haversine formula to calculate distances between candidate homeports and both other homeports and demand nodes. Using this distance calculation assumes both that the Earth is perfectly spherical, an acceptable approximation, and USCG assets travel by the distance-minimizing route to and from SAR events. Thus, the calculations neglect the additional distances to route assets around islands as well as any deviations from the most direct route due to asset traffic, tides, or weather.

4.2. Stochastic zonal distribution model results

As introduced in Section 3.1, we use the stochastic zonal distribution model to sequentially construct SAR demand zones, characterize the stochastic nature of SAR event demands within each zone, and identify the response levels of such SAR demands, in terms of the type and numbers of the various heterogeneous assets.

4.2.1. Step 1. Hierarchical clustering of historical SAR data

District 14 is comprised of three response organizations among the MISLE data: Sector Guam, Sector Honolulu, and District 14 Headquarters. As such, all SAR events were first sorted among four categories: (1) Sector Guam boat/helicopter events, (2) Sector Guam cutter/airplane events, (3) Sector Honolulu/District 14 Headquarters boat/helicopter events, and

Table 1. Data cleaning summary for SAR event records, Dec 2010–May 2018.

Category	No. Records
Initial Data Set	4315
MEDICO events	90
Missing GPS Data	38
Outside SAR Region	238
Final Data Set	3949

(4) Sector Honolulu/District 14 Headquarters cutter/airplane events. Sector Honolulu and District 14 Headquarters were combined because of a significant level of overlap between the geographic dispositions of historical SAR events to which they respectively responded.

The locations of the SAR events were represented on a two-dimensional Cartesian plane using their respective longitude and latitude coordinates, adjusting coordinates for the presence of the antimeridian to reference all coordinates via a common direction (i.e. west) with respect to the prime meridian. Although such a projection is not equivalent to the geometry along the surface of the Earth, we assume the error to be negligible, i.e. we assume SAR events clustered together on a planar projection would be clustered likewise on the surface of the a sphere. Alternatively, the same clustering procedures were implemented on the data when represented in a three-dimensional Cartesian space (i.e. considering direct, under-the-ocean-surface Euclidean distances), attaining similar results.

To determine the number of clusters within each of the four categories, a series of elbow curves were generated in Python. A noted limitation of the k-Means approach is the sensitivity of the procedure to the selection of starting centroid locations; ill-selected starting locations can lead to poor clustering results. A solution proposed by Arthur and Vassilvitskii (2007) is the k-Means++ approach, wherein the initial centroid point is randomly selected, and subsequent centroid points are selected based on a probability that is a function of the shortest distance between the proposed center point and previously selected center points. Once the k initial center points are selected, the traditional k-Means procedure is implemented to cluster the data points. The k-Means++ method of selecting initial center points was utilized for the clustering in this study.

Executing this clustering procedure, 15 clusters are generated. Of these 15 clusters, six clusters consisted of boat/helicopter events; two surrounding Guam (Guam 0, Guam 1) and four surrounding the Hawaiian Islands (Hawaii 2-5). Nine clusters consisted of cutter/airplane events; three within Sector Guam's AOR (Guam 6-8) and six within Sector Honolulu/District 14 Headquarter's AOR (Hawaii 9-14). Zones boundaries around the clusters were identified to partition the District 14 AOR, as depicted in Figure 2.

The zonal distribution model established by Azofra et al. (2007) utilizes 'superaccident' sites to represent the aggregated demand node of SAR events within each zone. The authors' model computes the location of these superaccidents via the arithmetic mean of the longitudes and latitudes for all events within the respective zones. Razi and Karatas (2016) also leveraged the concept of superaccident sites, but improved upon the work of Azofra et al. (2007) by accounting for varying weights of events; they implemented a weighted k-Means clustering algorithm to account for different event magnitudes in the zonal grouping of SAR events. We adopt a similar approach and calculate the superaccidents for all 15 clusters using weighted event data, establishing the magnitude of each SAR event as the total number of activities associated with the event's case file. An activity is created for each resource sortie assigned to the case or whenever the nature of a case has changed. The total number of activities was concluded to be an appropriate measure of SAR event magnitude, based upon the assumption that SAR events which are larger in scale are inclined to require more response assets. The weighted centroids of each cluster were computed, and these locations were designated as superaccident sites. Table 2 presents the superaccident sites identified in this study.

4.2.2. Step 2. Probabilistic representation of SAR demand for each zone

As discussed in Section 3.1, previous studies of SAR operations consider these events to be Poisson distributed. Reviewing the requirements for a Poisson process (e.g. see (Ross, 2014)), historic SAR events largely adhere to these criteria.

Of note, the adoption of a Poisson distribution requires the events to be both independent and stationary. Independence suggests that the probability of one event occurring does not effect the probability of another event occurring. We assume SAR events to be independent, in general, although we recognize that there do exist instances when this may not hold.

Stationarity requires that, for any interval in the considered time series, the rate of arrival remains constant. A frequent challenge to this assumption in Coast Guard studies results from seasonal trends in the event data. The determination of whether the SAR data exhibited statistically significant levels of seasonality was made by examining autocorrelation function plots generated using the time series analysis functions within JMP. The autocorrelation for a lag-time k is given by Equation 11, where y_t

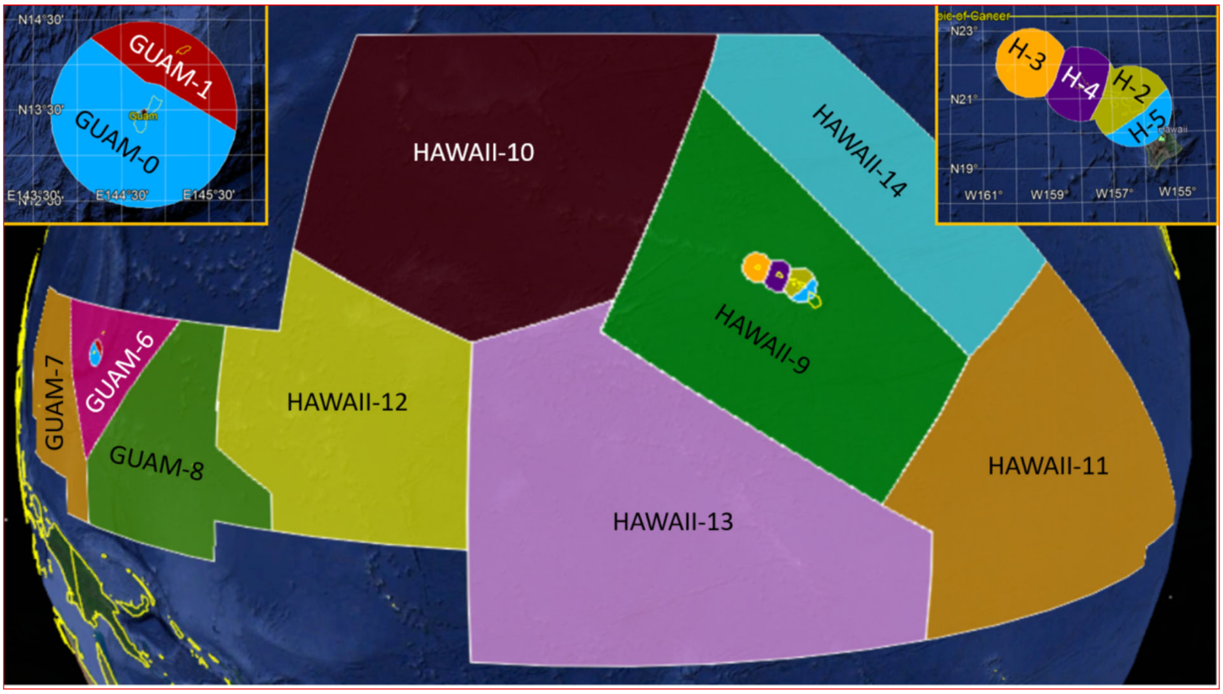

Figure 2. Geographical Approximation of the 15 SAR event zones for the District 14 Stochastic Zonal Distribution Model.

Table 2. Weighted superaccident locations for the district 14 stochastic zonal distribution model.

Zone	Coordinates
Guam-0	13°25′52.179″ N, 144°41′45.1104″ E
Guam-1	14°2′25.3788″ N, 145°9′29.6346″ E
Hawaii-2	20°48′36.1902″ N, 156°35′53.9484″ W
Hawaii-3	21°59′35.8044″ N, 159°24′40.143″ W
Hawaii-4	21°22′46.7472″ N, 157°56′10.5138″ W
Hawaii-5	19°58′4.332″ N, 156°0′57.852″ W
Guam-6	14°27′44.985″ N, 145°36′1.0074″ E
Guam-7	8°48′38.415″ N, 136°29′7.35″ E
Guam-8	6°59′52.548″ N, 153°28′20.3874″ E
Hawaii-9	20°3′10.011″ N, 156°35′43.8144″ W
Hawaii-10	29°42′5.022″ N, 179°43′38.6322″ E
Hawaii-11	8°4′46.416″ N, 131°15′44.3736″ W
Hawaii-12	10°41′58.4484″ N, 168°42′48.7764″ E
Hawaii-13	3°46′51.2034″ N, 164°55′1.362″ W
Hawaii-14	27°48′16.1058″ N, 147°54′4.2366″ W

represents the number of SAR events at time t. An autocorrelation of $|r_k|\approx 1$ is representative of a larger relationship, whereas an autocorrelation near 0 is indicative of little-to-no relationship between the data. In particular, the existence of recurring annual levels of seasonality would result in larger levels of autocorrelation near lag-times in increments of 12.

$$r_k = \frac{\sum_{t=k+1}^{N}(y_t - \bar{y})(y_{t-k} - \bar{y})}{(y_t - \bar{y})^2} \tag{11}$$

Although fluctuations in levels do occur, a visual review of the autocorrelation plots along with the autocorrelations for lag-times of 12- and 24-months, as reported in Table 3, provide no statistically significant evidence of a relationship between the levels of SAR activity. This lack of exhibited autocorrelation was further examined by a visual inspection of time series plots. The time series plots suggested that SAR events in the Pacific Ocean region do not exhibit seasonality, with the exception of a season spike in workload in the zone encompassing O'ahu during the summer months, particularly in July.

Data is considered to be stationary if, for any time interval in the series, the distribution remains the same. From Table 3, we note that all the autocorrelation levels are fairly close to zero, with only the following clusters exhibiting $|r_k|>0.1$ for 12-month lag times: Hawaii-3, Hawaii-4, Hawaii-5, Guam-8, and Hawaii-9. We conclude that the preponderance of the zonal SAR data is stationary, though there may be noticeable fluctuation in the rate of events for the excepted zones. Thus, we further conclude that not all zones were shown to be strictly Poisson-distributed because of these non-stationary elements.

To circumvent the non-stationary aspects of these clusters, Gamma-Poisson distributions were fit to the monthly time-series data. Gamma-Poisson is a mixture of the two probability distributions, specifically for models where the count of individual events x is Poisson distributed with a rate λ, which is itself Gamma distributed with parameters α and β. In other words, the count of events x is conditional on the Poisson parameter λ, and λ is conditional on the Gamma parameters α and β.

Utilizing the *Distribution* application in JMP, both Poisson and Gamma-Poisson distributions were constructed for the monthly time-series data in each of the zones, and a Pearson's chi-squared test

Table 3. Autocorrelations for each SAR event cluster at 12-month and 24-month lag times.

Zone	12 Month	24 Month
Guam-0	0.0284	−0.0506
Guam-1	0.0873	−0.0679
Hawaii-2	0.0957	−0.0561
Hawaii-3	−0.2557	−0.0172
Hawaii-4	0.1302	0.0377
Hawaii-5	−0.1089	−0.2341
Guam-6	0.0092	0.1627
Guam-7	−0.0548	−0.1102
Guam-8	−0.1302	0.0589
Hawaii-9	0.1122	−0.0357
Hawaii-10	−0.0332	−0.0327
Hawaii-11	0.0331	−0.0074
Hawaii-12	−0.0232	−0.1070
Hawaii-13	−0.0219	−0.0462
Hawaii-14	−0.0519	0.2372
All Clusters	0.0808	−0.0940

Table 4. Summary of Pearson's chi-squared goodness-of-fit test results.

	Poisson Dist.		Gamma-Poisson Dist.		
Zone	*p*-Value	λ	*p*-Value	α	β
Guam-0	0.2191	5.433	0.4575	52.748	0.103
Guam-1	0.1635	0.533	0.4458	4.069	0.131
Hawaii-2	0.8786	6.256	–	–	–
Hawaii-3	0.0126	3.044	0.4535	8.672	0.351
Hawaii-4	0.0101	13.022	0.3876	39.105	0.333
Hawaii-5	0.1137	1.378	0.4449	8.202	0.168
Guam-6	0.0605	2.689	0.4422	11.951	0.225
Guam-7	0.3751	1.756	0.4624	51.647	0.034
Guam-8	0.0325	1.733	0.3485	7.535	0.230
Hawaii-9	0.2693	3.644	0.4438	50.611	0.072
Hawaii-10	0.0053	0.978	0.4006	2.560	0.382
Hawaii-11	0.0775	0.833	0.5569	3.254	0.256
Hawaii-12	0.0307	0.700	0.5664	2.047	0.342
Hawaii-13	0.6819	0.833	–	–	–
Hawaii-14	0.0450	1.044	0.4248	4.332	0.241

was applied to evaluate the goodness-of-fit. The parameter estimates and corresponding goodness-of-fit *p*-values are displayed in Table 4. It was found that modeling the data with the Gamma-Poisson distribution resulted in better fits for all zones except for Hawaii-2 and Hawaii-13. In these zones, there was not evidence of a sufficient variation in λ to merit the use of a Gamma-Poisson distribution; these clusters were henceforth modeled by a Poisson distribution.

4.2.3. Step 3. Probabilistic representation of SAR event asset response requirements

In the MISLE data, there was an accompanying record of the assets dispatched to each SAR event. Among the data set were 1133 uniquely named assets that supported SAR responses over the approximately seven-year period. Some of these assets belonged to District 14, but most were other military, commercial, and private boats and aircraft. From an modeling perspective, the presence of these non-USCG assets cannot be guaranteed when a SAR event occurs, yet District 14 still has the responsibility to coordinate the SAR responses. Adopting a conservative view, the interpretation of these asset records focused less on the specific assets that participated in the SAR response and more on the general type and number of assets required to respond.

To gain insight into these general strategies of SAR operations, the 1133 uniquely named assets were categorized as either aeronautical or maritime assets. From the synthesis of these event records, three general strategies regarding SAR operations emerged: respond with aeronautical assets only, respond with maritime assets only, or respond with a combination of maritime and aeronautical assets. A fourth type of response in which no assets were dispatched was also observed. These events remained in the data set to inform the forecast for future demand locations but not the level of response required for SAR events, lest we accidentally assume away potential demands for District 14 asset response. Table 5 presents the relative response strategy rates for each zone.

Having determined the tendencies for District 14 to respond to various SAR events with these three general strategies, it was necessary to identify frequency of the different response volumes, by asset type, to SAR events for each strategy. Since the goal of this research is to inform the optimal location of organic assets, the deterministic location models herein only consider the allocation of USCG assets. Although SAR operations are often augmented by civilian assets in practice, the availability of such assets cannot be assumed. Hence, similar to (Armstrong & Cook, 1979), we make the conservative assumption that all demands must be covered by organic USCG District 14 assets. Thus, the number of aeronautical assets considered was limited to two, and the number of maritime assets considered was limited to four. If, for instance, a historical SAR event was supported by six maritime assets, that would be considered in this analysis as a four maritime asset case. To complete the third step of the stochastic zonal distribution model, we computed each of the conditional probabilities of each level of response for events, by zone, which we forgo presenting herein for the sake of brevity.

As an illustrative example, consider zone Guam-0. The stochastic zonal distribution model identified Guam-0 as a cluster of boat-supported SAR events coordinated by Sector Guam. The center of SAR operations for the zone was found to be $13^{\circ}25'52.179''$ N, $144^{\circ}41'45.1104''$ E, as reported in Table 2. The emergence of SAR events within the zone is modeled with the Gamma-Poisson probability distribution having $(\lambda, \alpha, \beta) = (5.433, 52.748, 0.103)$, as presented in Table 4. From Table 5 and the aforementioned conditional probability calculations, SAR events in this zone will require, e.g. 0 boats and 1 helicopter for 8.4% of the events; 0 boats and 2 helicopters for 0.2% of the

Table 5. Response strategy proportions (%), by zone, for the district 14 stochastic zonal distribution model.

Zone	Aircraft Only	Maritime Only	Maritime & Aircraft
Guam-0	8.642	73.827	17.531
Guam-1	59.524	33.333	7.143
Hawaii-2	13.586	67.261	19.154
Hawaii-3	18.386	53.812	27.803
Hawaii-4	28.066	50.118	21.816
Hawaii-5	44.928	13.043	42.029
Guam-6	23.636	56.364	20.000
Guam-7	1.220	91.463	7.317
Guam-8	11.111	61.111	27.778
Hawaii-9	48.691	22.513	28.796
Hawaii-10	32.000	54.000	14.000
Hawaii-11	9.375	75.000	15.625
Hawaii-12	28.947	36.842	34.211
Hawaii-13	40.000	37.778	22.222
Hawaii-14	30.357	50.000	19.643

events, and 1 boat and 0 helicopters for 60.9% of the events.

As a caveat to our implemented technique, we acknowledge that the data aggregation method utilized can affect the solution of the resulting analyses (e.g. see Gehlke & Biehl, 1934; Hillsman & Rhoda, 1978). Within the literature, there has been significant research to study the general problem of data aggregation, as well as the specific problem of aggregating spatio-temporal data. In the fields of geography and ecology this problem is referred to as the modifiable areal unit problem (MAUP) (Dark & Bram, 2007; Openshaw, 1984). It is non-trivial to identify the best aggregation methodology for any given analysis, where even the definition of *best* is subject to debate among experts. Prior to adopting the aforementioned stochastic zonal distribution model, a prequel study (Hornberger et al., 2019) to this research examined the effects of different aggregation methodologies, informing our modeling choice herein.

The outputs of the stochastic zonal distribution model informed a Monte Carlo simulation to replicate 10,000 months of activity for each of the 15 zones. For each zone, 10,000 months were simulated as follows: the number of SAR events for the zone in a given month was selected based upon the corresponding distribution in Table 4 and, for each event in that month, a SAR response was simulated using the respective probabilities. The resulting 10,000 months of simulated data were summarized by descriptive statistics: the mean, standard deviation, and percentiles (minimum, 25%, 50%, 75%, maximum). These percentile values can serve as the relative demand volumes for each asset type in each zone, depending on the desired level of robustness.

4.3. Location model results and analysis

Having parameterized the asset demand levels for each zone, the integer linear programming formulation set forth in Section 3.2 can be used to solve the relevant scenarios with appropriate, respective sets of objective function weights. We solve the model for each scenario using, alternatively, the 50th and 75th percentile levels of SAR asset demands for each zone from the Monte Carlo simulation. Whereas the 50th percentile levels are used to represent a typical month of SAR operations, the 75th percentile of demand depicts an elevated operational tempo for District 14, allowing for a risk averse perspective for strategic location of assets. Of note, the 100th percentile levels for clusters were not considered in this analysis; such an extreme situation would likely skew the results beyond what should be practically implemented. For both the 50th and 75th percentiles of SAR demand, the instances are iteratively solved via the ε-constraint Method. Instances were modeled in GAMS (version 32.2.0) and solved using CPLEX (version 12.10) via the NEOS server (Czyzyk et al., 1998; Dolan, 2001; Gropp & Moré, 1997). Given each instance was comprised of 17,160 decision variables and 16,682 constraints, CPLEX required an average of 0.34 s (with a standard deviation of 0.65 s) to identify an optimal solution for a given instance.

As an illustrative example that does not indicate the current locations of USCG District 14 assets (i.e. for the purpose of maintaining operational security), Table 6 presents the prescribed asset locations and event site assignments when responding to the 75th percentile demand levels, considering the larger set of possible ports and airfields where one could position assets across the Pacific region, and when preemptively prioritizing the minimization of total expected response time. Within Table 6, the specific assets are denoted by a code indicating the type of asset, with a suffix of '-1′, '-2′, and so forth to discriminate between specific assets. For example, 110' WPB-2 is the second of two island-class patrol boat having a length of 110 feet, and 87′ CPB-1 is the first of two marine protector class patrol boats having a length of 87 feet.

The solution identified in Table 6 does minimize the total expected response time to SAR events, but it does not use assets efficiently, and the prescribed solution should be tailored for implementation. For example, two of the 45′ Reponse Boat Medium (RBM) vessels are stationed in Nawilili Harbor, yet only one is assigned to respond to SAR events in the Hawaii-3 zone. The workload would surely be shared during operations. In general, the lack of assigning zones to 225' WLB-1, 45′ RBM-1, 45′ RBM-4, and 45′ RBM-6 indicates, for this instance, that District 14 has more vessels than needed *to attain this total expected response time* and for these relative objective function weights. Such a conclusion does not necessarily hold under differing

Table 6. Prescribed asset locations and allocations for the 75th% demand levels, Pacific region ports.

Asset Type	Asset	Homeport	Assigned Zones
Cutter	225′ WLB-1	Honolulu Harbor	–
	225′ WLB-2	Port of Kwajalein	Hawaii-12
	110′ WPB-1	Tomil Harbor	Guam-7
	110′ WPB-2	Port of Johnson Atoll	Hawaii-13
	FRC-1	Hilo Harbor	Hawaii-11, Hawaii-14
	FRC-2	Port of Kailua Kona	Hawaii-9, Hawaii-11
	FRC-3	Pohnpei Harbor	Guam-8
	87′ CPB-1	Port of Tinian	Guam-6
	87′ CPB-2	Port of Midway Islands	Hawaii-10
Boat	45′ RBM-1	Honolulu Harbor	–
	45′ RBM-2	Maalaea Harbor	Hawaii-2
	45′ RBM-3	Nawilili Harbor	Hawaii-3
	45′ RBM-4	Nawilili Harbor	–
	45′ RBM-5	Apra Harbor	Guam-0
	45′ RBM-6	Apra Harbor	–
	45′ RBM-7	Pearl Harbor	Hawaii-4
	45′ RBM-8	Kawaihae Harbor	Hawaii-5
Airplane	C-130J-1	Kona Intl Airport	Hawaii-9, 10, 13, & 14
	C-130J-2	Chuuk Intl Airport	Guam-6, Guam-8, Hawaii-12
Helicopter	HH-65-1	Kahului Airport	Hawaii-2, 3, 4, & 5
	HH-65-2	Antonio B Won Pat Apt.	Guam-0, Guam-1

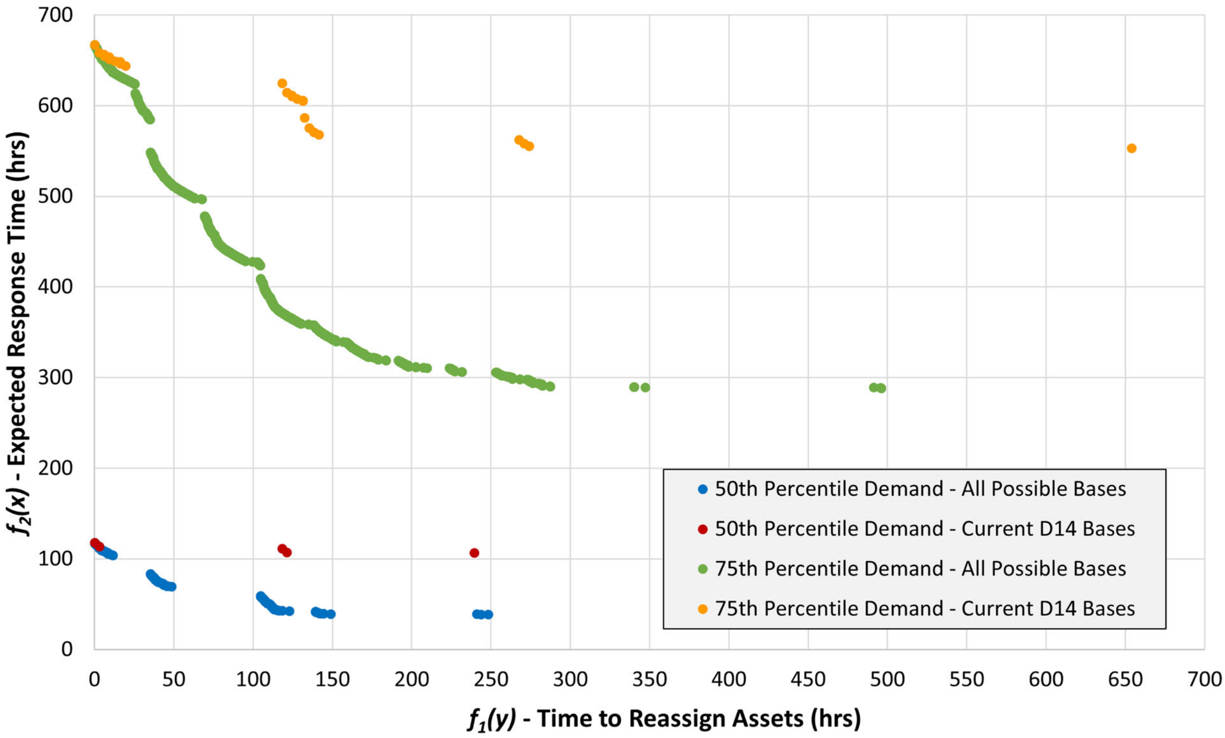

Figure 3. Non-dominated solutions for all four optimization models (i.e. 50th and 75th demand, for both the current set of District 14 bases, and the larger possible set of bases in the Pacific region.).

conditions, so we caution a reader against making generalizations. Also neglected from this solution are the potential efficiencies in training personnel and maintaining equipment gained from co-locating similar assets; thus, an extension to this research might consider either a reduced set of locations or provide an incentive to co-locate similar assets.

Figure 3 presents non-dominated solutions identified over the range of ε-values imposed, considering (1) either only current stations operated by District 14 or using a larger set of candidate homeports across the Pacific region, and (2) examining these basing options alternatively under either 50th or 75th percentile levels of asset demand.

From Figure 3, we note that, as expected when the ε-value is affixed such that no asset realignment is possible, all solutions for a given demand level have the same expected response time. From this extreme point on the Pareto frontier, for both the 50th and 75th percentile demand, as allowable reassignment time increases, the expected response time for the larger set of feasible bases decreases, and it does so more rapidly when considering all Pacific basing locations as opposed to only the set of current District 14 bases. Moreover, there are

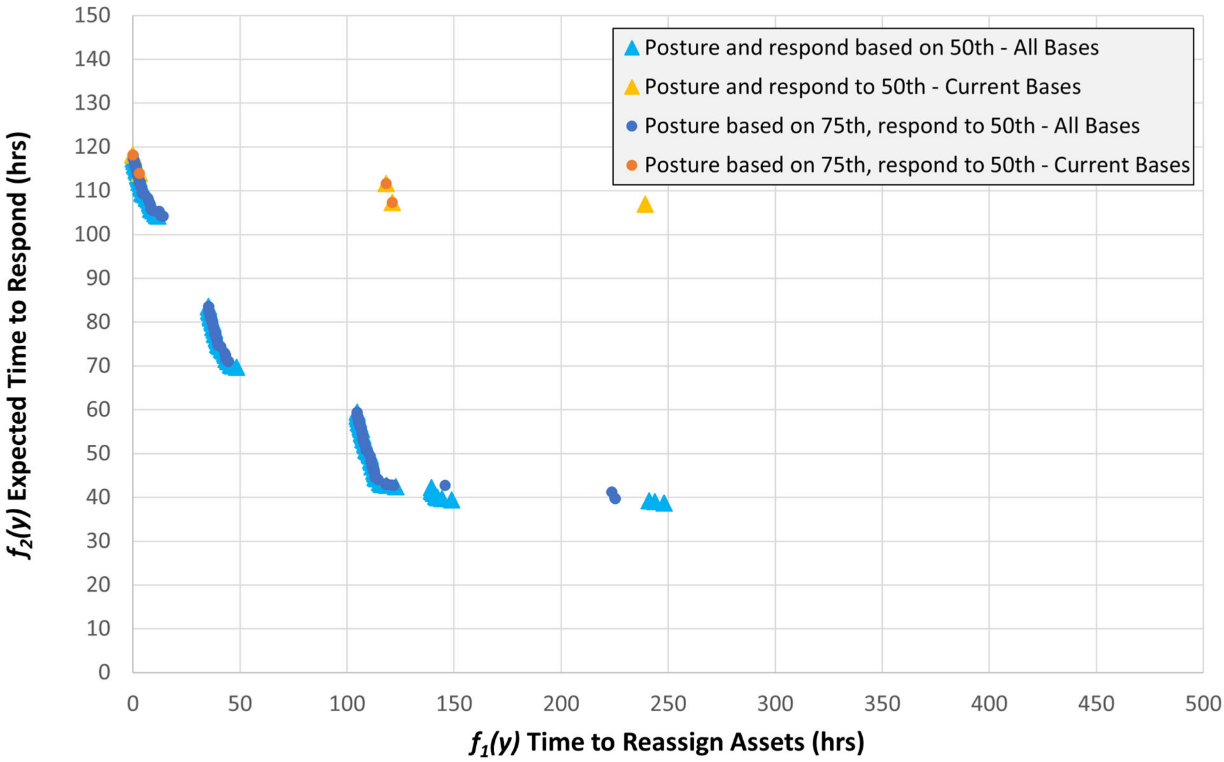

Figure 4. Non-dominated solutions for the cases when you posture assets to respond to the 75th percentile demand and respond to the 50th percentile demand, versus non-dominated solutions for the cases where you posture and respond to the 50th percentile demand. Note that no feasible solutions exist for the problem of posturing for the 50th percentile demand and responding to the 75th percentile demand.

more non-dominated solutions for both demand levels when considering the larger set of possible bases. Of pragmatic interest, there are several obvious clusters of non-dominated solutions within the respective Pareto frontier for each of the four models.

Moreover, a comparison of maximum and minimum expected response times illustrates significant potential for improvement. In the case of 50th percentile demand, limiting consideration to the smaller set of only District 14 bases, it is possible to reduce expected response time by 9.6% whereas, considering the larger set of all possible bases in the Pacific Region, the total expected response time has the potential to decrease by 67.3%. In the case of the 75th percentile demand, these potential improvements are 17.1% for the District 14 bases and 56.8% for the larger set of bases.

The rationale for considering the 75th percentile demand in addition to the 50th percentile demand levels was to provide strategic insight for decision makers that considered the probabilistic risk of occasionally high demand months for various clusters. This rationale leads one to question how posturing the fleet of assets with a more risk averse view (i.e. posture the fleet to handle the 75th percentile demand) might affect a steady-state (i.e. 50th percentile) performance of the enterprise. To answer this question for both the 'All possible bases', as well as the 'Current Homeports' basing options, the ε-constraint Method was applied over the general solution space and, for a given ε-value and optimal asset location solution, the expected response time was subsequently minimized to discriminate among any alternative optimal solutions that satisfied the ε-constraint. This examination was conducted for both affixing asset posture for 75th percentile demand and responding to 50th percentile demand (i.e. a *risk averse* approach), as well as the converse (i.e. a *risk seeking* approach).

When compared to the optimal solution that positions assets for, and responds to, the 50th percentile demands, the risk averse approach yields negligible differences in the expected response time for emergencies. Indeed, considering the larger set of bases, the minimum response time increases only 2.5% using this risk adverse approach to asset location. While, when considering the current set of homeports, the minimum response time grows by only 0.4%. These relationships are depicted in Figure 4. Moreover, this robustness with respect to total response time may incur a marginally higher time to reposition assets, a one-time fixed cost. In contrast, when adopting the optimal solutions identified for 50th percentile demand levels (i.e. the risk seeking approach), no feasible solution exists to support 75th percentile demands. Thus planning for 75th percentile demands is not (relatively) cost prohibitive, and it yields a robustness for operations that is far preferable to a risk-seeking approach comprised of planning for median levels of demand.

5. Conclusions and recommendations

In this study, we evaluated SAR operations across the Pacific Ocean for the USCG to inform the strategic posturing of District 14 maritime and aeronautical assets in anticipation of emerging missions.

We developed and demonstrated a two-stage modeling process to leverage historical event data and prescribe a location-and-demand-allocation solution for a heterogeneous fleet of assets to minimize a combination of the total expected response time to events and the time to relocate assets from their current bases. To accomplish the spatiotemporal forecasting in the first stage model, we developed a stochastic zonal distribution model to forecast the location, frequency, and corresponding operational response requirements of future events throughout a region of interest. To leverage different levels of demand generated via Monte Carlo simulation of the first stage results, we formulated an integer linear program to prescribe a location solution, subject to user-defined relative priorities among objectives, implemented via the ε-Constraint Method for multi-objective optimization.

Applying the two-stage model to over seven-and-a-half years of historical SAR event data for USCG District 14, we identified a set of non-inferior solutions under varying assumptions of demand levels and basing options. Within these Pareto optimal solutions, as developed for both the 50th and 75th percentiles of forecast event and asset demand distributions, we identified asset location strategies that respectively yield a 9.6% and 17.6% increase in coverage over current asset basing when allowing locations among current homeports and airports, and respective 67.3% and 57.4% increases in coverage when considering a larger set of feasible basing locations. Moreover, we illustrated via extended testing that, for the minimization of total expected response time to SAR events, a risk averse framework structured around the 75th percentile demand performs at worst within 0.5% of the 50th percentile demand framework with respect to the total expected response time, the more operationally relevant of the two objectives considered. In contrast, the 50th percentile demand framework cannot respond to all emergencies during a high-workoad month (i.e. a 75th percentile demand).

Numerous factors, ranging from operational efficacy to geopolitical alliances, may affect Department of Homeland Security resourcing decisions. Nevertheless, the authors find it encouraging, that within six months of the conclusion of this study, the USCG resourced District 14 to emplace three Fast Response Cutters in Guam (Doornbos, 2019; Wyatt, 2020), a posturing that aligns with recommendations presented in this research.

Several areas exist in which this research can be improved. Future research can improve both the process and implementation of the two-stage model developed and demonstrated in this research. A first extension should expand the scope of the stochastic zonal distribution model, particularly as it relates to the duration of SAR missions. Whereas our research assumed a static notional mission length, more accurate historical records could be evaluated (e.g. for a different region that, perhaps, has more detailed records), and the location models could be modified accordingly. By more accurately capturing the variability of mission length, the accuracy of projections for anticipated monthly asset utilization could be improved. Additional research incorporating robust optimization techniques could also prove fruitful to generating an asset location and mission tasking allocation schema that is robust to multiple scenarios for demand levels, as well to address resource unavailability. As Karatas et al. (2017) note, the assumption of equipment/asset availability is not realistic, and examining how asset allocation changes under varying levels of robustness has merit for future research.

Worth revisiting from this study is the assumption that vessels will travel at their maximum speeds when responding to search and rescue events. During inclement weather, such speeds may not be attainable. Parametric uncertainty is known to potentially affect solution quality. Indeed, Ben-Tal and Nemirovski (2000) demonstrated that, in 13 out of 94 NETLIB problems, a random 0.01% perturbation of an uncertain data parameter could render the nominally optimal solution "severely infeasible" - violating some constraints by 50%. Within that context, it may be enlightening to extend this research via alternative frameworks such as Robust Optimization or via a Sample Average Approximation approach.

Additionally, extensions to the location model adopted in this study should include two additional objectives: balancing the utilization rates of assets based upon their assignment of SAR event zones, and co-locating similar assets to afford synergy in training, operations, and maintenance.

Finally, we recommend future efforts consider other USCG missions in the two-stage modeling process. Previous studies seek to forecast the demand for and scheduling of USCG assets for other missions, and we conjecture that the application of our spatiotemporal forecasting model for other USCG missions could both provide meaningful insight regarding the total operational workload across District 14 and inform a more comprehensive asset location-allocation model to support operations.

Disclaimer

The views expressed in this article are those of the authors and do not reflect the official policy or position of the United States Air Force, the Department of Defense, the United States Coast Guard, the Department of Homeland Security, or the United States Government.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the the United States Coast Guard Research and Development Center. The authors thank the Editor-in-Chief, Associate Editor, and two reviewers for their constructive comments that helped improve the content and presentation of this paper.

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