Optimizing the Response for Arctic Mass Rescue Events

Mustafa C. Camur [12] Thomas C. Sharkey [2] Clare Dorsey [3] Martha R. Grabowski [45]
William A. Wallace[5]

Abstract

We propose and study a model that optimizes the response to a mass rescue event in Arctic Alaska. The model contains dynamic logistics decisions for a large-scale maritime evacuation with the objectives of minimizing the impact of the event on the evacuees and the average evacuation time. Our proposed optimization model considers two interacting networks - the network that moves evacuees from the location of the event out of the Arctic (e.g., a large city in Alaska such as Anchorage) and the logistics network that moves relief materials to evacuees during the operations. We model the concept of deprivation costs by incorporating priority levels capturing the severeness of evacuees' current medical situation and the period indicating the amount of time an evacuee has not received key relief resources. Our model is capable of understanding the best possible response given the current locations of response resources and is used to assess the effectiveness of an intuitive heuristic that mimics emergency response decision-making.

Keywords: OR in disaster relief, Network optimization

1 Introduction

The *Crystal Serenity*, the largest cruise ship to date to voyage in coastal Arctic waters, sailed between Anchorage, Alaska and New York City through the Northwest Passage with 1000 passengers and over 600 crew members in August 2016 and 2017 (Waldholz, 2016). In preparation for this event, a tabletop exercise (McNutt, 2016) was organized in collaboration with Crystal Cruises, the Canadian Coast Guard, Transport Canada, the Department of the Defense (U.S. Air Force) and the U.S. Coast Guard (USCG) in 2016. This exercise identified gaps in Arctic maritime search and rescue resources and highlighted the impacts of the resource gaps on evacuees being rescued. The conversations and activities suggested the need for greater attention to Arctic mass rescue operations, and for greater visibility and coordination of Arctic emergency response. We refer the interested reader to Elmhadhbi et al. (2020) and Sarma et al. (2020) who highlight the importance of coordination between different emergency responders during disaster response.

Recent changes in Arctic industrial activities, defense and tourism have amplified the need for attention to resource availability and evacuee impacts during an Arctic mass rescue event (MRE). Longer ice-free summers attract more tourists on expeditions and cruises. Ship traffic and maritime activity in the region has increased, and will likely continue to increase in the future (Østhagen, 2020) without agreements to limit the number of ships entering the region. In 2021, in recognition of these trends, the U.S. Navy and the USCG,

[1]Corresponding Author, e-mail: mcamur@clemson.edu.
[2]Industrial Engineering Department, Clemson University, Fernow St, Clemson, SC 29634.
[3]Mathematics Department, United States Coast Guard Academy, 31 Mohegan Ave Parkway, New London, CT 06320.
[4]Information Systems Program, Le Moyne College, 1419 Salt Springs Rd, Syracuse, NY 13214
[5]Department of Industrial and Systems Engineering, Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180.

for the first time, issued a joint Arctic strategy that cites expectations for increased Arctic maritime traffic due to commercial shipping, natural resource exploration, tourism and military presence (Eckstein, 2021). Increased Arctic maritime traffic occurs in waters that are largely uncharted because they have never been ice-free in modern times. Only 4.1% of Arctic waters have been charted using modern multi-beam sonar techniques (National Oceanic & Atmospheric Administration, 2021). Some waters were last surveyed by Captain Cook using hand-held ropes and lead lines in the 17^{th} century (Hoag, 2016). Risks associated with maritime trade, and needs to consider personnel evacuation on ships, are therefore significant and rising as maritime traffic increases, uncharted waters are increasingly ice-free, and the size of passenger vessels is increasing (Statista Research Department, 2020).

Arctic emergency response occurs in a setting that requires balancing activities related to territorial disputes (Schofield and Østhagen, 2020); fishing and subsistence economies; endangered species and wildlife habitats; industrial and commercial activity; and military operations (Allison and Mandler, 2018; Ruskin, 2018; Humpert, 2019). Impacts from these activities can be particularly significant in remote, seasonably variable, and infrastructure-poor settings with sparse populations such as the Arctic.

The increasing number of visitors to the region is concerning due to the size of Arctic communities. In Arctic Alaska, the *largest* community is Utqiaġvik (formerly known as Barrow), which has a population of 4335. The number of people on the *Crystal Serenity* was 34.6% of Utqiaġvik's population and would exceed the population of most Arctic communities (see Table 1). Of further concern is that the health care system in Alaska was not designed for surges resulting from potential Arctic MREs. There are currently 17 trauma centers in Alaska and only two are Level II (Alaska Department of Health and Social Services, 2018) (Level I handles the highest emergencies) and are located in Anchorage (700 miles away from Utqiaġvik). The only trauma centers in Arctic Alaska are in Nome, Kotzebue, and Utqiaġvik (see Table 1). It is neither reasonable nor desirable for the evacuees to stay in the Arctic Alaska communities for a long time during a MRE. Communities in the Arctic are not equipped to host a large number of evacuees for an extended period of time. In essence, responding to a MRE in Arctic Alaska becomes much more difficult than responding to one in the continental United States since an influx of 1,600 people would significantly strain the infrastructure of Arctic communities.

Table 1: Data on communities in Arctic Alaska (see Section F in the Online Appendix for the data sources)

Location	Nome	Kotzebue	Point Hope	Point Lay	Atqasuk	Wainwright	Utqiaġvik	*Crystal Serenity*
Population Number	3797	3245	692	247	237	584	4335	1600
% of Pop. of Passengers	39.50%	46.22%	216.76%	607.28%	632.92%	34.60%	34.60%	—
Trauma Center Status	Level IV	Level IV	—	—	—	—	Level IV	—

Maritime response operations require two sets of activities: (i) evacuating people from an affected area to 'safe zones' (e.g., in our case, out of the Arctic), and (ii) providing them with the logistic support (i.e., relief commodities) throughout a period of time. In most maritime mass rescues, once evacuees in distress are brought to shore, the response is often considered complete since existing infrastructure typically has the ability to handle the influx of passengers. However, in an Arctic MRE, two steps are required because of limited Arctic shelter, medical, food, and sanitary infrastructure. Transporting evacuees from the cruise ship out of the Arctic by sea is neither feasible nor preferred; for example, moving evacuees by sea to Anchorage from the North Slope of Alaska could take more than 10 days, and this assumes the ship could hold and support the evacuees for that length of time. As a result, maritime evacuation during this type of event comprises two aspects: moving evacuees from the location of the evacuation (e.g., cruise ship) to local Arctic communities and then out of the Arctic (e.g., into Anchorage, Alaska) and; providing evacuees their basic needs through allocating resources and equipment. Such an evacuation process was seen most recently in the grounding of the *Akademic Ioffe*, which ran aground about 45 miles away from Kugaaruk, Canada (in the Arctic) on August 24, 2018 (Struzik, 2018). The sister ship of the *Akademic Ioffe* reached it in 16 hours and brought all passengers to Kugaaruk (Humpert, 2018).

Our study, the first work to model both maritime mass rescue evacuation and logistics support, highlights the impacts and costs of resource constraints and unavailability, and the impact on evacuees of those resource constraints during an Arctic MRE. Because an infusion of evacuees in Arctic communities will strain the communities' existing infrastructure and resources, our model considers the communities' capacities to handle the evacuees, given available shelter, medical facilities and airport capacity, as well as system capabilities to bring resources and equipment into the area to support the evacuees during the Arctic MRE. This work, therefore, captures the characteristics of an infrastructure-poor setting such as the Arctic, and models the two requirements of MREs (i.e., evacuation and logistics suport), which are unique research contributions. It is the first work, to the best of our knowledge, to quantitatively assess disaster response to Arctic MREs, falling into the broad area of 'smart' disaster management (Neelam and Sood, 2020), where quantitative tools are used to assess disaster response.

Outside of Arctic Alaska, the situation where there may be two phases of transportation required for an evacuation would arise in other applications in remote regions, especially when considering tourism. For example, evacuating tourists from sudden onset wildfires may involve moving them immediately out of the area impacted by the event (e.g., using buses or cars) and then sending them home from these safe locations using aircraft. A similar situation could arise in popular remote trekking areas (i.e., the Himalayas) should avalanches occur preventing the trekkers from leaving the remote area. In this case, helicopters may be used to move the trekkers out of the remote region to local communities prior to sending them home. A major finding of our analysis on Arctic MREs is that the transportation resources are a major bottleneck in the process, which would also provide insights into these other applications.

In this paper, we propose an integer programming (IP) model to respond to a large-scale MRE in the Arctic. The remainder of this paper is organized as follows: Section 2 summarizes the related research. Section 3 gives a brief problem description. The details of our optimization problem are provided in Section 4. We then introduce the solution methodologies in Section 5. Our experimental results and our findings are shared in Section 6. The paper is summarized and future research is presented in Section 7.

2 Literature Review

An Arctic mass rescue operation is similar to evacuating people from an area either before, during, or after a disaster, with important distinctions especially since the closest communities to incident sites are relatively small and we still need to move the evacuees out of the Arctic due to the reasons discussed in Section 1. The following studies are the areas most closely related to our work.

2.1 Evacuation Models with Relief Distribution

At a high-level in evacuation models, evacuees are transported from an affected area to safe zones, such as shelters, hospitals or distribution centers, and the required commodities are delivered from major supply centers to support them. While Üster and Dalal (2017) develop a mixed integer linear programming model with multi-objectives to help the integration of the evacuation process and relief material distribution after a natural foreseeable disaster (e.g., a hurricane), Stauffer and Kumar (2021) analyze the importance of taking the disposal cost of unused items into consideration when making initial resource deployment decision before a predictable disaster. Sabouhi et al. (2019) design an optimization model whose goal is to provide relief commodities to evacuees and transport them to shelters in the aftermath of a natural disaster, along with making routing and scheduling decision for the vehicles used during the evacuation. Setiawan et al. (2019) propose three different models to determine the best distribution center locations to obtain the optimal relief resource deployment after a sudden-onset disaster (e.g., an earthquake). In another study, Li et al. (2020) addresses a scenario-based hybrid robust and stochastic network design problem to identify the best integrated logistics decisions in terms of relief commodity and casualty distribution. Shu et al. (2021) propose a network design model making emergency support location and supply pre-positioning decisions and design a cutting plane algorithm to solve it. Zhong et al. (2020) similarly look at a network design model and a detailed vehicle routing problem to deliver pre-positioned goods to key distribution points (which could include shelters).

There are several shortcomings of applying this previous work to an Arctic MRE. First, none of these studies consider deprivation costs, which is critical in post-disaster humanitarian logistics models in order to capture the actual impact of the event on people (Holguín-Veras et al., 2013). Second, they do not consider the potential to transport relief commodities between the ‘safe zones’ during the response, which is important in our situation since we can move existing stockpiles between Arctic communities. Third, these previous studies do not consider moving evacuees out of the ‘safe zones’ (Arctic communities) towards another location (Anchorage) and measure the time to reach this final location. To the best of our knowledge, our study is the first to consider all these features in an optimization model for Arctic MREs.

2.2 Prioritizing Victims During a Disaster

The concept of effectively prioritizing victims from a disaster has been well-studied. The idea is to quickly triage victims in order to group them together and prioritize who receives relief commodities. Existing triage methods include START (Elbaih and Alnasser, 2020) and SALT (McKee et al., 2020). Sung and Lee (2016) use a survival probability function to prioritize victims in order to optimize the transport of victims in ambulances to available hospitals in a mass casualty incident. Liu et al. (2019) develop a multi-objective optimization model that identifies temporary medical service facility locations and distributes the casualties to those facilities by taking casualty triage and limited resources into consideration. (Rambha et al., 2021) propose a stochastic model to identify the optimal patient distribution at a hospital after a hurricane where patients are categorized based on risk levels. Finally, Farahani et al. (2020) survey the operations research literature on mass casualty management and express the importance of on-site triage for successful disaster management.

The limitations of this previous work is that it does not model how relief commodities allocation decisions can impact the priority level of the victims (in our case, the evacuees). We believe that modeling the role of deprivation time has on increasing priority levels is important and, further, will help to better capture the impact of the event on the evacuees.

2.3 Modeling the Impact of Relief Commodities

It is likely that during a large-scale, non-routine event that there will be a surge in demand for relief commodities and therefore, the allocation of the scarce relief commodities is of utmost important in order to minimize the impact of the event. For example, Rodríguez-Espíndola et al. (2020) propose a multi-objective, stochastic optimization model to mitigate the shortage seen in relief aid, shelter and healthcare support during the disaster preparedness process. The authors show that shelter allocation decisions play a significant role to cope with deprivation of relief resources and its impact on evacuees. Li et al. (2018) employ a simulation model to emphasize the importance of having explicit knowledge of the scarce vaccine inventory at hand in the case of an influenza pandemic. The authors indicate that enhancing the visibility of inventory levels in vaccines brings several benefits including increasing the vaccine allocation efficiency and decreasing the impact of the pandemic.

Doan and Shaw (2019) discuss stochastic optimization techniques to allocate scarce relief resources among multiple locations in the face of multiple, simultaneous disasters. This work highlights the influence of political aspects (e.g., inequities between different regions) during resource allocation. Ramirez-Nafarrate et al. (2021) study a location-allocation problem to overcome the trade-off between insufficient relief resources and limited response time, and provide a heuristic algorithm to solve it. Lastly, we refer the reader to Ye et al. (2020) who provide an extensive review on successful management of disaster relief inventory.

This previous literature demonstrates that relief allocation plays an important role in the aftermath of a disaster. This is especially important in the Arctic context since it is expected that existing resources and equipment in Arctic communities will not be able to support the evacuees and, therefore, we must correctly plan how to allocate resources and equipment from a central hub (such as Anchorage). It further stresses the importance of dynamically updating our allocations over the duration of the response, factoring in the planned movements of evacuees out of the Arctic communities.

2.4 Deprivation Costs in Humanitarian Logistics

In our application, the evacuees have demand for relief commodities and it is likely that we will not be able to fulfill all demand. Holguín-Veras et al. (2013) were the first to argue that deprivation costs should be used instead of simply penalizing unmet demand as the former better captures the true costs of human suffering. The authors discuss the ethical implications of prioritizing the deprivation costs of the response as opposed to the logistics cost of the response. A key finding is that the actual estimation of the true parameters of the deprivation cost is not a primary concern - simply including a deprivation cost function is important. Following up on this work, Pérez-Rodríguez and Holguín-Veras (2015) propose an innovative mathematical model to address the challenges during inventory allocation in the aftermath of a disaster based on the notion of welfare economics and deprivation costs. The objective of the model is to minimize the social cost incurred during the response time and examine a heuristic method to solve this problem. In addition, Yu et al. (2019) propose a nonlinear integer programming model to measure the performance of resource allocation after a large-scale disaster by considering three metrics: efficiency, effectiveness, and equity. The authors capture the effectiveness component through deprivation costs.

We will incorporate the concept of deprivation cost since it is more suitable and realistic than to penalize unmet demands in a large-scale disaster. We discretize the deprivation cost function and further consider situations in which fulfilling resource demands does not eliminate the entire deprivation cost. While the model introduced by Pérez-Rodríguez and Holguín-Veras (2015) has a non-linear and non-convex objective function, we propose an integer linear programming model (by discretization) having a similar objective component which aims to minimize the impact of unmet demands on the evacuees.

2.5 Arctic Alaska and Emergency Response

Any tactical operation performed in Arctic Alaska would face major challenges due to (i) the remoteness of the region, (ii) the lack of infrastructure throughout the Arctic, and (iii) the difficulty of operating in Arctic conditions. Thus, existing policies and approaches for a MRE would not be fully applicable and must be adapted to understand an Arctic event. Garrett et al. (2017) create a mixed-integer linear programming model to understand how to site oil spill response resources to increase response capabilities in Arctic Alaska. The oil spill response modeling introduced the concepts of *follow-up tasks* to deal with the likely situation of missing deadlines of certain key response tasks. This directly models the remoteness of the region where previous research would not be applicable. The researchers address some policy questions, such as stockpile and infrastructure investments, that can be utilized in long-term planning efforts. We complement this work by examining a different type of emergency response, namely Arctic MREs. Future work in Arctic emergency response could consider the role of unmanned vehicles (Aiello et al., 2020), especially given the harsh environments that the response may be operating in.

2.6 Our Contribution

We believe that this is the first work presenting an optimization model designed specifically for an Arctic MRE, which is increasingly important as maritime activities in the area are projected to increase in the near future. Most importantly, our model and quantitative analysis can be used to assess gaps in Arctic MRE capabilities and can thus be used to prioritize investments to improve these capabilities. Beyond these technical contributions, our work is important since it introduces an important area where future transportation will likely take place due to changes in the Arctic.

Although detailed passenger evacuation aboard vessels has been well-studied (e.g., Hu et al. (2019)), models to assess the gaps in passenger evacuation in remote and infrastructure-poor settings have received less attention despite its practical importance. In Arctic workshops and tabletop exercises, emergency response leadership acknowledged that an Arctic MRE would likely not accommodate all passengers and would overwhelm Arctic villages because of inadequacies in evacuation transport, support logistics, and medical, berthing, sanitary and housing requirements (Arctic Domain Awareness Center, 2016). Tabletop exercises, such as the Arctic Incident of National Significance (Arctic Domain Awareness Center, 2016) and Arctic Maritime Horizons Workshop (Arctic Domain Awareness Center, 2021), help to lay out the challenges of Arctic emergency response. Our work contributes to these exercises since it seeks to quantify the impact of inadequacies. It also determines the gaps in planning exercises and preparation phases in terms of transportation and logistics operations and reveals the importance of the role of optimization in emergency response in the Arctic. Therefore, it moves beyond tabletop exercises and highlights the human costs associated with large-scale disaster response in infrastructure-poor settings: evacuees will not be evacuated in a timely manner, or at all, and there could be significant strain on local communities.

3 Problem Description and Overview of Modeling Considerations

Arctic mass rescue events (MREs) require moving evacuees from a distressed ship, transporting them to Arctic communities, and then transporting them out of the Arctic (we focus specifically on moving them to Anchorage) to complete the operations. This needs to occur while supporting the evacuees as well. Movement within our problem can be represented with a transportation network, an example of which is in Fig 1. Note that our modeling process involved observing tabletop planning exercises and discussions with stakeholders; we refer the interested reader to Section F of the Online Appendix for a discussion of this process.

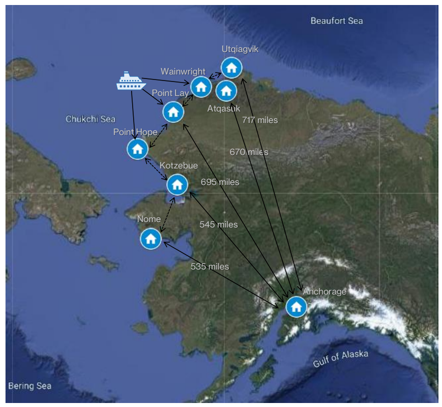


Figure 1: Visualization of a transportation network in Arctic Alaska

3.1 Important Concepts Used in Modeling

In order to model the impact of the event on the evacuees, we introduce three important discussions on *priority levels* of the evacuees, the relief commodities (classified as either resources or equipment) and their role, and then how to model when evacuees are *deprived* of those relief commodities.

3.1.1 Priority Level

The priority level of the evacuee is meant to model his/her medical status where a lower priority status is associated with a lower severity. If the demand (needs) of an evacuee are not fulfilled, then their priority level may increase. Alternatively, the level may decrease with appropriate medical care (although we note that is not likely to occur during the event given the limitations of health care facilities and number of medical personnel in Arctic Alaska). We aim to make logistics decisions in order to minimize the deterioration on evacuees' existing medical states and transport them to Anchorage as soon as possible in order to provide service there. It is important to note that having a higher priority level does not necessarily mean that it is best to provide relief commodities to a person since it may be important to be proactive and to prevent the medical status of the other evacuees from getting worse. Further, certain relief commodities may only be necessary for certain priority levels. Our proposed modeling will focus on allocating relief commodities in order to minimize the cumulative impact of the event across all evacuees.

3.1.2 Relief Commodities

Relief commodities are defined as items given to evacuees in order to meet their basic needs. Example commodities include food, water, shelter, and bedding. Based on these examples, it is clear that a finer categorization into resources and equipment is necessary to capture the differences between consumable and non-consumable commodities. Resources are defined as commodities where the evacuees will have a recurring demand for them. Equipment can be viewed as a 'one-time' demand that, once fulfilled, is satisfied. Further, equipment will become available once someone assigned the equipment leaves the particular Arctic community, e.g., a bed can be reassigned to another person. The re-allocation of equipment plays an important role in our model due to i) the limited number of stock in the region, ii) non-consumability, and iii) the non-transportability of certain equipment.

The demand for resources is likely similar for all priority levels, although missing the demand may result in more severe impacts for higher priority levels (which we will discuss in the next section) or may result in an evacuee increasing their priority level. However, the equipment needs for priority levels will change since medical support (via a bed in a medical center) is necessary for the highest priority level. This fact will complicate our models as the evacuee may be using equipment (e.g., a normal bed) when they enter the highest priority level and only release the equipment once their new equipment demand is met. We assume equipment demand is satisfied (except for medical support) while the evacuees are in transit since assets are already equipped to a certain extent.

3.1.3 Modeling the Impact of Deprivation on the Evacuees

The idea of deprivation-based penalty costs (Pérez-Rodríguez and Holguín-Veras, 2015) is to capture the fact that the longer an evacuee goes without having their basic needs (e.g., food and water) met, the more impactful it is on the evacuee. For instance, a six-hour lack of water does not have $1/4^{th}$ impact on a human body compared to having been without water for 24 hours. Hence, the deprivation cost is computed as an exponential-like function of the discrete deprivation time (Holguín-Veras et al., 2013). Furthermore, note that assuming that met demands fully eliminate the deprivation cost, which implies that all the impact of being without resources is alleviated, is not realistic. This is discussed in more detail as the hysteretic case in Pérez-Rodríguez and Holguín-Veras (2015) as well as our Online Appendix (see Section G).

Holguín-Veras et al. (2013) propose a continuous generic deprivation cost function shown in Eq 1:

$$\gamma(\delta_{it}) = e^{(1.5031+0.1172\delta it)} - e^{(1.5031)} \tag{1}$$

where δ_{it} is the deprivation time at node i representing an evacuee in time t. We will adapt this idea to account for the length of resource deprivation (defined as s^r), equipment deprivation (defined as s^e), and the priority level adjustment (defined as p). We note that when the demand of an evacuee for resources are met, we may not decrease s^r all the way to one in order to capture the hysteretic behavior.

Eq 2 demonstrates how to compute the deprivation time as a funtion of s^r and s^e and Eq 3 defines the adapted deprivation cost function:

$$\delta_t = \alpha \mathrm{s_r} + (1-\alpha)\mathrm{s_e}, \quad 0 \le \alpha \le 1 \tag{2}$$

$$\kappa(p, \delta_t) = e^{(1.5031+0.1172p\delta_t)} - e^{(1.5031)} \tag{3}$$

where α is a non-negative constant which is preferably set as close to 1 to emphasize the importance s^r since equipment deprivation is not nearly as impactful as resource deprivation. During so-called shoulder season MREs, where a lack of access to heat and shelter can have detrimental health impacts (Mak et al., 2011), we can tune α appropriately.

3.2 Objectives

There are many different criteria that may be used to evaluate the response. First, it is necessary to examine the average evacuation time of the evacuees through the different 'stages' of the response efforts (i.e., off the ship and then out of the Arctic). Second, it is necessary to understand the impact of the response on the evacuees, which will be measured through the use of deprivation costs. Third, it *may* be necessary to understand the variable costs incurred during the response. We now discuss each of these in more detail.

The average evacuation time consists of the time evacuees leave the cruise ship and the time evacuees arrive at Anchorage. Given the fact that we are evacuating a distressed cruise ship, we will enforce a penalty cost (in terms of time) for evacuees left on the cruise ship at the end of the response horizon. The evacuees that are left on the cruise ship or in the Arctic communities would still be evacuated but outside of the 'desired' target time of our planning horizon. In addition, we seek to move evacuees out of the Arctic communities and, therefore, we impose a similar penalty for evacuees in an Arctic community at the end of the response horizon. In most situations, it is likely that the evacuation time criteria will be quite important since it helps measure when people return to stable conditions.

During the evacuation, we aim to make sure that evacuees are properly taken care of, as best as possible. With this purpose, we examine the current status of evacuees in each time period. Modeling the current status of evacuees is conducted by a network called the *"status network"* consisting of nodes (p,s^r,s^e) where p represents the priority level, s^r represents the time without resources, and s^e represents the time without equipment. Each status is associated with a deprivation cost where higher priority levels and deprivation times imply higher costs (using Eq. (3))

Based on examining just these two criteria, we have a multi-criteria decision making problem (MCDMP). We refer the reader to Triantaphyllou (2000) and Chankong and Haimes (2008) for more details and further discussions on MCDMPs. In the MCDMP evacuation literature, work has used the weighted sum method (Stepanov and Smith, 2009) and the ϵ-constraint method (Jenkins et al., 2019). In preliminary modeling efforts, we considered the deprivation costs and evacuation times as separate objectives and explored the *efficient frontier* between these two objectives using a weighted objective. However, there were only two efficient solutions: (1) the one we present in this paper that focuses on the evacuation objective while doing the best to support the evacuees during this response and (2) one that evacuees would stay on the ship as long as possible to consume resources/equipment there since it is well-stocked. The solution (1) found that there was enough time and available air cargo capacity to 'prep' the villages for the incoming evacuees in order to support their basic needs; solution (2) was not practical since there is a desire to move the evacuees off the distressed ship as quickly as possible, which was confirmed by our partners. In rare events, the evacuation might not begin immediately upon rescue ships arriving at the incident location since hasty evacuation might cause detrimental cascading events (e.g., during poor weather). In this case, no evacuation decisions could be made until the poor weather lifted and our model would 'start' once these decisions begin.

In general, passenger vessel evacuation principles and operations are codified in international agreements through the International Maritime Organization (IMO), the branch of the United Nations that regulates global maritime shipping. The IMO Polar Code (International Maritime Organization, 2016), which the U.S. is a signatory, defines the international regulations for maritime operations in the Arctic. The IMO (United

Nations (2020)), in their Safety of Life at Sea principle, discusses that human life takes precedence over all other considerations in an evacuation. We have followed this code in examining our modeling process (see Section F of the Online Appendix).

3.3 Assumptions

We now discuss some of the underlying assumptions within our model. We examine a deterministic planning environment which implies that the priority levels of evacuees as well as the number of assets involved in the response are known in advance. We assume that there are deployment times for the assets to model the fact that they may need to prepare to help with the response. We assume partial allocation amongst evacuees within the same group (in a flow network) and that equipment demand may be met in transit with the exception of medical equipment demand. We also assume that there is no financial restriction on procurement and transportation of any resource and equipment (due to an emphasis on effective response). We also assume that there is a location (for example, Anchorage, Alaska) that has enough resources to fully support evacuees once they arrive there. This means the response for that evacuee is 'complete.' As for the cruise ship, we assume that there is an adequate amount of resources and equipment for a certain amount of time to take care of the evacuees' needs on board. We lastly assume that we will not distribute resources for consumption during travel (i.e., in transit).

Transportation and allocation decisions are performed at the end of each time period. Hence, the evacuation event is initiated at $t = 1$. If the resource demand is not satisfied for an evacuee in a time period, then s^r will increase by 1 and may cause a 'jump' in priority level. This assumption is considered realistic since resources to be dispatched (i.e., water and food) have vital importance in terms of the impact on a human. If $s^e > 1$ and equipment demand is not met, then s^e will increase by one; however, equipment will not cause an increase in medical status. If $s^e = 1$, then we have that the evacuee has equipment and, therefore, we can view $s^e = 1$ as an absorbing state, i.e., your equipment demand will remain satisfied. If resource demand is satisfied, then s^r will decrease according to the flow arcs (Section 3.4) connecting (p,s^r,s^e) nodes in the status network. If equipment demand is satisfied, then s^e is set to 1.

There are five decisions that can be implemented for an evacuee in a time period, which determines their status in the next period: i) an evacuee may receive all the required resources and equipment, ii) an evacuee may receive neither resources nor have its equipment demand met, iii) an evacuee may only receive the required resources but not have their equipment demand met, iv) an evacuee may have their equipment demand met but not be provided with resources, or v) an evacuee may be transported to another location - either a community or Anchorage via an asset. This implies that the equipment demand is satisfied. We create five sets of flow arcs to utilize in the balance constraints (Section 4.2) in order to model the impact of these situations on the evacuees. In the next section, the flow arcs designed to model the status of evacuees are introduced. We further explicitly discuss how priority levels might change after each decision.

3.4 Flow Arcs

We design five different sets of flow arcs to understand how the five possible decisions impacting an evacuee (based on resource and equipment allocation decisions) will impact their status. Remember that each (p,s^r,s^e) is represented as a node in the status network. An arc is present between node (p,s^r,s^e) and $(\hat{p},\hat{s}^r,\hat{s}^e)$ if the decision represented by the corresponding arc set causes a status change from (p,s^r,s^e) to

($\hat{p}$,$\hat{s}^r$,$\hat{s}^e$). We will use ($\hat{p}$,$\hat{s}^r$,$\hat{s}^e$) to represent the status change of the evacuee. The first four arc sets are taken into consideration when an evacuee is in a location. The last one is used when an evacuee travels to another location. In the Online Appendix, we present an example to provide insights into these networks and discuss the importance of modelling these decisions (see Section A). The sets of flow arcs are:

1. The Resource Satisfied Set (E^{RSS}) : When an evacuee receives only the required resources, the E^{RSS} is utilized to decide the (p,s^r,s^e) situation of the evacuee in the following time period. We will always have that $\hat{p} = p$ (since the priority level cannot increase due to unmet equipment demand) and $\hat{s}^r < s^r$. If $s^e = 1$, then $\hat{s}^e = 1$. Otherwise, $\hat{s}^e = s^e + 1$.
2. The Equipment Satisfied Set (E^{ESS}): The E^{ESS} is utilized when equipment is the only commodity allocated to an evacuee. In this case, we have that $\hat{s}^e = 1$ and $\hat{s}^r = s^r + 1$. The priority level, however, may increase by 1, i.e, $p \leq \hat{p} \leq p+1$ if s^r was the last time period before a priority level jump. There is an exception, though, where if p is the transition priority level (meaning that a person needs medical support but has yet to be assigned to a medical shelter) than satisfying the equipment demand also has the priority level jump to a different priority level.
3. Both Resource and Equipment Satisfied Set (E^{BSS}): Both resource and equpiment demands are met. In this case, we have that $\hat{p} = p$, $\hat{s}^r \leq s^r$ (it may be equal if $s^r = 1$), and $\hat{s}^e = 1$.
4. Both Resource and Equipment Non-Satisfied Set (E^{BNS}): The worst-case scenario is not being able to allocate any resource and equipment to an evacuee. The E^{BNS} is utilized to determine the p-s^r-s^e condition of an evacuee if no resource and equipment is provided to him. We have that $\hat{s}^r = s^r + 1$, $\hat{s}^e = s^e + 1$, and $p \leq \hat{p} \leq p + 1$ where $\hat{p} = p + 1$ if s^r was the threshold for the priority level jump.
5. Travel Set (E^{TS}): It is unlikely that the evacuees would receive any resources while traveling on rescue ships. Therefore, when an evacuee is being transported on an asset, the corresponding s^r increases based on the travel time. If an evacuee is being transported from location i to location j via asset a with travel time $\tau_{ija} \in \mathbb{Z}^+$, then the evacuee's resource period increases by τ_{ija} and becomes $s^r + \tau_{ija}$ once the evacuee reaches location j. Note that s^e keeps increasing only for those who are in either the highest priority level or transition priority level, since no medical service can be provided on an asset. Lastly, the priority level might go up if s^r reaches the same bound set in the E^{ESS}.

4 An Optimization Model for Arctic MREs

We present the optimization model for Arctic MREs in this section. Our model and analysis assumes that there is a centralized decision-maker (or, equivalently, full coordination and awareness by all involved agencies). This is reasonable as we are using it to assess capability gaps and understand where vulnerabilities exist in potential response efforts. This further means that we do not need to specifically consider the areas of responsibility for an individual organization.

It is our goal to capture all features of the problem to truly identify 'gaps' in response capabilities. In our study, the majority of the parameters presented in Table 4 (e.g., airport capacities, hosting capacities) can be gathered from existing data sources. With this regard, we provide a wide range of what-if analysis (see Section 6.3) to understand key factors surrounding policies within Arctic Alaska. In terms of the deprivation cost function, and its parameters, it is hard to estimate but Holguín-Veras et al. (2013) discuss that simply including this type of cost function is often sufficient for modeling purposes (as opposed to capturing its exact parameters).

The definitions of sets, variables, and parameters are shown in Table 2, Table 3, and Table 4, respectively. Note that we use *C. Ship*, *Anc.*, *P. Shelter*, and *Med.* for the cruise ship, Anchorage, portable shelter, and medical support, respectively as abbreviations.

Table 2: Set definitions

Set	Definition
$\mathcal{A}$	Transportation assets (fixed-wing aircraft, large and small ships)
$\mathcal{A}^a$	Planes (fixed-wing aircraft)
CR	Consumable resources (water, food)
RE	Reusable equipment (portable shelters, sleeping bags, medical support)
T	Time periods
S^r	Periods representing the amount of time passed without access to resources
S^e	Periods representing the amount of time passed without access to equipment
C	Locations (the cruise ship, communities and Anchorage)
V	Communities
P	Priority levels
$\mathcal{V}$	Set of nodes where each node is represented by priority level $p \in P$ and periods $s^r \in S^r, s^e \in S^e$
E^{RSS}	Set of arcs showing the transitions between each pair of node $u = (p_i, {s^r}_j, {s^e}_k)$ and node $v = (p_l, {s^r}_m, {s^e}_n)$ where $u, v \in \mathcal{V}$, for satisfied resource and non-satisfied equipment demands
E^{ESS}	Set of arcs showing the transitions between each pair of node $u = (p_i, {s^r}_j, {s^e}_k)$ and node $v = (p_l, {s^r}_m, {s^e}_n)$ where $u, v \in \mathcal{V}$, for non-satisfied resource and satisfied equipment demands
E^{BSS}	Set of arcs showing the transitions between each pair of node $u = (p_i, {s^r}_j, {s^e}_k)$ and node $v = (p_l, {s^r}_m, {s^e}_n)$ where $u, v \in \mathcal{V}$, for satisfied resource and equipment demands
E^{BNS}	Set of arcs showing the transitions between each pair of node $u = (p_i, {s^r}_j, {s^e}_k)$ and node $v = (p_l, {s^r}_m, {s^e}_n)$ where $u, v \in \mathcal{V}$, for non-satisfied resource and equipment demands
E^{TS}_τ	Set of arcs showing the transitions between each pair of node $u = (p_i, {s^r}_j, {s^e}_k)$ and node $v = (p_l, {s^r}_m, {s^e}_n)$ where $u, v \in \mathcal{V}$, in τ time periods of transit
$A^{RSN}(p, s^r, s^e)$	The set of arcs $A^{RSN}(p, s^r, s^e) = \{(p', s^{r\prime}, s^{e\prime}) \mid ((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) \in E^{RSS}\}$
$A^{ESN}(p, s^r, s^e)$	The set of arcs $A^{ESN}(p, s^r, s^e) = \{(p', s^{r\prime}, s^{e\prime}) \mid ((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) \in E^{ESS}\}$
$A^{BSN}(p, s^r, s^e)$	The set of arcs $A^{BSN}(p, s^r, s^e) = \{(p', s^{r\prime}, s^{e\prime}) \mid ((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) \in E^{BSS}\}$
$A^{BNN}(p, s^r, s^e)$	The set of arcs $A^{NSN}(p, s^r, s^e) = \{(p', s^{r\prime}, s^{e\prime}) \mid ((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) \in E^{BNS}\}$
$A^{TN}_\tau(p, s^r, s^e)$	The path set $A^{TN}_\tau(p, s^r, s^e) = \{(p', s^{r\prime}, s^{e\prime}) \mid ((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) \in E^{TS}_\tau$ where $d((p', s^{r\prime}, s^{e\prime}), (p, s^r, s^e)) = \tau\}$ states that $\exists$ paths of length τ from $(p', s^{r\prime}, s^{e\prime})$ to (p, s^r, s^e)

4.1 Objective function

The objective function of our mass rescue operation model is:

minimize: (1)

$$\sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{\substack{i\in C/\\ \text{“Anc.”}}}\sum_{t\in T}\kappa_{ps^rs^e}Q_{ps^rs^eit} + \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{i\in C}\sum_{j\in C}\sum_{a\in\mathcal{A}}\sum_{t\in T}\Gamma_{ps^rs^eij\tau_{ija}}f_{ps^rs^eijat}$$

$$+\sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{i\in V}2|T|Q_{ps^rs^ei|T|} + \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}3|T|Q_{ps^rs^e\text{“C. Ship”}|T|}$$

$$\sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{i\in C}\sum_{a\in\mathcal{A}}\sum_{t\in T}(t+\tau_{i\text{“Anc.”}a})f_{ps^rs^ei\text{“Anc.”}at} + \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{j\in C}\sum_{a\in\mathcal{A}}\sum_{t\in T}tf_{ps^rs^e\text{“C. Ship”}jat}$$

The objective function has six components. The first two components examine the total deprivation costs associated with evacuees in each location excluding Anchorage and in transit, respectively. The following two components help to drive evacuees, if possible, to Anchorage and off of the cruise ship, respectively, by incurring penalties for those that remain in the communities or on the cruise ship at the end of the planning

Table 3: Variable definitions

Variable	Definition
I_{rit}	the amount of resource $r \in CR$ in location $i \in C$ at time $t \in T$
B_{eit}	the amount of equipment $e \in RE$ in location $i \in C$ at time $t \in T$
g_{rijat}	the amount of resource $r \in CR$ sent from location $i \in C$ to location $j \in C$ via asset $a \in \mathcal{A}$ at time $t \in T$
h_{eijat}	the amount of equipment $e \in RE$ sent from location $i \in C$ to location $j \in C$ via asset $a \in \mathcal{A}$ at time $t \in T$
$f_{ps^rs^eijat}$	the number of people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ sent from location $i \in C$ to location $j \in C$ via asset $a \in \mathcal{A}$ at time $t \in T$
X_{ait}	whether asset $a \in \mathcal{A}$ is in location $i \in C$ at time $t \in T$. If a is in i, then $X_{ait} = 1$, $X_{ait} = 0$ otherwise
Z_{ait}	whether asset $a \in \mathcal{A}$ stays in location $i \in C$ at time $t \in T$. If a stays in i, then $Z_{ait} = 1$, $Z_{ait} = 0$ otherwise
Y_{aijt}	whether asset $a \in \mathcal{A}$ leaves location $i \in C$ at time $t \in T$ heading towards location $j \in C$. If a departs, then $Y_{aijt} = 1$, $Y_{aijt} = 0$ otherwise
$D_{eips^rs^et}$	the amount of equipment $e \in RE$ in location $i \in C$ used for people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ at time $t \in T$
$K_{rips^rs^et}$	the amount of resource $r \in CR$ in location $i \in C$ used for people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ at time $t \in T$
$Q_{ps^rs^eit}$	the number of people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ who require resource and equipment in location $i \in C$ at time $t \in T$
$BS_{ps^rs^eit}$	the number of people in priority $p \in P$ with periods$s^r \in S^r$, $s^e \in S^e$ whose resource and equipment demand is met in location $i \in C$ at time $t \in T$
$BN_{ps^rs^eit}$	the number of people in priority $p \in P$ with periods$s^r \in S^r$, $s^e \in S^e$ whose resource and equipment demand is not met in location $i \in C$ at time $t \in T$
$ES_{ps^rs^eit}$	the number of people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ whose resource demand is not met, while equipment demand is met in location $i \in C$ at time $t \in T$
$RS_{ps^rs^eit}$	the number of people in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ whose resource demand is met while equipment demand is not met in location $i \in C$ at time $t \in T$

Table 4: Parameter definitions

Parameter	Definition
α_{rp}	the amount of resource $r \in CR$ required to satisfy an evacuee's demand in priority $p \in P$
ζ_{ep}	the amount of equipment $e \in RE$ required to satisfy a evacuee's demand in priority $p \in P$
ρ_{ri}	the amount of resource $r \in CR$ positioned in location $i \in C$ at time $t = 1$
ξ_{ei}	the amount of equipment $e \in RE$ positioned in location $i \in C$ at time $t = 1$
$\nu_{ps^rs^ei}$	the number of evacuees in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ being in location $i \in C$ at time $t = 1$
μ_a	the maximum cargo capacity of asset $a \in \mathcal{A}$
Ψ_a	the maximum passenger capacity of asset $a \in \mathcal{A}$
π_{ai}	whether location $i \in C$ is the closest location to asset $a \in \mathcal{A}$ at time $t = 1$.
Ω_a	the travel time of asset $a \in \mathcal{A}$ to the closest location
θ_{ai}	whether asset $a \in \mathcal{A}$ can land on location $i \in C$. If a can land, then $\theta_{ai} = 1$, $\theta_{ai} = 0$ otherwise
τ_{aij}	the travel time of asset $a \in \mathcal{A}$ from location $i \in C$ to location $j \in C$
ω_r	the weight of one unit resource $r \in CR$
ε_e	the weight of one unit equipment $e \in RE$
ϕi	the ground capacity of location $i \in C$
$\kappa_{ps^rs^e}$	deprivation cost for a person in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$
$\Gamma_{ps^rs^eijl}$	cumulative in-transit deprivation cost for an evacuee in priority $p \in P$ with periods $s^r \in S^r$, $s^e \in S^e$ traveling from location $i \in C$ to location $j \in C$ which takes l time unit
ϑ_i	the available capacity of location $i \in C$ to host evacuees
γ_i	the available capacity of public spaces in location $i \in C$
p'_{max}	the transition priority level in which an evacuee needs medical support but has yet to be assigned to a medical facility
t_{lim}	the earliest time period when an evacuee can be in the transition priority
p_{max}	the highest priority level

horizon. The fifth component is focused on the total evacuation time of evacuees arriving in Anchorage while the sixth component is focused on the total evacuation time of moving people off of the cruise ship.

4.2 Constraints

We present the constraints based on two categories: those on how we use the assets to move evacuees and resources and those modeling the allocation decisions and their impact on the status on the evacuees.

4.2.1 Asset Constraints

The asset constraints presented in this section are grouped into two categories. The first one are capacity-based constraints and the second one focuses on initial assignments and routing of the assets.

Capacity Constraints

$$\sum_{\substack{e \in RE\setminus \\ \text{“Med.”}}} \varepsilon_e h_{eijat} + \sum_{r \in CR} \omega_r g_{rijat} \leq \mu_a Y_{aijt} \quad \forall a \in \mathcal{A}^a, \forall i \in C, \forall j \in C, \forall t \in T \tag{2}$$

Constraint (2) ensures that the total weight of resources and equipment carried by a plane does not exceed its capacity. Medical support is not considered due to fact we assume it cannot be transported.

$$\sum_{p \in P} \sum_{s^r \in S^r} \sum_{s^e \in S^e} f_{ps^r s^e ijat} \leq \Psi_a Y_{aijt} \quad \forall a \in \mathcal{A}, \forall i \in C, \forall j \in C, \forall t \in T \tag{3}$$

Constraint (3) ensures that an asset cannot carry more evacuees than its passenger capacity.

$$\sum_{a \in \mathcal{A}^a} X_{ait} \leq \phi_i \quad \forall i \in C, \forall t \in T \tag{4}$$

Constraint (4) guarantees that the number of planes landing at an airport does not violate the airport capacity in a location (i.e., the communities and Anchorage) during a time period.

Positioning and Travel Constraints

$$\sum_{t \in T: t < \Omega_a} X_{ait} = 0 \quad \forall a \in \mathcal{A}, \forall i \in C \tag{5}$$

$$X_{ait=\Omega_a} = \pi_{ai} \quad \forall a \in \mathcal{A}, \forall i \in C \tag{6}$$

Constraints (5) and (6) make the initial assignment of each asset by taking the deployment times into consideration. This ensures that the asset goes to the closet (acceptable) community to prepare for deployment.

$$\sum_{i \in C} X_{ait} \leq 1 \quad \forall a \in \mathcal{A}, \forall t \in T \tag{7}$$

Constraint (7) implies that an asset can be located at most in one location during a time period.

$$Y_{aijt} \leq \theta_{aj} \quad \forall a \in \mathcal{A}, \forall i \in C, \forall j \in C, \forall t \in T \tag{8}$$

Constraint (8) prevents an asset from landing at locations not meeting its required specifications.

$$X_{ait} = Z_{ait} + \sum_{j \in C} Y_{aijt} \quad \forall a \in \mathcal{A}, \forall i \in C, \forall t \in T \tag{9}$$

Constraint (9) ensures that in each time period, an asset either stays in its location or travels to another one.

$$X_{ait} = Z_{ai(t-1)} + \sum_{j \in C} Y_{aji(t-\tau_{aji})} \quad \forall a \in \mathcal{A}, \forall i \in C, \forall t \in T/\{1\} \tag{10}$$

Constraint (10) ensures that if an asset is at a location in t then either asset a stayed in location i at time $t-1$ or asset a left location j at time $t - \tau_{aji}$ to arrive at location i.

4.2.2 Resource and equipment allocation and its impact on the status of the evacuees

The constraints introduced in this section capture the resource and equipment allocation decisions to the evacuees and the influence of this allocation on their status.

Resource and Equipment Balance Constraints

$$I_{ri(t=1)} = \rho_{ri} - \sum_{p \in P} \sum_{s^r \in S^r} \sum_{s^e \in S^e} K_{rips^r s^e (t=1)} \quad \forall r \in CR, \forall i \in C \tag{11}$$

Constraint (11) initiates the resource inventories in each location at $t = 1$. Note that no transportation decision is conducted during the first time period. This is because each asset takes at least one time unit to be assigned to the initial locations (i.e., deployment time).

$$B_{ei(t=1)} = \xi_{ei} - \sum_{p \in P} \sum_{s^r \in S^r} \sum_{s^e \in S^e} D_{eips^r s^e (t=1)} \quad \forall e \in RE \setminus \{\text{“P. Shelter”}\} \quad \forall i \in C \tag{12}$$

$$B_{\text{“P. Shelter”}i(t=1)} = \gamma_i + \xi_{\text{“P. Shelter”}i} - \sum_{p \in P} \sum_{s^r \in S^r} \sum_{s^e \in S^e} D_{\text{“P. Shelter”}ips^r s^e (t=1)} \quad \forall i \in C \tag{13}$$

Constraints (12) and (13) position equipment in each location at $t = 1$, including incorporating the public spaces located into each community into their ‘shelter’ inventory level (Constraint (13)).

$$I_{rit} + \sum_{p \in P} \sum_{s^r \in S^r} \sum_{s^e \in S^e} K_{rips^r s^e t} + \sum_{j \in C} \sum_{a \in \mathcal{A}} g_{rijat} = I_{ri(t-1)} + \sum_{j \in C} \sum_{a \in \mathcal{A}} g_{rjia(t-\tau_{aji})} \quad \forall r \in CR, \tag{14}$$

$\forall i \in C, \forall t \in T \setminus \{1\}$

Constraint (14) is the resource inventory balance equation. At time t, the inventory level in each location is equal to the amount of the resources remaining from the previous time period and the resources transported from other locations. Furthermore, resources in the current location can be carried to the other locations at time t and can be distributed to the evacuees.

$$B_{eit} + \sum_{p \in P} \sum_{s^r \in S^r} \sum_{s \in S^e} D_{eips^r s^e t} + \sum_{j \in C} \sum_{a \in \mathcal{A}} h_{eijat} = B_{ei(t-1)} + \sum_{j \in C} \sum_{a \in \mathcal{A}} h_{ejia(t-\tau_{aji})} + \tag{15}$$

$$\sum_{\substack{p\in P\setminus \\ \{p_{\max},p_{\max}'\}}}\sum_{s^r\in S^r}\sum_{j\in C}\sum_{a\in\mathcal{A}} f_{ps^r(s^e=1)ija(t-1)} + \sum_{s^r\in S^r}\sum_{s^e\in S^e}\sum_{j\in C}\sum_{a\in\mathcal{A}} f_{p_{\max}'s^rs^eija(t-1)} +$$

$$\sum_{s^r\in S^r}\sum_{s^e\in S^e} BS_{p_{\max}'s^rs^ei(t-1)} + \sum_{s^r\in S^r}\sum_{s^e\in S^e} ES_{p_{\max}'s^rs^ei(t-1)} \quad \forall e\in RE\setminus\{\text{“Med.”}\}, \forall i\in C, \forall t\in T\setminus\{1\}$$

$$B_{\text{“Med.”}it} + \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s\in S^e} D_{\text{“Med.”}ips^rs^et} = B_{\text{“Med.”},i,t-1} + \sum_{s^r\in S^r}\sum_{j\in C}\sum_{a\in\mathcal{A}} f_{p_{\max}s^r(s^e=1)ija(t-1)} \tag{16}$$

$$\forall i\in C, \forall t\in T\setminus\{1\}$$

Constraints (15) and (16) are an equipment inventory balance equations similar to Constraint (14). However, since equipment is considered non-consumable, the equipment of those who depart the location during the previous time period become available at time t. Further, recall that those in the transition priority (i.e., $p_{\max'}$) will release their 'normal' equipment once they are assigned the medical support necessary for their priority level (e.g., they will move from a bed to a bed in the medical center). Further, as mentioned previously, medical support is only provided in medical centers, which are non-transportable. Hence, an individual equipment balance constraints (see Constraint (16)) is generated for medical support.

$$B_{\text{“P. Shelter”}it} + \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e} D_{\text{“P. Shelter”}ips^rs^et} + \sum_{\substack{p\in P\setminus \\ \{p_{\max},p_{\max}'\}}}\sum_{s^r\in S^r}\sum_{s^e\in S^e} BS_{ps^r(s^e=1)it} + \tag{17}$$

$$\sum_{\substack{p\in P\setminus \\ \{p_{\max},p_{\max}'\}}}\sum_{s^r\in S^r}\sum_{s^e\in S^e} ES_{ps^r(s^e=1)it} + \sum_{s^r\in S^r}\sum_{s^e\in S^e} BN_{p_{\max}'s^rs^eit} + \sum_{s^r\in S^r}\sum_{s^e\in S^e} RS_{p_{\max}'s^rs^eit} \geq \gamma_i$$

$$\forall i\in C, \forall t\in T$$

Constraint (17) ensures that public spaces are not transported to other communities by ensuring that the total capacity of a location never goes down the true capacity. In particular, the left hand side of the constraint sums up the inventory of shelter at location i carrying over into the next period, the amount of shelter assigned in t, the amount of people in normal priority levels (not $p_{\max}$ or $p'_{\max}$) that currently have shelter ($s^e = 1$), and the amount of people at $p'_{\max}$ that are currently using the normal shelter. The constraint ensures this summation is great than or equal to the capacity of public space.

Evacuees Balance Constraints

$$Q_{ps^rs^eit=1} = \nu_{ps^rs^ei} \quad \forall p\in P, \forall s^r\in S^r, \forall s^e\in S^e, \forall i\in C \tag{18}$$

Constraint (18) assigns the initial populations in each location. Clearly, the ship is the only location where evacuees are located at $t = 1$. We further constrain the number of evacuees that can be in an Arctic community at a particular time:

$$\sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e} Q_{ps^rs^eit} \leq \vartheta_i \quad \forall i\in C, \forall t\in T \tag{19}$$

We now describe the constraints governing the transitions of the evacuees into different statuses both out of and into different time periods. We first present the constraints where $s^e = 1$, i.e., the equipment demand has already been met for all priorities besides the transition priority (p'_{max}).

$$Q_{ps^r(s^e=1)it} = BS_{ps^r(s^e=1)it} + ES_{ps^r(s^e=1)it} + \sum_{j \in C} \sum_{a \in \mathcal{A}} f_{ps^r(s^e=1)ijat} \quad \forall p \in P \setminus \{p_{\text{max}}'\}, \tag{20}$$

$\forall s^r \in S^r, \forall i \in C, \forall t \in T$

$$Q_{ps^r(s^e=1)it} = \sum_{\substack{(p',s^{r'},s^{e'}) \in \\ A^{BSN}(p,s^r,s^e=1)}} BS_{p's^{r'}s^{e'}i(t-1)} + \sum_{\substack{(p',s^{r'},s^{e'}) \in \\ A^{ESN}(p,s^r,s^e=1)}} ES_{p's^{r'}s^{e'}i(t-1)} \quad \forall p \in P \setminus \{p_{\text{max}}'\}, \tag{21}$$

$\forall s^r \in S^r, \forall i \in C, \forall t \in T \setminus \{1\}$

Constraint (20) implies that after receiving the required equipment, evacuees either stay in $s^e = 1$ by continuing to "receive equipment" (i.e., once equipment demand is met, no extra allocation decision is done after the first assignment) or they move to another location. Constraint (21) states that evacuees can be in the absorbing equipment state if and only if they receive the required equipment (i.e., $BS_{ps^rs^eit}$ and $ES_{ps^rs^eit}$) during the previous time period. As mentioned before, evacuees cannot arrive at a location with $s^e = 1$ and, therefore, transportation decisions are not included in Constraints ((20)-(21)). We now turn our attention to the constraints for $s^e \neq 1$ and all priorities besides the transition priority (p'_{max}).

$$Q_{ps^rs^eit} = BS_{ps^rs^eit} + BN_{ps^rs^eit} + ES_{ps^rs^eit} + RS_{ps^rs^eit} + \sum_{j \in C} \sum_{a \in \mathcal{A}} f_{ps^rs^eijat} \tag{22}$$

$\forall p \in P \setminus \{p_{\text{max}}'\}, \forall s^r \in S^r, \forall s^e \in S^e \setminus \{1\}, \forall i \in C, \forall t \in T$

$$Q_{ps^rs^eit} = \sum_{\substack{(p',s^{r'},s^{e'}) \in \\ A^{BNN}(p,s^r,s^e)}} BN_{p's^{r'}s^{e'}i(t-1)} + \sum_{\substack{(p',s^{r'},s^{e'}) \in \\ A^{RSN}(p,s^r,s^e)}} RS_{p's^{r'}s^{e'}i(t-1)} + \tag{23}$$

$$\sum_{j \in C} \sum_{a \in \mathcal{A}} \sum_{\substack{(p',s^{r'},s^{e'}) \in \\ A^{TN}_{\tau_{aji}}(p,s^r,s^e)}} f_{p's^{r'}s^{e'}jia(t-\tau_{aji})} \quad \forall p \in P \setminus \{p_{\text{max}}'\}, \forall s^r \in S^r, \forall s^e \in S^e \setminus \{1\}, \forall i \in C,$$

$\forall t \in T \setminus \{1\}$

Constraint (22) indicates that any of the *five* allocation and/or transportation decisions can be made for evacuees with $p \neq p'_{\text{max}}$ and $s^e \neq 1$: they can have both their demands satisfied, $BS_{ps^rs^eit}$, they can have neither demands satisfied, $BN_{ps^rs^eit}$, the can have just their equipment demand satisfied, $ES_{ps^rs^eit}$, they can have just their resource demand satisfied, $RS_{ps^rs^eit}$, or they can be transported out of i, $f_{ps^rs^eijat}$. Constraint (23) captures how evacuees can end up in location i at time t with a particular status where $p \neq p'_{\text{max}}$ and $s^e \geq 2$: they can have both demands unsatisfied, they can have just their resource demand satisfied, or they can arrive from another location. We now present the constraints governing the behavior of evacuees with the transition priority level, p'_{max}.

$$Q_{p_{\text{max}}'s^rs^eit} = BS_{p_{\text{max}}'s^rs^eit} + BN_{p_{\text{max}}'s^rs^eit} + RS_{p_{\text{max}}'s^rs^eit} + ES_{p_{\text{max}}'s^rs^eit} + \sum_{j \in C} \sum_{a \in \mathcal{A}} f_{p_{\text{max}}'s^rs^eijat} \tag{24}$$

$\forall s^r \in S^r, \forall s^e \in S^e, \forall i \in C, \forall t \in T \setminus \{1, \ldots, t_{\text{lim}}\}$

$$Q_{p_{\max}'s^rs^eit} = \sum_{\substack{(p',s^{r'},s^{e'})\in \\ A^{BNN}(p_{\max}',s^r,s^e)}} BN_{p's^{r'}s^{e'}i(t-1)} + \sum_{\substack{(p',s^{r'},s^{e'})\in \\ A^{RSN}(p_{\max}',s^r,s^e)}} RS_{p's^{r'}s^{e'}i(t-1)} + \sum_{\substack{(p',s^{r'},s^{e'})\in \\ A^{ESN}(p_{\max}',s^r,s^e)}} ES_{p's^{r'}s^{e'}i(t-1)} \tag{25}$$

$$\forall i \in C, \forall t \in T \setminus \{1,\ldots,t_{\text{lim}}\}, \forall s^r \in S^r, \forall s^e \in S^e$$

The first difference is that once equipment demand is met in the transition priority level, then we move the evacuee into the highest demand level (recall that the transition priority level is meant to represent an evacuee who already has 'normal' equipment demand met but then requires 'normal plus medical' equipment demand). The second difference in these constraints is that no evacuee can reach a location in a transition priority thus altering Constraint (25). There are two reasons for this: i) equipment demand of evacuees in normal priority levels is satisfied in transit, ii) evacuees in transition priority getting on an asset transition to the highest priority level due to releasing the current equipment being held. One can arrive into the status by having their equipment demand satisfied *if* they were making the jump to the transition priority level.

Allocating Resources and Equipment to Demand Constraints

$$\alpha_{rp}(BS_{ps^rs^eit} + RS_{ps^rs^eit}) = K_{rpits^rs^e} \quad \forall p \in P \setminus \{p'_{\max}\}, r \in CR, \forall s^r \in S^r, \forall s^e \in S^e \setminus \{1\}, \tag{26}$$

$$\forall i \in C, \forall t \in T$$

$$\alpha_{rp}BS_{ps^r(s^e=1)it} = K_{rpits^r(s^e=1)} \quad \forall p \in P \setminus \{p'_{\max}\}, \forall s^r \in S^r, r \in CR, \forall i \in C \tag{27}$$

Constraints (26) and (27) connect the satisfied flow decisions for resources and equipment, respectively, to evacuees in location i at time t with a certain status to the allocation decisions made for evacuees in that location at that time with that status. Note that since Constraint (27) is created for those who are in $s^e = 1$, it does not contain the RS component since the equipment demand is satisfied for those with $s^e = 1$.

$$\alpha_{rp_{\max}'}(BS_{p_{\max}'s^rs^eit} + RS_{p_{\max}'s^rs^e}it) = K_{rip_{\max}'s^rs^et} \quad \forall r \in CR, \forall s^r \in S^r, \forall s^e \in S^e, \forall i \in C, \tag{28}$$

$$\forall t \in T \setminus \{1,\ldots,t_{\text{lim}}\}$$

$$\zeta_{ep_{\max}'}(BS_{p_{\max}'s^rs^eit} + ES_{p_{\max}'s^rs^eit}) = D_{eip_{\max}'s^rs^et} \quad \forall e \in RE, \forall s^r \in S^r, \forall s^e \in S^e, \forall i \in C, \tag{29}$$

$$\forall t \in T \setminus \{1,\ldots,t_{\text{lim}}\}$$

Constraints (28) and (29) connect the satisfied flow decisions for resources and equipment, respectively, to evacuees in a location at a time t in a certain status in the transition priority level to the amount that is allocated to evacuees at that status in transition priority level at that location at that time.

$$\zeta_{ep}(BS_{pits^rs^e} + ES_{pits^rs^e}) = D_{eis^rs^ept} \quad \forall p \in P \setminus \{p'_{\max}\}, \forall s^r \in S^r, \forall s^e \in S^e \setminus \{1\}, \forall e \in RE, \tag{30}$$

$$\forall i \in C, \forall t \in T$$

Constraint (30) ensures that equipment is allocated to satisfy the demand of those evacuees who will have their equipment demands satisfied in location i at time t. The last constraints focus on variable restrictions.

$$I_{rit}, T_{eit}, K_{rips^rs^et}, D_{eips^rs^et}, g_{rijat}, h_{eijat}, f_{ps^rs^eijat}, Q_{ps^rs^eit}, BS_{ps^rs^eit}, BN_{ps^rs^eit}, ES_{ps^rs^eit}, \tag{31}$$

$$RS_{ps^rs^eit}, m_{ijat}, w_{it} \in \mathbb{Z}_+ \quad \forall r \in CR, \forall e \in RE, \forall i \in C, \forall p \in P, \forall s^r \in S^r, \forall s^e \in S^e, \forall a \in \mathcal{A}, \forall t \in T$$

$$X_{ait}, Z_{ait}, Y_{ijat} \in \{0,1\} \quad \forall a \in \mathcal{A}, \forall i \in C, \forall j \in C, \forall t \in T \tag{32}$$

5 Overview of Solution Methodologies

The mathematical model is a large-scale IP that has characteristics similar to problems in evacuation and resource allocation. It is, therefore, important to recognize that solving our model directly with a commercial solver may be time-prohibitive and that customized solution approaches may be necessary. We describe two heuristic approaches for identifying quality solutions quickly. As shown in the Online Appendix, solving the IP using a warm-start heuristic solution outperforms solving the IP directly (see Section E).

5.1 Conservative One-by-One Heuristic (COBOH)

We approach the problem by asking the following question: *How can the model be solved if we consider the problem through a practitioner's eyes?*. The focus would likely be on the allocating assets to move the evacuees around and then using availability capacity to bring relief commodities when possible. A practitioner naturally would carry the evacuees to the closest *available* villages via the available ships in a greedy manner. The practitioner would use the planes to transport everyone to Anchorage. In other words, first a ship carries a certain amount of evacuees to a village, then a plane takes action and carries the evacuees to Anchorage at some point later in time. This pair of operations can be repeated in an iterative way by taking all the capacity constraints into consideration.

This heuristic focuses on the transportation decisions only and we then optimize the resource allocation decisions with fixed transportation decisions. In other words, we look at the best possible use of the response resources once we know when we planned on evacuating passengers from the cruise ship to the villages and the villages to Anchorage. Therefore, we are examining best possible resource allocation decisions whereas, in practice, triage and rationing may be implemented to make these decisions. The insight that we expect to obtain from the heuristic approach is: i) when we really need an OR model for an Arctic MRE, and ii) the benefits of applying the complex model to determine the response decisions rather than focusing solely on the transportation decisions. The pseudocode of the heuristic can be found in the Online Appendix (see Section D). Here, we focus on explaining the heuristic in an informal way.

Each asset is assigned to the initial location by taking the deployment times into consideration. As a second step, all available ships are routed towards the cruise ship to assist with the evacuation. We then start our iterative method and examine the ship and plane sets in sequence.

For every ship, we calculate the maximum number of evacuees that can be transported to each village, which is reachable from the cruise ship, together with the earliest arrival time. A higher ratio implies that we can carry more evacuees within a shorter time period to a village. Each ship links with one village which has the highest ratio for that ship. The amount of evacuees that can be carried to a village depends on the hosting capacity of a village, the passenger capacity of the ship, and the number of evacuees currently at the village. Once every ship is associated with a village, we pick the ship with the earliest arrival time. In the case of a tie, we prefer the ship with the higher ratio.

We then proceed to make a transportation decision for a plane. Each plane is examined one by one and a similar analysis is conducted with slight changes. We compute the last minimum number of positive population within the total evacuation time horizon for every village after the earliest possible departure time. The calculation of the minimum number of evacuees that can be transported from a village is a significant step since it ensures feasibility with respect to the population numbers in the locations.

The number of evacuees that can be carried by the plane is set as the minimum of population amount in terms of evacuees and the passenger capacity of the plane. Then, we essentially proceed in the same way as the ship portion of the heuristic except that we also examine the airport capacities and make sure that the constraint related to airport capacities is not violated. If a plane cannot be associated with any village, then there is no way to utilize the plane for the remainder of the horizon. In this case, we make an idle transportation decision for that plane. The asset either stays in its current location or moves to another location while checking the airport capacity.

If a ship or a plane reaches the end of the time horizon, we eliminate the corresponding asset from consideration. The iterative method is continued until both the ship and plane sets become empty implying that there is no more transportation decisions required or all evacuees arrive in Anchorage. Once the heuristic is over, we obtain a full set of transportation variables. We refer to this heuristic as the one-by-one heuristic since we are allocating assets individually, in what is essentially a greedy manner.

5.2 Optimizing Transportation Heuristic (OTH)

In the second method, we focus on optimizing *just* the transportation decisions focusing on the *evacuation* first and then optimizing support decisions based on these 'greedy' evacuation decisions. In particular, we move all the transportation variables related to the assets and evacuees (i.e., X_{aij}, Y_{aijt}, and $f_{ps^r s^e ijat}$) into an optimization problem and ignore the ones related to the relief materials (i.e., g_{rijat} and h_{eijat}). With this conversion, we intend to optimize the transportation decisions. We first define two new variables shown in Table 5 that focus on the number of people in a location and/or being transported and we 'remove' the $f_{ps^r s^e jiat}$ variables since they are dictated by relief/support decisions.

Table 5: New variables defined

Variable	Definition
w_{it}	the number of people staying in location $i \in C$ at time $t \in T$
m_{ijat}	the number of people leaving location $i \in C$ to go to location $j \in C$ at time $t \in T$

We rearrange the last four components of the Objective Function (1) and update the correlated constraints. Then, the new modified evacuation IP (EvacIP) focusing on evacuation can be represented as:

$$\text{(EvacIP):}\ \max \sum_{i\in C}\sum_{a\in A}\sum_{t\in T}(t+\tau_{i\text{“Anc”}a})m_{i\text{“Anc”}at} + \sum_{j\in C}\sum_{a\in A}\sum_{t\in T}(t)m_{\text{“C. Ship”}jat} + \sum_{i\in V} 2|\mathrm{T}|w_{i|T|} + 3|\mathrm{T}|w_{\text{“C. Ship”}|T|} \tag{33}$$

$$s.t.\ m_{ijat} \le \Psi_a Y_{aijt}, \quad \forall a \in A, \forall i \in C, \forall j \in C, \forall t \in T \tag{34}$$

$$\mathrm{w}_{i(t=1)} = \sum_{p\in P}\sum_{s^r\in S^r}\sum_{s^e\in S^e} \nu_{ps^r s^e i}, \quad \forall i \in C \tag{35}$$

$$\mathrm{w}_{it} + \sum_{j\in C}\sum_{a\in A} m_{ijat} \le \vartheta_i, \quad \forall i \in C, \forall t \in T, \tag{36}$$

$$w_{i,t} + \sum_{j\in C}\sum_{a\in A} m_{ijat} = w_{i(t-1)} + \sum_{j\in C}\sum_{a\in A} m_{jia(t-\tau_{aji})}, \quad \forall i \in C, \forall t \in T \tag{37}$$

$$(4)-(5)-(6)-(7)-(8)-(9)-(10)-(32)$$

$$w_{it} \in \mathbb{Z}_+, \quad \forall i \in C, \forall t \in T \tag{38}$$

$$m_{ijat} \in \mathbb{Z}_+, \quad \forall i \in C, \forall j \in C, \forall a \in A, \forall t \in T. \tag{39}$$

Note that Constraints (34), (35), and (36) replace Constraints (3) , (18), and (19), respectively and play the same role. The left hand side of Constraint (37) captures the number of evacuees staying and leaving location i at time t. The right hand side of the constraint determines; i) how many evacuees stayed in location i at time $t-1$, and ii) how many evacuees left other locations to arrive at i at time $t - \tau_{aji}$.

In particular, EvacIP answers the following question: *What happens when we prefer to focus on the evacuation decisions without worrying about distributing any relief sources?* We then use the model as a heuristic approach and warm start the original IP model via the partial solution obtained through this EvacIP.

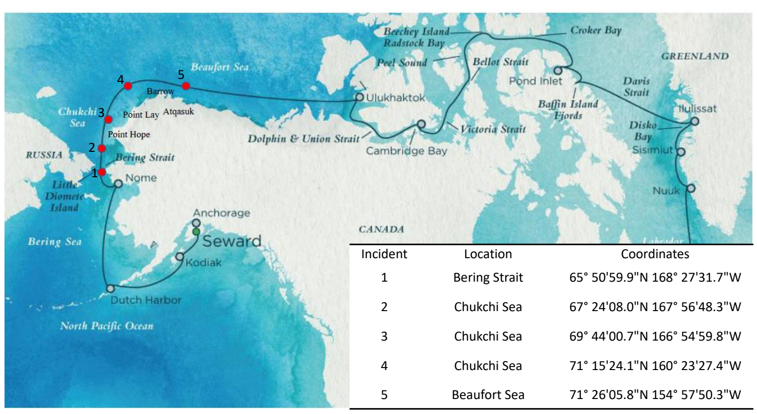
6 Computational Study: Data Set Description and Baseline Analysis

The objective of our computational study is to analyze different potential response events in Arctic Alaska and obtain insights into policy questions by applying our novel MRE model. All the experiments are conducted in the Optimization Programming Language (OPL) using CPLEX 12.8.1 as the IP solver on an Dell machine with an Intel Core i7-8700 CPU at 3.20GHz, 64 GB Ram.

6.1 Case Study Description

In this section, we discuss the data collected for our case study. We utilize online sources that are publicly available from institutions operating in Arctic Alaska. We have discussed the application and data with experts from the region. The case studies were also created based on discussions with District 17 of the USCG, although the data and model have yet to be fully verified and validated with them.

We separate our test cases into five incident locations. The purpose is to identify the areas where there are 'capability gaps' for MREs from Anchorage through the Northwest Passage. The largest cruise ship that has entered the region is the *Crystal Serenity* (Waldholz, 2016) and have used its planned route shown in Figure 2 for selecting five incident locations. We are interested in the region starting from the Bering Strait, through the Chukchi Sea, and into the Beaufort Sea. The number of evacuation time periods is set equal to sixteen and there are three priority levels where we assume that 65%, 25% and 10% of the evacuees are at level 1, 2, and 3. We consider MREs where there are 800, 1200, and 1600 people on the cruise ship.



Incident	Location	Coordinates
1	Bering Strait	65° 50'59.9"N 168° 27'31.7"W
2	Chukchi Sea	67° 24'08.0"N 167° 56'48.3"W
3	Chukchi Sea	69° 44'00.7"N 166° 54'59.8"W
4	Chukchi Sea	71° 15'24.1"N 160° 23'27.4"W
5	Beaufort Sea	71° 26'05.8"N 154° 57'50.3"W

Figure 2: Incident locations selected on the Crystal Serenity's planned routes (Waldholz, 2016)

In our data, Utqiaġvik, Nome, Kotzebue, Point Hope, Point Lay, and Wainwright are the communities where the evacuees can be used in an Arctic MRE. Note that Point Hope, Point Lay, and Wainwright are relatively small (i.e., ones that have a population of fewer than 1000 people) but are included since they are located in the North Slope Borough, which has a robust emergency management department (Brooks, 2020). Each community has an airport implying that it is feasible to take off and land there via certain planes (Federal Aviation Administration, 2019). It would be inappropriate for large planes to use airports in the small villages due to their short runways. For instance, Point Hope, Point Lay, and Wainwright each have a single runway of no longer than 4,500 feet (GCR, 2017), which does not fit the normal requirements of landing the HC-130H or Boeing 737-700. Communities also have a number of small boats and vehicles that can be used for local transport (i.e., to shuttle evacuees from offshore ships to shore or helping to move from the shore to the airport). Since there is no capacity issue regarding such local transportation operations, we do not model them. We also consider the potential use of the inland community of Atqasuk as a pre-positioning site for resources and equipment. Each community has a carrying capacity standing for the number of evacuees that can be hosted, which is set equal to 40% of its population (see Table 6).

Table 6: Populations and capacities in locations

Location	Nome	Kotzebue	Point Hope	Point Lay	Atqasuk	Wainwright	Utqiaġvik	Anchorage
Num. of People	3,841	3,266	709	269	244	584	4,438	294,356
Carrying Capacity	1,536	1,306	283	107	97	233	1,775	∞
Airport Capacity	3	3	1	1	1	1	3	5

The distance between each location is calculated by *Google Maps* in miles. Travel routes are separated into two categories: i) sea distance (i.e., travel that accounts for the shoreline) and ii) air distance. Discussions with USCG suggested that transportation directly from the cruise ship to Anchorage is undesirable since (1) the ships that the evacuees would be moved to (including sister ships) are not designed for passenger travel and (2) it could take a significant amount of time to reach Anchorage from the Arctic via the sea. To obtain the number of time periods travel requires, we calculate the travel time between two locations via each asset by $\lceil(\text{distance})/(6 \times \text{cruise speed})\rceil$. We assume there are 6 hours per time period.

The available assets play an important role in transportation and logistics operations. Examining various tabletop exercises (Coast Guard News, 2016; McNutt, 2016) have led us to incorporate a set of available assets owned by USCG, Alaska Air National Guard (AANG), North Slope Borough (NSB), U.S. Air Force (USAF), and the commercial airlines operating in the region (i.e., Alaska Airlines and Ravn Alaska).

Moving all evacuees directly out of the Arctic (where evacuees can be supported), or even into a single Arctic community, is not practical since existing infrastructure and transportation assets may not be capable of providing sufficient support or it may not be desirable to have evacuees on those assets for long periods of time. While planes are utilized to transfer people from the communities to Anchorage, as well as to deliver commodities to the communities, rescue ships are only used to carry people from the cruise ship to the communities. As a result, cargo capacity of ships are set as zero. Aircraft are not considered in the operation of taking people off the cruise ship. Note that helicopters are not *specifically modeled* in the set of air assets, although they would play an important role in the response in transporting high-priority evacuees off the cruise ship, possibly lightering passengers from the cruise ship to rescue ships, and moving responders onto the ship (see Harila (2019)). The main reason for not including helicopters is that they would be used in conjunction with rescue ships except in cases of extreme medical duress.

Since military and commercial assets require mobilization time, we assume that planes owned by USAF and commercial airlines will be available to support the MRE within 24 hours of the event. USCG, AANG, and NSB's assets tend to be dedicated to this type of emergency more than USAF and commercial airlines.

Given the assumptions mentioned, we include relevant planes that we believe would be available for the response (see Table 7). In our baseline experiment, we have examined the length of the runway required for each plane to land and have disallowed the landing of large planes, such as the HC 130H, Lockheed HC-130, and Boeing 737-700 in the small villages (Point Lay, Point Hope, and Wainwright). This restriction will be lifted in certain analyses, which would represent investments to the runways of these small villages. However, we do note that who pays the costs associated with the response is a question outside the scope of this paper (i.e., the cruise ship company or its insurance may pay the costs of the response back to the federal government). We will create scenarios in a way that only a subset of these assets are ready to use to observe the impact of different asset types. For ships, the passenger capacity is set as the maximum number of crew members allowed on board. For each plane, we use 60% of its cargo capacity to ensure that no problem is faced during loading resources and/or equipment without looking at the detailed packing plan.

We now discuss some remaining assumptions used when creating this data set. We focus on situations where ships are the only asset type that can carry evacuees from a cruise ship to the communities, because planes cannot land on ships. We assume evacuees need equipment such as shelter (either in 'public space', such as a school or portable shelter) and sleeping bags. Public space is different than a portable shelter since it cannot be transported. We further assume that the time to refuel an asset is sufficiently small compared to the travel time of the asset and, therefore, does not need to be accounted for in our model.

Table 7: List of assets (see Section F in the Online Appendix for the data sources)

Asset	Type	Owner	Available Num.	Num. in Basline	Passenger Cap.	Cargo Cap. (lbs)	Cruise Speed (mi.)
HC 130H	Aircraft	USCG	2	2	92	51,000	374
Lockheed HC-130	Aircraft	AANG	1	1	20	30,000	251
Learjet 31A	Aircraft	NSB	2	2	6	2,000	441
Boeing 737-700	Aircraft	Alaska Airlines	1	1	124	16,505	460
Beechcraft 1900C	Aircraft	Ravn Alaska	1	1	12	2,030	250
WLB 206	Buoy Tender	USCG	1	1	86	0	17.3
WLB 212	Buoy Tender	USCG	1	1	86	0	17.3
WLM 175	Buoy Tender	USCG	1	1	24	0	13.8
282 WMEC	Endurance Cutter	USCG	1	1	99	0	13.8
378 WHEC	Endurance Cutter	USCG	1	1	160	0	12.7
154 WPC	Fast Response Cutter	USCG	2	1	24	0	32.2

Assets are assigned to the closest locations, which is assumed to be known a priori, when the rescue event is initiated. The majority of the planes are located around Anchorage and Kodiak with a few exceptions. For instance, the Learjet 31A type aircraft is often positioned in Utqiaġvik (Griner, 2013) and will be deployed there. These initial locations for the planes are kept the same regardless of the incident area throughout our analysis. On the other hand, since Coast Guard ships are actively used for normal operations, we prefer not to fix a location to ships. Ships are deployed to their initial locations based on the incident area meaning that initial locations may vary across instances. For example, data for the incidents can capture the case where certain ships (e.g., sister ship(s)) 'move' with the cruise ship in order to respond to an incident.

The stock levels of available resources and equipment in each location are illustrated in Section B of the Online Appendix. We assume that the cruise ship would have enough supplies to satisfy all evacuees' demands for the first six time periods of the response. We assume that no resource can be taken out from the ship when an evacuee is placed on a ship. Equipment demand will be satisfied while the evacuees are on the ship. Given the relative population sizes of Utqiaġvik, Kotzebue and Nome, we assume that there is some level of water and food that can be used in the MRE. In addition, as a result of having Level 4 Trauma Centers, there is medical support in Utqiaġvik, Nome, and Kotzebue. We assume a large stockpile in Anchorage for all the commodity types. Public facilities (e.g., churches, sport centers etc.) could be utilized in response events in lieu of portable shelters and will be included in our analysis. We also note that the level of resources available in Anchorage are at least an order of magnitude larger than those available in the villages and, therefore, for the purposes of modeling the MRE, we do not need to capture allocation decisions there.

Please see Section B in the Online Appendix for tables describing: i) the initial deployments locations for ships according to the incident area, ii) details around resources and equipment and how they impact the evacuees, and iii) the flow networks designed for the evacuation balance constraints.

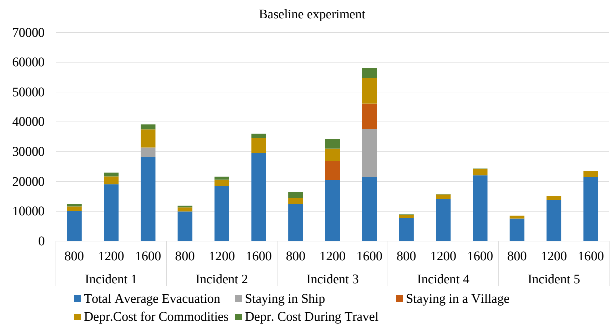
6.2 Baseline Experiment

During our experiments, we set a time limit of 60 minutes. If the solution method does not converge to the optimal solution within the time limit, the best solution obtained by then together with its optimality gap is reported. Lastly, for each experiment, we examine a total of fifteen different scenarios consisting of five different incident locations along with three different levels of evacuees. We start our discussion with a baseline experiment where we assume that there is a sufficient set of resources and conditions (e.g., travel times) are in an ideal setting. We will vary certain parameters from this baseline (e.g., when planes are available) in examining critical aspects of the response. For this baseline, we consider only a subset of the previously described assets during the response (see Table 7).

We discuss the computational performance of various approaches to solve the problem in the Online Appendix (see Section E). Of note, warm-starting CPLEX with either heuristic significantly outperforms directly solving the model. Further, the intuitive COBOH results in solutions with gaps well over 10%, thus indicating the importance of using optimization to examine response efforts. Based on this analysis, we will conduct the remaining experiments by warm-starting the IP with the solution identified by OTH.

We now provide detailed analysis on the baseline experiment. Fig 3 depicts the objective values for each scenario. The total average evacuation time is computed as the sum of the average time to leave the cruise ship and the average time to arrive at Anchorage. Recall that lower objectives indicate a more 'successful' response since we are focusing on minimizing the total of evacuation time and the impact on the evacuees.

It is important to mention that the model is able to successfully complete the response event in all the scenarios except Incident 1-1600 and Incident 3-1600. The reason for the failure in Incident 1-1600 lies behind the fact that the travel times from Incident 1 to the closest communities of Kotzebue and Nome are longer compared to the other incident areas. In fact, the model does not transport any evacuee to other communities (see Fig 4) since there exist sufficient hosting and airport capacities in both communities. As for Incident 3, since large planes, which comprise 87% of the total capacity provided by all the planes, cannot be utilized in the small villages, the model transports a number of evacuees to the farther communities (e.g., Kotzebue and Utqiaġvik). This results in higher travel times when using ships which also causes another negative impact since it takes more time to evacuate people from the cruise ship.



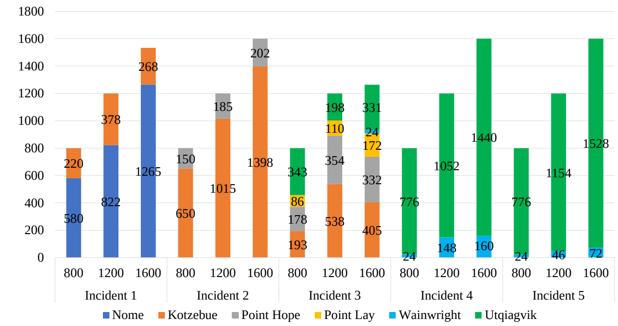


Figure 3: Objective val. in the baseline experiment Figure 4: The villages used in the baseline experiment

Further, we observe high penalty costs due to leaving some evacuees in the villages in Incident 3 when there are 1200 and 1600 passengers. The shorter runways in the airports prevent the use of large planes from landing in the small villages close to Incident 3, thus delaying transport of evacuees or causing them to go to large villages far away from the incident location. For instance, the number of evacuees who cannot not make it to Anchorage and have to stay in in Point Hope and Point Lay by the end of the rescue operation is equal to 200 and 267 for 1200 and 1600 passengers, respectively. These people would not stay in these villages indefinitely but there are significant penalties for them being there at the end of the horizon.

Overall, the transportation decisions have the greatest influence on the objective. When evacuating people from the incident and from the local communities is delayed, it not only increases the total evacuation time, but it exponentially increases the total deprivation costs due to the limited amount of available resources. However, the bottleneck is the transportation decisions concerning passengers. We observed that the planes are able to move resources and equipment into the villages at or before the time evacuees arrive into the village and, therefore, the 'arrival time' into the village has the most impact on deprivation costs. Therefore, resources and equipment enter the Arctic quickly enough in support of a rescue operation. Although we did not specifically model the concept of an Arctic fulfillment package, our results show that if these packages are the quickest way to provide resources and equipment, then they play an important role in the response.

It can be seen that the worst response performances are observed in Incidents 1 and 3. This clearly indicates that there exists a strong correlation between the closeness of the incident area to the local communities and the capacities. Even though we have plenty of capacity around Incident 1, as a result of long travel distances, the evacuees suffer and the rescue event is challenging. While we have close communities located around Incident 3, these small villages have limitations on how they can be used during the response (e.g., the types of planes that can land there). Hence, the rescue event is still challenging.

Another significant finding is that the response to Incident 4 is slightly worse than the response to Incident 5 in each scenario (i.e., 800, 1200, and 1600 passengers). This is somewhat counter-intuitive in the sense that Incident 4 could more easily take advantage of Point Lay, Wainwright and Utqiaġvik. However, the response to Incident 5 performs better since the incident is closer to the larger community of Utqiaġvik.

Lastly, we provide the list of the villages used in each incident location in Fig 4, where each column shows the villages together with the number of evacuees transported there. Overall, Utqiaġvik and Kotzebue are important large communities and Point Hope stands as a significant small community.

Managerial insights: It would be important to either increase the number of ships around Nome and Kotzebue or locate ships that improve upon capacity or speed in order to address the 'response gap' in this area. It could also be quite useful to incorporate some infrastructure developments in small villages to be able to utilize larger aircraft and/or host more evacuees. In our remaining analysis, we will focus on the impacts of such decisions.

6.3 'What If' Analysis

In this section, we focus on examining various what-if scenarios that alter the data associated with our baseline experiment to understand key issues around response capabilities. Our experiments address: (i) the improvement in response when new infrastructure is developed in the Arctic, (ii) the impact on response when it faces challenges (e.g., weather), and (iii) situations that combine (i) and (ii).

6.3.1 Experiment 1: Improving Infrastructure in the Arctic

There may be opportunities to invest in improving infrastructure in order to increase the 'slack' in these systems so that they may be able to better handle emergency response. We look to answer the following question: *"How much positive effect may be seen when airport and hosting capacities are increased and the runway lengths are upgraded in the small villages?"*. Here, the airport and hosting capacities are increased by one and 20%, respectively, and runways lengths are upgraded in order to land any type of aircraft.

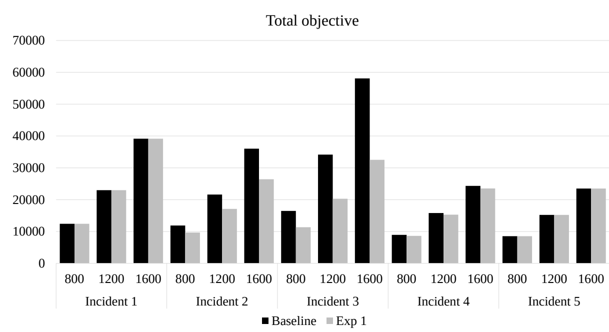


Figure 5: The total objective values in the baseline experiment and Experiment 1

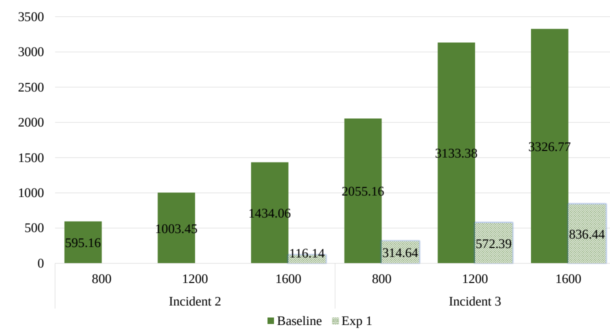


Figure 6: The deprivation costs incurred during travel in the baseline experiment and Experiment 1

First, we point out that the investments that are proposed for the small villages did not improve the response for Incidents 1 and 5 (see Fig 5). Reaching the small villages still takes the same amount of time via the ships. Hence, utilizing the closest villages, which are known to have high capacities, under the baseline is still preferred. For example, although Wainwright has improved its capabilities, Utqiaġvik still has significant response capacity and we use it as the center of the response in Incident 5.

We do see an improvement of between 15%-25% and 30%-45% in response capabilities for Incidents 2 and 3, respectively (see Fig 5). For Incident 2, while on average 84% of the evacuees are transported to Kotzebue in the baseline experiment, this ratio drops sharply to 7% in Experiment 1. Point Hope becomes a more appealing location to move the evacuees since there are major infrastructural improvements in the small villages. We observe a significant decrease in the deprivation costs during travel (see Fig 6). This is because all the ships can reach the cruise ship from Point Hope within one time period while it takes, on average, 1.8 periods to reach Kotzebue. We observe a very similar pattern in Incident 3 and the model no longer transports any evacuee to Utqiaġvik. Further, improvements in the objective value in Incident 3 occur due to the fact that no evacuee is left in the villages as a result of the improvements to the airports.

As for Incident 4, Wainwright becomes nearly as important as Utqiaġvik by hosting roughly half of the total evacuees. As a result, the total average evacuation time and the deprivation costs for commodities decrease. Yet, we observe only a 3.5% decline on average in terms of the total objective. We believe that the reason behind such a small decrease is the fact that though Wainwright is highly utilized, it takes longer time to reach Wainwright compared to Utqiaġvik from the cruise ship. For example, while we do not observe any deprivation costs during travel in the baseline experiment in Incident 4, this trend changes in Experiment 1.

Managerial insights: We believe that infrastructure investments in terms of both improving the runways and increasing the hosting capacities in Point Hope and Wainwright would be quite beneficial. Both communities could play an important role in different incidents due to their central locations in areas between larger Arctic communities. However, our results suggest that additional infrastructure investment in some communities may have limited benefit, as incidents close to Nome, Kotzebue, and Utqiaġvik are responded to better than those incidents in more remote areas.

6.3.2 Experiment 2: Restricting the Air Transportation as a Result of the Bad Weather Conditions

We ask the following question: *"What is the (negative) impact to response capabilities when air operations are impacted by weather conditions?"*. To answer this, we introduce a new constraint such that no flight is operated between $t = 1$ and $t = 8$, which helps to model a storm that would ground air operations.

We provide a comparison of the objective values with the baseline experiment in Fig 7. When air operations are restricted as a result of bad weather conditions seen in the region, the model fails to bring everyone to Anchorage when there are 1600 passengers in every incident, which is why there is a high penalty cost due to leaving some evacuees in the villages. In addition, the model leaves 57 more evacuees in the cruise ship in Incident 3 when there are 1600 passengers. It is worth mentioning that airport restrictions in the small villages create a bottleneck and remain tight after the air operations are started. Therefore, this indicates that investments to improve the airports in the small villages would be quite beneficial in a response.

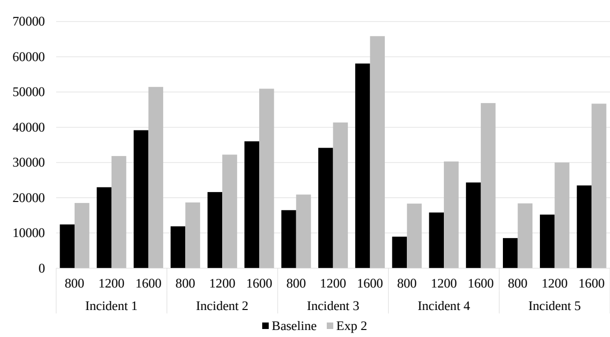


Figure 7: The total objective values in the baseline experiment and Experiment 2

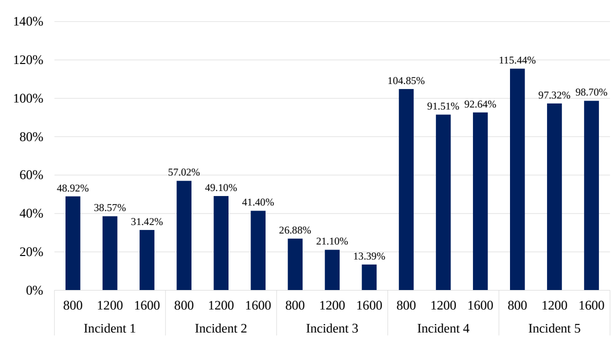


Figure 8: The percentage increase in the objective in Experiment 3 compared to the baseline experiment

Restricting the air transportation has another negative impact since we can no longer move resources and equipment into villages. This results in a significant increase in the deprivation costs for commodities in every scenario (i.e, 63% on average). For instance, the deprivation cost increases more than five times in Incident 5-1600 (e.g., from 2000.83 to 10,620.59). This helps to indicate that resource and equipment stockpiles are not sufficient to support evacuees for long periods of time without replenishment.

In terms of the impact on response capabilities, Fig 8 provides the increase in the objective functions across all incidents from the baseline to this particular situation. We can view large gaps as significantly decreasing response capabilities. Incidents 4 and 5 are most impacted in terms of an increase to the objective. This is because we were able to evacuate people quickly through Utqiaġvik for these incidents in the baseline but since the planes are now grounded, we now need to have evacuees wait in this community. Incident 3 experiences the relative smallest increase. This is due to the fact that the arrival times into the villages from the distressed ship were a significant part of the objectives and this does not change as air operations are grounded. We observe that the percentage increase decreases in a linear way in Incidents 1,2 and 3 while the number of passengers are increasing. Meanwhile, the objective value rises approximately half in Incident 3 and the response becomes nearly identical with Incident 1 in terms of the objective values.

Managerial insights: It could be useful to stockpile more relief commodities to be used during an emergency response event in larger villages including both Kotzebue and Utqiaġvik when infrastructure development is not possible. The response tends to favor utilizing larger villages to transport evacuees. Hence, if an infrastructure improvement is not possible in the region, then holding extra relief commodities in larger villages would be preferred as an alternative in order to ensure longer support for evacuees as they arrive into the larger communities or as resources are transported to the smaller communities where evacuees may be.

6.3.3 Experiment 3: Decreasing the Speed of Ships Due to Navigating with Sea Ice

Weather conditions do not only cause problems in the air operations but also ships traveling in the sea. In particular, there may be sea ice in and around the ships as they travel in the Arctic. The USCG owns polar-class icebreakers should ships become iced-in. Navigation in the uncertain conditions surrounding sea ice may also reduce the speed at which ships can travel. We, therefore, examine the response under conditions where the ship travel times would increase to move between the cruise ship and the villages. In this case, the travel time of each ship is increased by one. One important observation in this case is that the model fails to evacuate everyone from the cruise ship in all the incident locations with 1600 passengers as shown in Fig 9. Note that the model does not utilize a different transportation path for the evacuees in any of the incidents and use the same villages as presented in Fig 4, but may leave more evacuees in the cruise ship.

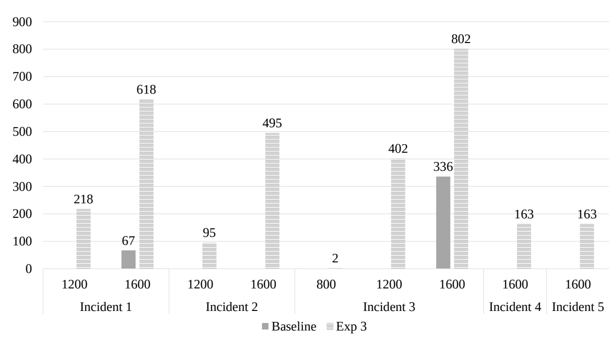


Figure 9: The number of evacuees stayed in the C. ship at $|T|$ in the baseline experiment and Exp. 3

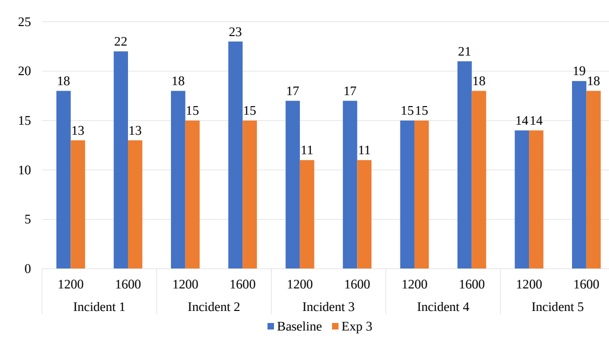


Figure 10: The total number of tours completed by the ships in the baseline experiment and Exp. 3

The impact to response capabilities can be explained by examining the number of 'tours' that are made from the cruise ship to the villages by ships. We define a tour as the travel from a village to cruise ship and from cruise ship to a village for a ship. Fig 10 compares the number of tours under the baseline and this experiment with 1200 and 1600 passengers. Note that the number of tours does not really change with 800 passengers due to the available total passenger capacity provided by the ships. Under Experiment 3, the total number of tours made by the ships ends up significantly decreasing from their baseline when there are 1600 evacuees for Incidents 1,2, and 3 (i.e., 35% decrease) and slightly decreases for Incidents 4 and 5. In these cases, we no longer have the capacity to evacuate everyone from the cruise ship within the planning horizon.

Furthermore, Incident 2 and 4 are negatively impacted as a result of the evacuees who are left in the villages. For instance, the number of evacuees sent to Point Hope increases by around 40% with 1200 and 1600 passengers compared to the baseline experiment in Incident 2. Since the ship speeds are decreased, the model sends more evacuees to Point Hope due to its closeness to the incident area (i.e., Incident 2) in spite of its limitations. As for Incident 4, the number of the evacuees sent to Wainwright doubles when there are 1600 passengers. It is worth mentioning that no hosting capacity of a village is fully utilized here, confirming that the airport limitations are the bottleneck (not hosting capacity) of the small villages.

Managerial insights: We have identified that a larger number of ships may need to be present in challenging navigation conditions (which causes its own problems) in order to achieve the same response as our baseline experiments. In addition, increasing airport capacities in terms of upgrading the runways is more critical than investing in the hosting capacities. Therefore, our results suggest airport improvements as a critical aspect of potentially improving emergency response.

6.3.4 Experiment 4: Increasing Infrastructure in Small Villages and Decreasing the Speed of Ships

We now examine if improving the infrastructure systems in the small villages improve response capabilities (similar to Experiment 1) when ships are moving slower than their ideal speed (similar to Experiment 3). We will increase the airport capacities by one, improve the length of their runways, and decrease the speed of ships by one time unit. We will then determine the improvement in response capabilities from Experiment 3 from the infrastructure improvements. We do not see any improvement in response capabilities from Experiment 3 for Incidents 1 and 5 (see Fig 11), since almost all evacuees in these incidents are routed through Nome, Kotzebue, and Utqiaġvik. We see slight improvements in response capabilities in Incident 4 and major improvements in Incidents 2 and 3 (on average a 5.84%, 20.66% and 24.12% decrease, respectively), which are similar to the ones from the baseline to Experiment 1.

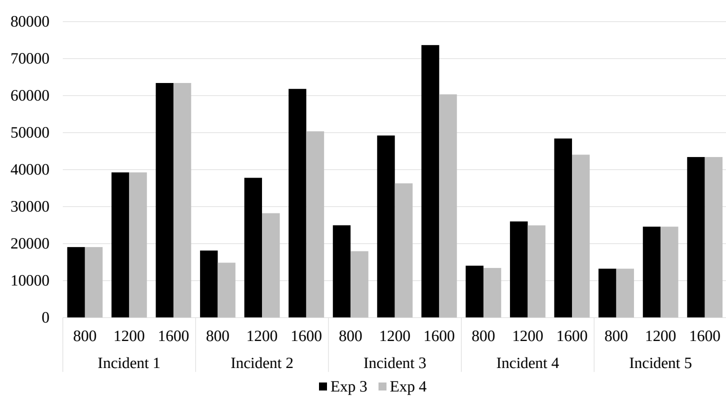


Figure 11: The total objective values in Experiment 3 and Experiment 4

The impact of the extra airport capacity together with the upgraded runways is twofold. First, the model completely changes the transportation path for the evacuees in Incidents 2, 3 and 4. For example, while there are evacuees transported to Kotzebue and Utqiaġvik in Incident 3, all the evacuees left the cruise ship are transported only to Point Hope and Point Lay with Experiment 4. Second, in Incident 4, although it does not change the number of evacuees left in the cruise ship, it decreases the number of evacuees (i..e, from 184 to 24) that cannot make it out of the Arctic due to the improvements in Wainwright.

We emphasize that Point Hope is the key village for both Incidents 2 and 3. When improving the airport infrastructure in Pont Hope, the model no longer uses Kotzebue and Utqiaġvik in Incident 3. More evacuees are carried to Point Hope in Incident 2 while Kotzebue is less used.

Managerial insights: This experiment reveals that airport investments in Point Hope would likely be important (depending on their feasibility) in improving response capabilities in the face of challenging situations. Thus, we believe that Point Hope could be the key location in the entire region for the infrastructure investments.

6.3.5 Experiment 5: Increasing the Number of Evacuees in Higher Priority Levels

Here, we increase the number of evacuees in Priority 2 (i.e., 35% of the total evacuees), and decrease in Priority 1 (i.e., 55% of the total evacuees). Our goal is to test whether a) transportation decisions would change, and b) logistic decisions would experience major changes. In this analysis, the core transportation decisions remain the same and, therefore, the evacuation portion of the objective remains the same. Therefore, priority is still given to this piece of the MRE. As expected, we do see a slight increase in deprivation costs since more evacuees are at a higher priority level. The only major increase occurs in Incident 3 (e.g., an increase of 11% for the deprivation costs when evacuating 1600 people). This is because the evacuees stay longer in the Arctic and the penalty from the change to the priority levels in this experiment accumulates.

Managerial insights: Although each air asset uses its maximum capacity, enough relief commodities cannot be carried when the priority levels have shifted. Hence, improving the infrastructure in one of the small villages and/or pre-positioning relief commodities might be an effective solution for such scenario.

7 Conclusion

In this study, we have focused on how to respond to a MRE in Arctic Alaska. Our contributions are that we propose a novel IP model whose main objective is to evacuate people from the distressed ship to the local villages around the Arctic and then transport them out of the Arctic while minimizing the negative impact of the event on them. We conduct extensive analysis of potential MREs along the route the *Crystal Serenity* traveled through Arctic Alaska. Our work helps to focus on concerns about Arctic MREs that are increasingly likely to occur given the shift in Arctic maritime transportation and tourism.

The human costs we identify and the emergency response gaps that are modeled are capable of assessing situations broader than the U.S. Arctic and impact all Arctic nations to varying degrees. This work helps to make a case that optimization models can help to address operational gaps for Arctic MREs, where these gaps have been practically recognized but not modeled previous to our efforts. Our paper models the tradeoffs that policy makers, regulators and transportation logistics professionals must consider as transportation in remote and infrastructure-poor settings increases due to climate and ecosystem changes.

Highlights obtained from our computational analysis are as follows. The accidents occurring around Nome and Kotzebue (Incidents 1 and 2) had a major issue that not everyone would be able to evacuate from the cruise ship within a reasonable evacuation horizon due to the long distances between the incident and Arctic villages. This is due both to the speed which ships can travel and the number of ships involved in the response. Therefore, in order to mitigate this vulnerability, it is suggested that additional ships are made available to respond to an incident in this area (near the Bering Strait). In addition, the response capabilities for these incidents are the least sensitive to both infrastructure improvements and challenges in the response.

The most impactful change in improving response capabilities for Incident 2 is in improving airport capacity and upgrading the runway of Point Hope since it is closer to Incident 2 than Kotzebue but has significantly fewer people. In addition, this investment would help the response to Incident 3. When infrastructure investments are made in the small villages, evacuees no longer travel to communities further away from the incident and Point Hope plays the central role during the rescue operation. One recommendation to help improve response capabilities in the Arctic would be to invest in the necessary capabilities to have Point Hope (or a similar village in the area) play a more significant role in the response. Note that Point Hope may not be the only option (it was in our case study since it is in the North Slope Borough) for these potential upgrades. Wales sits at the smallest part of the Bering Strait and could also significantly impact response capabilities.

We further observed how critical the village of Utqiaġvik (the largest village in Arctic Alaska) was in responding to MREs. The response to Incidents 4 and 5 route the majority of evacuees through this village (although for Incident 4, it collaborates with Wainwright in the response). These experiments indicate that the 'ground' capacity of Utqiaġvik is sufficient to move evacuees through it during the response. We do assume that larger ships are relatively close to the incidents when they occur, which helps to indicate that these should be in the area while the cruise ship travels through it.

In terms of future work, it will be critical to understand the practical feasibility of the optimized responses. Although the model was built based on discussions with subject matter experts, the output of the model has not been carefully vetted with both those involved in the response and those that represent the villages that would be impacted. This type of vetting may lead to the discovery that certain core assumptions in the model should be updated. Community buy-in to the optimization model will allow for its practical deployment. Further, we can improve upon this work by modeling how infrastructure investments should be made across Arctic Alaska to best improve our overall response capabilities. It is our long-term goal to build such infrastructure investment models that not only account for response capabilities but also capture the benefits (or negative impacts) of the infrastructure development on the communities which it is built.

Acknowledgments

This work was supported by the U.S. National Science Foundation the CMMI division under grant number 1825486. The support of Thomas A. Birkland and Marie Lowe in the verification of the modelling assumptions and analysis of the results are gratefully acknowledged. Lastly, we appreciate the suggestions of anonymous reviewers that have greatly helped improve the content in this paper.

References

Aiello, G., Hopps, F., Santisi, D., Venticinque, M., 2020. The employment of unmanned aerial vehicles for analyzing and mitigating disaster risks in industrial sites. IEEE Transactions on Engineering Management 67, 519–530.

Alaska Airlines, 2020. Our aircraft. https://www.alaskaair.com/content/travel-info/our-aircraft/. (Accessed on 11/03/2020).

Alaska Department of Health and Social Services, 2018. Trauma System in Alaska. http://dhss.alaska.gov/dph/Emergency/Pages/trauma/default.aspx. (Accessed on 12/29/2019).

Allison, E., Mandler, B., 2018. Oil and Gas in the U.S. Arctic. https://www.americangeosciences.org/geoscience-currents/oil-and-gas-us-arctic. (Accessed on 01/07/2020).

Arctic Domain Awareness Center, 2016. Arctic-related incidents of national significance workshop. https://arcticdomainawarenesscenter.org/Downloads/PDF/Arctic%20IoNS/ADAC_Arctic%20IoNS%202016_Report_160906.pdf. (Accessed on 03/03/2021).

Arctic Domain Awareness Center, 2021. Arctic maritime horizons workshop. https://arcticdomainawarenesscenter.org/Events. (Accessed on 03/22/2021).

Brady, C., 2019. Boeing 737 Detailed Technical Data. http://www.b737.org.uk/techspecsdetailed.htm. (Accessed on 12/04/2019).

Brooks, A.D., 2020. Search & Rescue in The North Slope Borough. http://www.north-slope.org/departments/search-rescue. (Accessed on 01/20/2020).

Cessna, 2019. Cessna Caravan. https://cessna.txtav.com/en/turboprop/caravan. (Accessed on 12/04/2019).

Chankong, V., Haimes, Y.Y., 2008. Multiobjective decision making: Theory and methodology. Courier Dover Publications.

Coast Guard News, 2016. Coast guard partners industry conduct mass rescue tabletop exercise in Anchorage Alaska. https://coastguardnews.com/coast-guard-partners-industry-conduct-mass-rescue-tabletop-exercise-in-anchorage-alaska/2016/04/21/. (Accessed on 12/29/2019).

Division of Homeland Security & Emergency Management, 2019. Resource Catalog. https://www.ready.alaska.gov/SEOC/ResourceCatalog. (Accessed on 12/04/2019).

Doan, X.V., Shaw, D., 2019. Resource allocation when planning for simultaneous disasters. European Journal of Operational Research 274, 687–709.

Eckstein, M., 2021. New Arctic Strategy Calls for Regular Presence as a Way to Compete With Russia, China . https://news.usni.org/2021/01/05/new-arctic-strategy-calls-for-regular-presence-as-a-way-to-compete-with-russia-china. (Accessed on 03/08/2021).

Elbaih, A.H., Alnasser, S.R., 2020. Teaching approach for START triage in disaster management. Medicine 9, 4.

Elmhadhbi, L., Karray, M.H., Archimède, B., Otte, J.N., Smith, B., 2020. A semantics-based common operational command system for multiagency disaster response. IEEE Transactions on Engineering Management , 1–15. doi:10.1109/TEM.2020.3013109.

Farahani, R.Z., Lotfi, M., Baghaian, A., Ruiz, R., Rezapour, S., 2020. Mass casualty management in disaster scene: A systematic review of OR&MS research in humanitarian operations. European Journal of Operational Research 287, 787–819.

Federal Aviation Administration, 2019. Alaskan Region Airports Division. https://www.faa.gov/airports/alaskan/. (Accessed on 03/11/2020).

Garrett, R.A., Sharkey, T.C., Grabowski, M., Wallace, W.A., 2017. Dynamic resource allocation to support oil spill response planning for energy exploration in the Arctic. European Journal of Operational Research 257, 272–286.

GCR, 2017. AirportIQ 5010. https://www.airportiq5010.com/5010web/. (Accessed on 01/31/2020).

Griner, C., 2013. Learjet 31A Rescue Bird in search and rescue. https://www.flickr.com/photos/air_traveller/10392962794. (Accessed on 12/04/2019).

Harila, L.A., 2019. Emergency response logistics in the High Arctic–Rescue helicopter coverage in the Norwegian High Arctic in the event of an expedition cruise ship mass-evacuation. Master's thesis. Nord Universitet.

Hoag, H., 2016. NOAA is Updating its Arctic Charts to Prevent a Nautical. https://deeply.thenewhumanitarian.org/arctic/community/2016/08/29/noaa-is-updating-its-arctic-charts-to-prevent-a-nautical-disaster. (Accessed on 03/08/2021).

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L.N., Aros-Vera, F., 2013. On the appropriate objective function for post–disaster humanitarian logistics models. Journal of Operations Management 31, 262–280.

Hu, M., Cai, W., Zhao, H., 2019. Simulation of passenger evacuation process in cruise ships based on a multi-grid model. Symmetry 11, 1166.

Humpert, M., 2018. Arctic Cruise Ship Runs Aground in Canada's Northwest Passage. https://www.highnorthnews.com/en/arctic-cruise-ship-runs-aground-canadas-northwest-passage. (Accessed on 12/29/2019).

Humpert, M., 2019. New Satellite Images Reveal Extent of Russia's Military and Economic Build-Up in the Arctic. https://www.highnorthnews.com/en/new-satellite-images-reveal-extent-russias-military-and-economic-build-arctic. (Accessed on 12/04/2019).

International Maritime Organization, 2016. International code for ships operating in polar waters. http://www.imo.org/en/MediaCentre/HotTopics/polar/Documents/POLAR%20CODE%20TEXT%20AS%20ADOPTED.pdf. (Accessed on 09/14/2020).

Jenkins, P.R., Lunday, B.J., Robbins, M.J., 2019. Robust, multi-objective optimization for the military medical evacuation location-allocation problem. Omega , 102088.

Li, Y., Zhang, J., Yu, G., 2020. A scenario-based hybrid robust and stochastic approach for joint planning of relief logistics and casualty distribution considering secondary disasters. Transportation Research Part E: Logistics and Transportation Review 141, 102029.

Li, Z., Swann, J.L., Keskinocak, P., 2018. Value of inventory information in allocating a limited supply of influenza vaccine during a pandemic. PLOS One 13, 206–293.

Liu, Y., Cui, N., Zhang, J., 2019. Integrated temporary facility location and casualty allocation planning for post-disaster humanitarian medical service. Transportation Research Part E: Logistics and Transportation Review 128, 1–16.

Mak, L., Farnworth, B., Wissler, E.H., DuCharme, M.B., Uglene, W., Boileau, R., Hackett, P., Kuczora, A., 2011. Thermal requirements for surviving a mass rescue incident in the Arctic: Preliminary results, in: ASME 2011 30th International Conference on Ocean, Offshore and Arctic Engineering, American Society of Mechanical Engineers Digital Collection. pp. 375–383.

McKee, C.H., Heffernan, R.W., Willenbring, B.D., Schwartz, R.B., Liu, J.M., Colella, M.R., Lerner, E.B., 2020. Comparing the accuracy of mass casualty triage systems when used in an adult population. Prehospital Emergency Care 24, 515–524.

McNutt, C., 2016. Northwest Passage 2016 Exercise, After Action Report. `https://www.hsdl.org/?abstract&did=802138`. (Accessed on 12/29/2019).

National Oceanic & Atmospheric Administration, 2021. NOAA surveys the unsurveyed, leading the way in the U.S. Arctic. `https://nauticalcharts.noaa.gov/updates/noaa-surveys-the-unsurveyed-leading-the-way-in-the-u-s-arctic/`. (Accessed on 03/08/2021).

Neelam, S., Sood, S.K., 2020. A scientometric review of global research on smart disaster management. IEEE Transactions on Engineering Management 68, 317–329.

Office of Aviation Forces, 2019. USCG Fixed Wing & Sensors Division (CG-7113). `https://www.dco.uscg.mil/Our-Organization/Assistant-Commandant-for-Capability-CG-7/Office-of-Aviation-Force-CG-711/Fixed-Wing-Sensors-Division-CG-7113/`. (Accessed on 12/04/2019).

Østhagen, A., 2020. Maritime Tasks and Challenges in the Arctic, in: Coast Guards and Ocean Politics in the Arctic. Springer, pp. 25–32.

Pérez-Rodríguez, N., Holguín-Veras, J., 2015. Inventory–allocation distribution models for postdisaster humanitarian logistics with explicit consideration of deprivation costs. Transportation Science 50, 1261–1285.

Rambha, T., Nozick, L.K., Davidson, R., Yi, W., Yang, K., 2021. A stochastic optimization model for staged hospital evacuation during hurricanes. Transportation Research Part E: Logistics and Transportation Review 151, 102321.

Ramirez-Nafarrate, A., Araz, O.M., Fowler, J.W., 2021. Decision assessment algorithms for location and capacity optimization under resource shortages. Decision Sciences 52, 142–181.

RavnAir Alaska, . The Ravn Aircraft Fleet Specifications. https://www.flyravn.com/about-us/aircraft-fleet/. (Accessed on 12/04/2019).

Rodríguez-Espíndola, O., Alem, D., Da Silva, L.P., 2020. A shortage risk mitigation model for multi-agency coordination in logistics planning. Computers & Industrial Engineering 148, 106676.

Ruskin, L., 2018. China seeks bigger role in Arctic. https://www.alaskapublic.org/2018/02/06/china-seeks-bigger-role-in-arctic/. (Accessed on 02/05/2020).

Sabouhi, F., Bozorgi-Amiri, A., Moshref-Javadi, M., Heydari, M., 2019. An integrated routing and scheduling model for evacuation and commodity distribution in large-scale disaster relief operations: A case study. Annals of Operations Research 283, 643–677.

Sarma, D., Das, A., Dutta, P., Bera, U.K., 2020. A cost minimization resource allocation model for disaster relief operations with an information crowdsourcing-based mcdm approach. IEEE Transactions on Engineering Management , 1–21. doi:10.1109/TEM.2020.3015775.

Schofield, C., Østhagen, A., 2020. A Divided Arctic: Maritime Boundary Agreements and Disputes in the Arctic Ocean, in: Handbook on Geopolitics and Security in the Arctic. Springer, pp. 171–191.

Setiawan, E., Liu, J., French, A., 2019. Resource location for relief distribution and victim evacuation after a sudden-onset disaster. IISE Transactions 51, 830–846.

Sherman, R., 2000. C-17 Globemaster III. https://fas.org/man/dod-101/sys/ac/c-17.htm. (Accessed on 12/04/2019).

Shu, J., Lv, W., Na, Q., 2021. Humanitarian relief supply network design: Expander graph based approach and a case study of 2013 flood in northeast china. Transportation Research Part E: Logistics and Transportation Review 146, 102178.

Statista Research Department, 2020. Cruise industry statistics & facts. https://www.statista.com/topics/1004/cruise-industry/. (Accessed on 03/08/2021).

Stauffer, J.M., Kumar, S., 2021. Impact of incorporating returns into pre-disaster deployments for rapid-onset predictable disasters. Production and Operations Management 30, 451–474.

Stepanov, A., Smith, J.M., 2009. Multi-objective evacuation routing in transportation networks. European Journal of Operational Research 198, 435–446.

Struzik, E., 2018. In the Melting Arctic, a Harrowing Account from a Stranded Ship. https://e360.yale.edu/features/in-the-melting-arctic-harrowing-account-from-a-stranded-ship. (Accessed on 03/11/2020).

Sung, I., Lee, T., 2016. Optimal allocation of emergency medical resources in a mass casualty incident: Patient prioritization by column generation. European Journal of Operational Research 252, 623–634.

Triantaphyllou, E., 2000. Multi-criteria decision making methods, Springer, pp. 5–21.

United Nations, 2020. Passenger Vessels. London, UK: The International Maritime Organization (IMO). http://www.imo.org/en/OurWork/Safety/Regulations/Pages/PassengerShips.aspx. (Accessed on 09/05/2020).

United States Air Force, 2008. HC-130P/N. https://www.106rqw.ang.af.mil/About-Us/Fact-Sheets/Display/Article/1041575/hc-130pn/. (Accessed on 12/04/2019).

U.S. Bureau of the Census, 2019. The United States Census 2020. https://www.census.gov/. (Accessed on 12/29/2019).

US EPA, 2020. Summary of the Oil Pollution Act: Laws & Regulations. https://www.epa.gov/laws-regulations/summary-oil-pollution-act#:~:text=33%20U.S.C.&text=The%20Oil%20Pollution%20Act%20(OPA,or%20unwilling%20to%20do%20so. (Accessed on 09/05/2020).

USCG, 2016. Operational Assets. https://www.work.uscg.mil/Assets/. (Accessed on 12/04/2019).

Waldholz, R., 2016. In Warmer Climate, A Luxury Cruise Sets Sail Through Northwest Passage. https://www.npr.org/2016/08/27/491337521/in-warmer-climate-a-luxury-cruise-sets-sail-through-northwest-passage. (Accessed on 12/29/2019).

World Health Organization, 2019. Publications on water sanitation and health. https://www.who.int/water_sanitation_health/publications/en/. (Accessed on 12/04/2019).

Ye, Y., Jiao, W., Yan, H., 2020. Managing relief inventories responding to natural disasters: Gaps between practice and literature. Production and Operations Management 29, 807–832.

Yu, L., Yang, H., Miao, L., Zhang, C., 2019. Rollout algorithms for resource allocation in humanitarian logistics. IISE Transactions 51, 887–909.

Zhong, S., Cheng, R., Jiang, Y., Wang, Z., Larsen, A., Nielsen, O.A., 2020. Risk-averse optimization of disaster relief facility location and vehicle routing under stochastic demand. Transportation Research Part E: Logistics and Transportation Review 141, 102015.

Online Appendix

A Illustrative Example

We provide an illustrative example to elaborate on how the allocations decisions are conducted and start our discussion with the assumptions specifically made for this example. We only consider allocating one resource for the sake of simplicity. Thus, only resource allocation decisions are taken into consideration: (i) an evacuee receives the required resource or (ii) an evacuee cannot receive the required resource.

Note that all the decisions (i.e., transportation and allocation) are made at the end of each time period. We are currently in time period 4 of the evacuation and seven evacuees have reached communities. There are two priority levels and three communities. We focus on a single type of resource (e.g., food) so we are only keeping track of s^r and travel between the communities requires one time period.

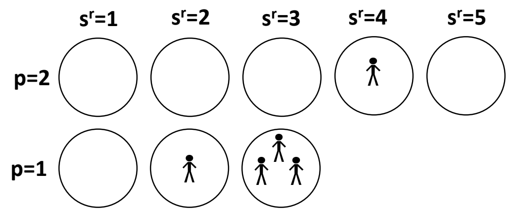


Figure 12: Evacuees in community 1 at time 4

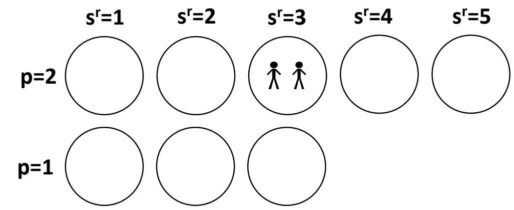


Figure 13: Evacuees in community 2 at time 4

Fig 12 and Fig 13 illustrate the status of the seven evacuees across the two communities they are located. In Community 1, we have one evacuee with ($p = 1, s^r = 2$), three evacuees with ($p = 1, s^r = 3$), and one with ($p = 2, s^r = 4$). In Community 2, we have two evacuees with ($p = 2, s^r = 3$). In Community 1, there is enough food to satisfy three evacuees' demands. There is not enough food in Community 2 to satisfy the demands of the evacuees.

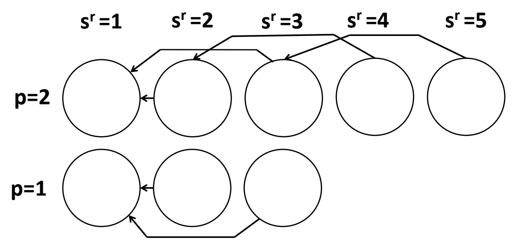


Figure 14: Movements when resource demand is not satisfied

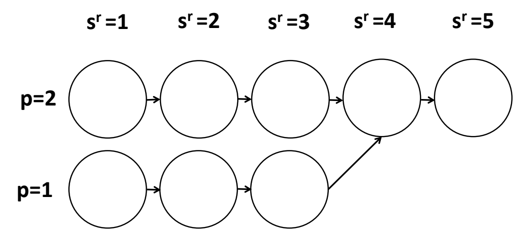


Figure 15: Movements when resource demand is satisfied

In order to understand the (p,s^r) status of the evacuees in the next time period, $t = 5$, resource allocation decisions are made and evacuees move along arcs represented in Fig 14 and Fig 15. Note that the 'priority jump' occurs when $s^r = 3$.

The following allocation decisions were made in time period $t = 4$ resulting in the movements pictured in Fig 16 and Fig 17:

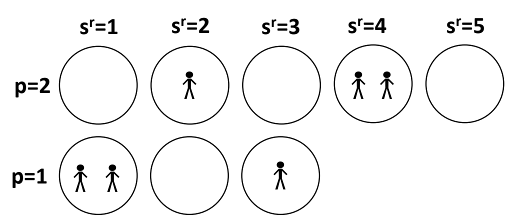


Figure 16: Evacuees in community 1 at time 5

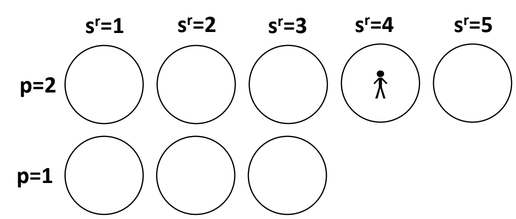


Figure 17: Evacuees in community 3 at time 5

- In Community 1, food is allocated to the evacuee at node ($p = 2, s^r = 4$) due to their higher priority level and this person will transition to ($p = 2, s^r = 2$) in the next time period. The two other units of food are distributed to two evacuees in ($p = 1, s^r = 3$), which prevents them from jumping the next priority level (see Fig 16).
- The third evacuee in Community 1 with ($p = 1, s^r = 3$) is transported to Community 3 by a plane.

When this evacuee arrives in Community 3, his status level will be ($p = 2, s^r = 4$) since he reached the jump (see Fig 17). The evacuee in Community 1 with ($p = 1, s^r = 2$) will not receive food and therefore transition to ($p = 1, s^r = 3$) in the next time period.

- The two evacuees who are in Community 2 depart the community towards Community 1. They do no receive food and, therefore, they will arrive in Community 1 in the next time period at ($p = 2, s^r = 4$). The logic behind such a transportation decision could be that the 'grouping' of evacuees will make it easier (and quicker) to move the group to Anchorage in the coming time periods, thus making better use of plane capacities. For example, we may then choose to transport all 6 evacuees in Community 1 to Anchorage in time period 5 (thus arriving in time period 6) where moving the 2 evacuees directly to Anchorage would result in the other 4 (currently in Community 1) not arriving in Anchorage until time period 7 since we must travel from Community 2 to Anchorage then to Community 1 and then back to Anchorage. The average evacuation time with the 'grouping' would be 6 while the average evacuation time would be 6.33.

Table 8: Decisions conducted at the end of time 5 and their consequences

		Evacuee 1	Evacuee 2	Evacuee 3	Evacuee 4	Evacuee 5	Evacuee 6	Evacuee 7
Beginning of Time 4	Location	Comm. 1	Comm. 1	Comm. 1	Comm. 1	Comm. 1	Comm. 2	Comm. 2
	Priority	1	1	1	1	2	2	2
	Period	2	3	3	3	4	3	3
End of Time 4	Decision	Non Satisfied	Satisfied	Satisfied	Transported	Satisfied	Transported	Transported
Beginning of Time 5	Location	Comm. 1	Comm. 1	Comm. 1	Comm. 3	Comm. 1	Comm. 1	Comm. 1
	Priority	1	1	1	2	2	2	2
	Period	3	1	1	4	2	4	4

The summary of all the decisions conducted between time 4 and 5 along with the consequences of these decisions are provided in Table 8. Note that transportation decision also implies a non-satisfied demand.

The importance of modeling these allocation decisions, rather than allowing a greedy allocation of resources, is that it helps decrease the impact of the event on the evacuees. For example, we have examined a test scenario with 75 evacuees in the lowest priority level are in a village having 144 available units of a relief resource over a horizon of six periods. If a greedy allocation was used, i.e., allocating this resource whenever there is a demand for it, then we obtain a deprivation cost of 438.87 and 69 evacuees jumps to the next priority level. On the other hand, when using our optimization model to allocate resources, we observe that not a single evacuee jump to next priority level and the total deprivation cost turns out the be nearly the half of the greedy one (i..e, 283.89). The use of the model allows us to allocate relief resources efficiently and identify the bottlenecks in the logistical decisions.

B Extra Data Material

We illustrate the stock levels of available resources and equipment in each location in Table 9. We then share the list of resources and equipment together with the unit weight and the required amount for each priority level in Table 10.

Table 9: Initial inventory in each location

Name	Nome	Kotzebue	Point Hope	Point Lay	Atqasuk	Wainwright	Utqiaġvik	Anchorage
Water	150	150	0	0	300	0	200	5000
Food	150	150	0	0	300	0	200	5000
Sleeping Bag	0	0	0	0	75	0	0	500
Portable Shelter	0	0	0	0	50	0	0	150
Public Space	200	200	50	50	50	50	250	2000
Medical Support	25	25	0	0	0	0	45	400

Table 10: Resource and equipment list (Division of Homeland Security & Emergency Management, 2019; World Health Organization, 2019)

Name	Type	Weight (lbs)	Priority Level 1	Priority Level 2	Priority Level 3′	Priority Level 3
Water	Resource	1.54	1	2	3	3
Food	Resource	2.35	1	1	1	1
Sleeping Bag	Equipment	7.50	1	1	0	0
Portable Shelter	Equipment	26.40	1	1	0	0
Medical Support	Equipment	—	0	0	1	1

Lastly, Table 11 presents the initial deployment locations for each ship used in the baseline experiment according to each incident location.

Table 11: Initial deployment locations for ships

Ship	Incident 1	Incident 2	Incident 3	Incident 4	Incident 5
WLB 206	Point Lay	Nome	Nome	Utqiaġvik	Utqiaġvik
WLB 207	Utqiaġvik	Point Lay	Utqiaġvik	Nome	Kotzebue
WLB 212	Point Hope	Point Lay	Wainwright	Point Lay	Point Lay
WLM 175	Point Hope	Point Hope	Point Hope	Point Hope	Point Lay
282 WMEC	Kotzebue	Point Hope	Point Hope	Wainwright	Wainwright
378 WHEC	Nome	Nome	Utqiaġvik	Utqiaġvik	Utqiaġvik
154 WPC	Kotzebue	Kotzebue	Kotzebue	Kotzebue	Kotzebue

C Flow Arcs Designed

In this section, we represent the flow arcs designed for the evacuation balance constraints. If an evacuee receives equipment at any time period, the corresponding s^e becomes one regardless of the previous s^r and s^e. Recall that this implies that evacuee's equipment demand is fully met. On the other hand, if the resource demand is satisfied, then the changes, which are demonstrated in Table 12, take place according to the evacuee's priority level. Since a priority level symbolizes the seriousness of an evacuee's medical situation, decreases in periods occur slower for higher priority levels. As for the changes in priority levels, alternation takes place mainly based on the value of s^r. The situations where an evacuee's priority level increase are shown in Tables 13 and 14 (i.e., arc jumps taken place between the layers).

Table 12: Changes in s^r when resource demand is met

Priority Level	Transition
Priority Level 1	$s^r \leftarrow 1$
Priority Level 2	If $s^r \leq 4$, then $s^r \leftarrow 1$; otherwise $s^r \leftarrow s^r - 3$
Priority Level 3	If $s^r \leq 3$, then $s^r \leftarrow 1$; otherwise $s^r \leftarrow s^r - 2$

Table 13: Jumps in $A^{BNN}(p, s^r, s^e)$

Priority Level	Jump (from → to)
Priority Level 1	$(p = 1, s^r = 4, s^e \geq 2) \rightarrow (p = 2, s^r = 5, s^e + 1)$
Priority Level 2	$(p = 2, s^r = 8, s^e \geq 2) \rightarrow (p = 3, s^r = 9, s^e + 1)$
Priority Level 3	—

Table 14: Jumps in $A^{ESN}(p, s^r, s^e)$

Priority Level	Jump (from → to)
Priority Level 1	$(p = 1, s^r = 5, s^e \geq 1) \rightarrow (p = 2, s^r = 6, s^e = 1)$
Priority Level 2	$(p = 2, s^r = 9, s^e \geq 1) \rightarrow (p = 3, s^r = 10, s^e = 1)$
Priority Level 3	—

D Pseudocode of Conservative One-by-One Heuristic

In this section, we present the pseudo-code of Conservative One-by-One Heuristic

Algorithm 1: ConservativeOneByOneHeuristic

```
Input: 𝒜, 𝒜^a, C
Initialization(𝒜, C)
for v ∈ 𝒜 \ 𝒜^a do
    SendAsset(v)
nextShip ← true
nextPlane ← true
while nextShip or nextPlane do
    if nextShip then
        nextShip ← ShipAssignment(𝒜 \ 𝒜^a)
    if nextPlane then
        nextPlane ← PlaneAssignment(A)
Finalize(𝒜, 𝒜^a)
```

Algorithm 2: Initialization

```
Input: 𝒜, C
lastTime[i] := the last time period when asset i is used
lastLoc[i] := the location of asset i at lastTime
for a ∈ 𝒜 do
    for c ∈ C do
        if π_{a,i} = 1 then
            X_{a,c,ω_a} ← 1
            lastTime[a] ← ω_a
            lastLoc[a] ← c
```

E Method Selection

In this section, we compare the performance of solving the IP directly, warm-starting with both OTH and COBOH. We first conduct our comparison in the baseline experiment. We then create another setting where the runway lengths of the airports located in the small villages are assumed to be upgraded implying that all

Algorithm 3: POPULATIONUPDATE

Input: $i \in C, depart, j \in C, arrival, carry$

for $depart \leq t \leq |T|$ **do**
  $w_{i,t} \leftarrow w_{i,t} - carry$
for $arrival \leq t \leq |T|$ **do**
  $w_{j,t} \leftarrow w_{j,t} + carry$

Algorithm 4: FINALIZE

Input: $\mathcal{A}, \mathcal{A}^a$

for $a \in \mathcal{A}^a$ **do**
  while $lastTime[a] \leq |T|$ **do**
    $num \leftarrow$ number of planes located in $lastLoc[a]$ at $lastTime[a]$
    if $num + 1 \leq \kappa_{lastLoc[a]}$ **then**
      $X_{a,lastLoc[a],lastTime[a]} \leftarrow 1$
      $lastTime[a] += 1$
    else
      $loc \leftarrow$ a location where there is enough airport capacity at $t = lastTime[a] + \tau_{a,lastLoc[a],loc}$ and plane a can land in (i.e., $\theta_{loc,i} = 1$)
      $Y_{lastLoc[a],loc,a,lastTime[a]} \leftarrow 1$
      $X_{a,loc,t} \leftarrow 1$
      $lastTime[a] \leftarrow t$
      $lastLoc[a] \leftarrow loc$
for $v \in \mathcal{A} \setminus \mathcal{A}^a$ **do**
  while $lastTime[v] \leq |T|$ **do**
    $lastTime[v] += 1$
    $X_{a,lastLoc[v],lastTime[v]} \leftarrow 1$

Algorithm 5: SENDASSET

Input: $a \in \mathcal{A}$

if $a \in \mathcal{A} \setminus \mathcal{A}^a$ **then**
  $target \leftarrow CruiseShip$
else
  $target \leftarrow Anchorage$
$arrival \leftarrow lastTime[a] + \tau_{a,lastLoc[a],target}$
if $arrival \leq |T|$ **then**
  $Y_{lastLoc[a],target,a,lastTime[a]} \leftarrow 1$
  $X_{a,target,arrival} \leftarrow 1$
  $lastTime[a] \leftarrow arrival$
  $lastLoc[a] \leftarrow target$
else
  while $lastTime[a] < |T|$ **do**
    $X_{v,lastLoc[a],lastTime[a]+1} \leftarrow 1$
    $lastTime[a] += 1$
  $\mathcal{A} \leftarrow \mathcal{A} \setminus a$

Algorithm 6: AIRPORTCHECK

Input: $a \in \mathcal{A}^a, \nu \in V, depart, t, transit$

$decision \leftarrow true$
if $transit$ **then**
  $airportTime \leftarrow depart - t$
  $num \leftarrow$ number of planes located in ν at $airportTime$
  if $num + 1 > \kappa_\nu$ **then**
    $decision \leftarrow false$
  else
    while $airportTime > lastTime[a]$ **do**
      $num \leftarrow$ number of planes located in $lastLoc[a]$ at $airportTime$
      if $num + 1 > \kappa_{lastLoc[a]}$ **then**
        $decision \leftarrow false$
        $break$
      else
        $airportTime- = 1$
else
  $airportTime \leftarrow lastTime[a]$
  while $airportTime \leq depart$ **do**
    $num \leftarrow$ number of planes located in ν at $airportTime$
    if $num + 1 > \kappa_\nu$ **then**
      $decision \leftarrow false$
      $break$
    else
      $airportTime+ = 1$
return *decision*

Algorithm 7: ShipAssignment

```
Input: 𝒜 \ 𝒜^a, V
map[] ← null
for v ∈ 𝒜 \ 𝒜^a do
    stay ← false
    r_v ← 𝕄
    if lastTime[v] = |T| then
        𝒜 ← 𝒜 \ {v}
        next v
    for ν ∈ V do
        t ← τ_{v,Ship,ν}
        if ∄t > 0 then
            next v
        popCruiseShip ← min. number of population in CruiseShip between lastTime[v] and
          |T|
        minCap ← the last min. non-zero available capacity in ν between lastTime[v] + t and |T|
        minTime ← the corresponding time period of minCap
        arrival ← max(lastTime[v] + t, minTime)
        if minCap = 0 or arrival > |T| then
            next ν
        if lastTime[v] + t < minTime then
            stay ← true
        carry ← min(μ_v, popCruiseShip, minCap)
        if r_v < carry/arrival then
            r_v ← carry/arrival
            map[v] ← {ν, r_v, arrival, carry, stay}
v* ← argmin_{m∈map} m.get(arrival). If there is a tie, then v* ← argmax_{m∈map} m.get(r_v)
ν*, r_v*, arrival*, carry*, stay* ← map[v*]
t* ← τ_{v*,CruiseShip,ν*}
if stay* then
    depart ← arrival* − t*
    Y_{CruiseShip,ν*,v*,depart} ← 1
    X_{v*,ν*,arrival*} ← 1
    PopulationUpdate(CruiseShip, depart, ν*, arrival*, carry*)
    while lastTime* < depart do
        X_{v*,CruiseShip,depart} ← 1
        depart− = 1
else
    Y_{CruiseShip,ν*,v*,lastTime[v*]} ← 1
    X_{v*,ν*,arrival*} ← 1
    PopulationUpdate(CruiseShip, lastTime[v*], ν*, arrival*, carry*)
lastTime[v*] ← arrival*
lastLoc[v*] ← ν*
SendAsset(v*)
```

$rem \leftarrow$ the remaining population in *CruiseShip* after $arrival^*$
if $rem = 0$ ***or*** $\mathcal{A} \setminus \mathcal{A}^a = \emptyset$ **then**
  return *false*
else
  return *true*

Algorithm 8: PLANEASSIGNMENT

Input: $\mathcal{A}^a, V$
$map[] \leftarrow null$
for $a \in \mathcal{A}^a$ **do**
  $transit \leftarrow false$
  $r_v \leftarrow \mathbb{M}$
  if $lastTime[a] = |T|$ **then**
    $\mathcal{A}^a \leftarrow \mathcal{A}^a \setminus \{a\}$
    next a
  for $\nu \in V$ **do**
    $t \leftarrow 0$
    if $\nu = currentLoc$ **then**
      $minPop \leftarrow$ the last min non-zero available population in ν between $lastTime[a] + t$ and $|T|$
      $depart \leftarrow$ the corresponding time period of $minPop$
    else if $\theta_{v,i} = 1$ **then**
      $t \leftarrow \tau_{a,\text{lastLoc[a]},\nu}$
      $minPop \leftarrow$ the last min. non-zero available pop. in ν between $lastTime[a]$ $+t$ and $|T|$
      $depart \leftarrow$ the corresponding time period of $minPop$
      $transit \leftarrow true$
    else
      continue
    $canLand \leftarrow AirportCheck(a, \nu, depart, t, transit)$
    if $depart \geq |T|$ ***or*** $minPop = 0$ ***or*** $!canLand$ **then**
      next a
    $carry \leftarrow min(minPop, \psi_a)$
  if $r_v < \frac{carry}{depart}$ **then**
    $r_v \leftarrow \frac{carry}{depart}$
    $map[a] \leftarrow \{\nu, r_v, depart, carry, transit\}$

for $a \in \mathcal{A}^a$ **do**
  if $a \subsetneq map$ **then**
    $num \leftarrow$ number of planes located in $lastLoc[a]$ at $lastTime[a]+1$;
    if $num + 1 \leq \kappa_{lastLoc[a]}$ **then**
      $X_{a,lastLoc[a],lastTime[a]+1} \leftarrow 1$;
      $lastTime[a]+=1$;
    else
      for $\nu \in V$ **do**
        $t \leftarrow lastTime[a] + \tau_{a,lastLoc[a],\nu}$;
        $totalPop \leftarrow$ total number of population in ν after $lastTime[a]+t$;
        $num \leftarrow$ number of planes located in ν at $lastTime[a]+t$;
        if $totalPop = 0$ ***and*** $num + 1 \leq \kappa_\nu$ **then**
          $Y_{lastLoc[a],\nu,a,lastTime[a]} \leftarrow 1$;
          $X_{a,\nu,t} \leftarrow 1$;
          $lastTime[a] \leftarrow lastTime[a] + t$;
          $lastLoc[a] \leftarrow \nu$;
          break ;
$a^* \leftarrow \arg\min_{m \in map} m.get(depart)$. If there is a tie, then $a^* \leftarrow \arg\max_{m \in map} m.get(r_v)$
$\nu^*, r_v{}^*, depart^*, carry^*, transit^* \leftarrow map[a^*]$
if $transit$ **then**
  $t \leftarrow \tau_{a^*,lastLoc[a^*],\nu^*}$
  $leave \leftarrow depart^* - t$;
  $Y_{lastLoc[a^*],\nu^*,a^*,leave} \leftarrow 1$
  $X_{a^*,\nu^*,leave} \leftarrow 1$
  $lastLoc[a^*] \leftarrow \nu^*$
  $arrival \leftarrow depart^* + \tau_{a^*,\nu^*,Anchroage}$
  $PopulationUpdate(\nu^*, depart^*, Anchroage, arrival, carry^*)$;
  while $lastTime[a^*] < depart^*$ **do**
    $X_{a^*,\nu^*,depart^*} \leftarrow 1$
    $depart^* -= 1$
else
  $arrival \leftarrow depart^* + \tau_{a^*,\nu^*,Anchroage}$
  while $lastTime[a^*] \leq depart^*$ **do**
    $X_{a^*,\nu^*,depart^*} \leftarrow 1$
    $depart^* -= 1$
  $PopulationUpdate(\nu^*, depart^*, Anchorage, arrival, carry^*)$
$lastTime[a^*] \leftarrow depart^*$
$SendAsset(a^*)$
if $\mathcal{A}^a = \emptyset$ **then**
  return *false*
else
  return *true*

plane types can land in and take off from those airports. With the latter experiment, our goal is to examine the performance of the solution methods when there is a change in the baseline setup and we observed that the decisions become more difficult in this setting.

We present how the two heuristic approaches performed with respect to their initial optimality gaps in Tables 15 and 16 which correspond to the baseline experiment and the experiment with the upgraded runways, respectively. The optimality gaps are calculated as follows. After obtaining a solution vector via a heuristic method, the IP model is warm-started with the transportation variables X_{ait} and Y_{ijat}. Note that even though we can include the number of evacuees transported (i.e., m_{ijat}) in the solution vector, our preliminary experiments indicated that providing only the former variables yields better initial objective values. After warm-starting the model, the initial objective value and the best bound reported by the solver by the end of the time limit are used as a UB and an LB, respectively. The optimality gap then is computed as $\frac{(UB-LB)}{LB}$.

Table 15: Comparison of the initial optimality gaps in the baseline experiment

Incident	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5
Num. of People	800	1200	1600	800	1200	1600	800	1200	1600	800	1200	1600	800	1200	1600
OTH	0.54%	0.01%	0.05%	0.22%	1.01%	0.16%	2.53%	3.09%	2.65%	0.01%	0.08%	0.77%	0.40%	0.09%	0.36%
COBOH	0.38%	0.88%	0.65%	12.36%	18.81%	6.45%	52.78%	24.99%	16.57%	23.43%	15.57%	9.89%	0.05%	0.09%	0.33%

Table 16: Comparison of the initial optimality gaps in the experiment with the upgraded runways

Incident	1	1	1	2	2	2	2	3	3	4	4	4	5	5	5
Num. of People	800	1200	1600	800	1200	1600	800	1200	1600	800	1200	1600	800	1200	1600
OTH	0.06%	0.39%	0.20%	0.62%	2.41%	0.66%	0.09%	0.05%	0.16%	3.99%	1.71%	1.71%	4.63%	3.84%	2.10%
COBOH	0.38%	0.95%	1.29%	4.10%	5.72%	7.69%	6.51%	6.64%	8.06%	6.69%	7.13%	7.90%	0.05%	0.09%	0.33%

Recall that heuristic approaches proposed solely focus on the transportation decisions and in essence the OTH solves the transportation version of the model to the optimality. In both experiments, it can be seen that the OTH produces a better initial optimality gap compared to the COBOH in most of the instances. However, the COBOH method outperforms the OTH with respect to the initial optimality gaps in Incident 5 in both experiments. In addition, it produces a better initial gap in Incident 1-800 in the baseline experiment. This can be explained by the observation that if there are large local communities capacity-wise around an incident area (e.g., Incident 1 and Incident 5), the COBOH gives a good approximation of the optimal solution. An important observation with respect to this table is that significant improvements in terms of the objective can be obtained by using optimization-based approaches (i.e., OTH) as opposed to relying on intuitive approaches to responding to the mass rescue event.

We now focus on the final results obtained with three methods in two experiments. Tables 17 and 18 summarize the comparisons in terms of the solution times and the final optimality gaps for the baseline experiment and the experiment with the upgraded runways, respectively. In the baseline experiment, while we observe that the number of instances solved to optimality with three methods are close to each other, the IP model solved with CPLEX did not return any incumbent solution for Incident 3-1200. As for the experiment with the upgraded runways, while the IP model reaches the optimal solution via CPLEX in six scenarios, the problem is solved to optimality in seven scenarios with the support of the heuristic approaches.

However, while CPLEX did not produce any solution within an hour for Incident 4-1600, it returned a poor solution (i.e., an optimality gap of 5.90%) for Incident 4-1200. Overall, we observe that since the larger local communities with higher capacities (i.e., Kotzebue, Nome, and Utqiaġvik) are closer to the Incidents 1,2, and 5, it becomes relatively easier to obtain a high quality solution with CPLEX for those specific incident areas in both experiments.

Table 17: Comparison of the solution methods in the baseline experiment [Time (in mins), Gap ($\%$)]

		IP		OTH		COBOH	
Incident	Num. of People	Time	Gap	Time	Gap	Time	Gap
Incident 1	800	16.43	0.00	9.72	0.00	13.05	0.00
Incident 1	1200	60.00	0.26	51.00	0.00	60.00	0.07
Incident 1	1600	60.00	0.12	60.00	0.03	60.00	0.15
Incident 2	800	12.22	0.00	4.49	0.00	14.41	0.00
Incident 2	1200	13.89	0.00	13.49	0.00	6.42	0.00
Incident 2	1600	51.55	0.00	60.00	0.14	60.00	0.19
Incident 3	800	60.00	1.65	60.00	1.55	60.00	4.00
Incident 3	1200	60.00	—	60.00	0.47	60.00	0.59
Incident 3	1600	60.00	0.89	60	1.19	60.00	0.87
Incident 4	800	41.1	0.00	7.62	0.00	13.78	0.00
Incident 4	1200	24.29	0.00	6.61	0.00	7.02	0.00
Incident 4	1600	28.31	0.00	4.82	0.00	8.41	0.00
Incident 5	800	3.69	0.00	3.01	0.00	2.53	0.00
Incident 5	1200	3.57	0.00	3.13	0.00	2.79	0.00
Incident 5	1600	4.46	0.00	3.07	0.00	2.86	0.00

As for warm-starting the model with the solutions generated by the heuristic approaches, even though the OTH produces a better initial solution (see Tables 15 and 16) in most of the cases, when it comes to the overall performance in terms of the solution time, we do not observe a consistent difference. The warm-start with the OTH produces better final results in more scenarios than warm-start with the COBOH (e.g., Incident 1-1200 and Incident 1-1600 in both Tables 15 and 16).

Table 18: Comparison of the solution methods in the experiment with the upgraded runways

		IP		OTH		COBOH	
Incident	Num. of People	Time	Gap	Time	Gap	Time	Gap
Incident 1	800	45.28	0.00	17.78	0.00	26.02	0.00
Incident 1	1200	60.00	0.31	60.00	0.14	60.00	0.24
Incident 1	1600	60.00	0.29	60.00	0.12	60.00	0.27
Incident 2	800	7.60	0.00	11.23	0.00	9.53	0.00
Incident 2	1200	60.00	0.85	60.00	0.05	60.00	0.05
Incident 2	1600	60.00	1.01	60.00	0.19	52.44	0.00
Incident 3	800	39.74	0.00	60.00	0.04	60.39	0.04
Incident 3	1200	60.00	1.19	60.00	0.02	60.00	0.02
Incident 3	1600	60.00	1.54	60.00	0.16	60.00	0.30
Incident 4	800	60.00	0.02	7.20	0.00	33.34	0.00
Incident 4	1200	60.00	5.90	10.35	0.00	60.35	0.02
Incident 4	1600	60.00	—	60.00	0.05	60.39	0.04
Incident 5	800	5.90	0.00	5.71	0.00	3.80	0.00
Incident 5	1200	7.39	0.00	5.12	0.00	4.07	0.00
Incident 5	1600	8.11	0.00	5.77	0.00	5.27	0.00

F Summary of Other References and Modelling Process

We obtain the population numbers and trauma centers status in Arctic Alaska presented in Table 1 via U.S. Bureau of the Census (2019) and Alaska Department of Health and Social Services (2018), respectively. In addition, the reference list used to generate Table 6 where we list the type of assets together with their specifications include (Griner, 2013; USCG, 2016; Office of Aviation Forces, 2019; Sherman, 2000; United States Air Force, 2008; Alaska Airlines, 2020; Brady, 2019; RavnAir Alaska; Cessna, 2019).

The modeling process for our study involved observing tabletop planning exercises and stakeholder interviews to form some of the core assumptions of our model. We were able to observe the Northwest Passage Tabletop Exercise in 2017 involved a variety of stakeholders from Canada and the United States and served as a planning exercise to understand the response to a MRE. This helped to highlight some of the considerations that would go into decision-making in real-time. We also asked initial scoping questions to officials in District 17 of the United States Coast Guard (USCG), which covers the entire state of Alaska. These officials had significant experience in search and rescue (including participating in the aforementioned tabletop exercise). We were also able to answer important questions from the practitioner's perspective in building our model and data including:

- What would be the process of moving evacuees out of the Arctic? Answer: evacuate them using vessels to Arctic communities and then use air assets to move them out of these communities.
- What type of assets would be used to transport evacuees to shore? Answer: a combination of USCG vessels and vessels of opportunity.

- Where and how would evacuees be transported once on-shore? Answer: A combination of federal, state, and privately-owned aircraft.

- How would the Air National Guard and the U.S. Air Force be involved? Answer: They would be significant in terms of the logistics required to support evacuees with resources and assets.

We now discuss the operational/physical costs incurring during the transportation of evacuees. We note that much of these costs are paid pre-response (e.g., if the USCG responds, the personnel in the response are salaried and, as a second example, stockpiles of dedicated response resources are often maintained). In terms of variable costs, it is initially assumed that the responsible party, likely the operator of the cruise ship, will assume the the costs of search, rescue, recovery and salvage operations. However, the U.S. Oil Pollution Act of 1990 required that when the RP is not solvent, able to assume the costs or cannot be located, the event is federalized and the response and rescue operations are funded by federal funding, including the Harbor Maintenance Trust Fund (US EPA, 2020).

In terms of examining costs, we focus on variable costs associated with the response. For example, if a plane carries relief commodities to a village and leaves the location without taking any evacuee, we consider such operation a 'cost' since it has not moved evacuees out of the Arctic. On the other hand, if the plane leaves its location with evacuees on board, then incorporating operating costs to the objective would only change the trade-offs between costs and evacuation times if we chose to increase the evacuation time portion of the objective. We ran some experiments and discovered that when we restrict the number of air operations, where a plane goes into a village with resources and/or equipment and leaves without picking anyone up, the solutions obtained remains the same in every incident compared to the 'original' setting. This implies that the model produces the same objective with or without incorporating the operational costs or air flights. In other words, even if we associate each air operation with a cost, the model would produce the same / similar solutions in each incident as the ones we have obtained unless we prioritized cost above evacuation. A similar observation would occur should we begin limiting the number of ships used in moving passengers from the cruise ship to the villages. Therefore, despite these costs being a potential criteria to evaluate the response, they do not need to be examined in more detail in our experiments.

G Illustration of Deprivation Cost Function

In order to best illustrate the concept of the hysteric case in the deprivation cost function, Fig 18 depicts the costs as the time without a resource increases. Suppose an evacuee has not been provided with water for eight time periods (from A to C). For simplicity, also assume that if the demand is satisfied at time t corresponding period 8 (at point C), the deprivation time declines to period 5 - in other words, to point B. Note that the curves D-E and C-B are identical. This implies that though the demand is met, some amount of deprivation cost is still incurred due to the human suffering as a result of high deprivation time.

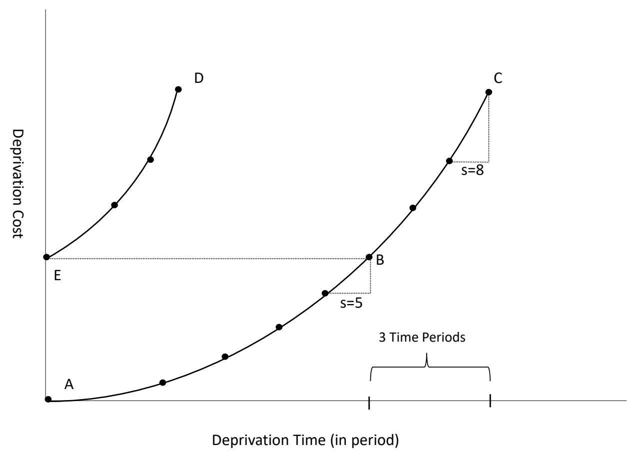


Figure 18: Illustration of deprivation cost function (adapted from Pérez-Rodríguez and Holguín-Veras (2015))